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BEAST: A model for the assessment of system-wide risks and macroprudential policies

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Abstract

The Banking Euro Area Stress Test (BEAST) is a large-scale semi-structural model developed to analyse the euro area banking system from a macroprudential perspective. The model combines the dynamics of approximately 90 of the largest euro area banks with those of individual euro area economies. It reflects the heterogeneity of banks by replicating the structure of their balance sheets and profit and loss accounts. Additionally, it allows banks to adjust their assets, funding mix, pricing decisions, management buffers, and profit distribution along with individual bank conditions, including their capital and liquidity requirements, and other supervisory limits. The responses of banks impact credit supply conditions and have feedback effects on the macroeconomic environment. Stochastic solutions of the model provide a solid foundation for investigating multiple scenarios, deriving at-risk measures, and estimating model uncertainty. The model is regularly utilised to assess the resilience of the euro area banking sector, including in the biennial ECB macroprudential stress tests, as well as to analyse the effects of regulatory, macroprudential, and monetary policy changes.

Keywords: macro stress test, macroprudential policy, banking sector deleveraging, real economy-financial sector feedback loop

JEL Classification: E37, E58, G21, G28

Non-technical summary

Macroprudential policy assessment and stress testing play vital roles in supporting the ECB's macroprudential mandate. This paper introduces the Banking Euro Area Stress Test (BEAST), a semi-structural macro-micro model designed to fulfil tasks derived from this mandate. The BEAST model incorporates a macroeconomic block with cross-country spillovers, a comprehensive representation of the banking sector, and dynamic interdependencies between the real economy and the banking sector. It captures the diverse behaviour of approximately 90 individual euro area banks, subject to system-wide and bank-specific capital requirements, buffers, and liquidity standards, and influenced by both conventional and unconventional monetary policy.

The BEAST model serves as a "workhorse model," a versatile tool for macroprudential stress testing, scenario analysis, and policy impact assessment with implications for financial stability. As the ECB's primary tool for macroprudential stress testing, the model features an advanced micro-macro design, simultaneous feedback loops, and high flexibility. It allows for conducting top-down stress tests with dynamic balance sheet adjustments, considering amplification mechanisms such as the interplay between solvency and funding costs and the potential disruptive effects of stress in the banking system on the real economy. Its detailed specification of supervisory, macroprudential, and monetary policy measures, along with their transmission channels within banks and the broader economic system, enables effective support for a banking sector-targeted policy assessment.

The model's regular and versatile applications have led to the development of a sophisticated infrastructure, facilitating seamless model updates and its application at short notice. The updates concern the latest macrofinancial and bank-level data, as well as forward-looking aspects such as the future economic outlook based on ECB staff's macroeconomic projections and expected policy paths. The semi-structural design of the model accommodates the dynamic absorption of many more qualitative and supervisory information sources.

The model has supported multiple methodological innovations in bank stress testing and policy assessment. It has allowed for exploring the use of parametric and bootstrapped stochastic shocks to inject and assess macrofinancial uncertainty, examining the evolution of at-risk measures, redefining scenario designs to ensure consistency with desired narratives, and exploring parameter uncertainty and its impact on model results in policy exercises.

Although the infant version of the model and its core mechanisms were documented in Budnik et al. [2020], this paper presents a snapshot of a mature model fully integrated into the policy process. Over four years of development, the model has been expanded with new blocks, evolving and maturing through its support of various analytical projects. New equations have been added, and earlier fine-tuned and further empirically validated. This paper marks the completion of the model and serves as a testament to the capabilities and limitations of semi-structural models in the realm of financial stability. It also aims to inspire further exploration of risk and policy assessment techniques that strike a balance between computational intensity and economic relevance.

1 Introduction

The string of bank failures during the global financial crisis (GFC) resulted in deep scepticism about bank-reported capital adequacy and prompted supervisors to look for new ways to reliably assess and set targets for bank solvency (Schuermann [2014]). The crisis exposed the limitations of the so-called microprudential supervision, where supervisors focused primarily on individual institutions to ensure that they are safe, sound, and resilient to adverse shocks. However, system-wide financial risks could grow unchecked. Since the GFC, regulators have been expanding their toolkit to achieve a more holistic approach to financial supervision, commonly known as a macroprudential perspective (IMF [2022]). The ultimate objective of macroprudential policy is to ensure financial stability[1]. Following this ambition, the new Basel III regulatory framework introduced new capital and liquidity standards coupled with an arsenal of new macroprudential tools. Furthermore, supervisory bodies adopted stress testing and internal risk management tools previously used by banks, to analyse institutions' complex balance sheets, uncover their vulnerabilities, and respond promptly to their capital and liquidity needs (Bookstaber et al. [2013]).[2]

Macroprudential policy assessment and stress testing are two crucial analytical building blocks that support the macroprudential mandate of the ECB. The EU regulatory framework has been revised to incorporate a macroprudential perspective, with the ECB (and central banks in general) receiving a new mandate.[3] Moreover, the recent ECB's strategy review (ECB [2022]) recognises the importance of effective macroprudential policy for the smooth conduct of monetary policy and states that "there is a clear conceptual case for the ECB to take financial stability considerations into account in its monetary policy deliberations". This paper describes a semi-structural macro-micro Bank Euro Area Stress Test (BEAST) model developed to support the ECB's macroprudential mandate. The BEAST is a widely used "workhorse model" used in macroprudential stress testing, scenario analysis, and impact assessments of policies that influence financial stability. It incorporates a macroeconomic block including cross-country spillovers via trade linkages, a detailed representation of around 90 individual euro area banks (covering roughly 70% of the euro area banking sector), and dynamic interdependencies between the real economy and the banking sector. Banks are subject to system-wide and bank-specific capital requirements and buffers, liquidity standards, and can be impacted by conventional and unconventional monetary policy measures. The model's macro-financial and be-

[1] Financial stability is defined as a condition in which the financial system as a whole is capable of withstanding shocks and the unravelling of financial imbalances. This includes making the entire financial system more resilient and limiting the build-up of vulnerabilities, in order to mitigate systemic risk and ensure that financial services continue to be provided effectively to the real economy (ECB [2022a]).

[2] Supervisory stress testing broadly refers to exercises designed and executed by supervisory authorities. For a history and comparison of supervisory stress testing in different jurisdictions, see, for example, Baudino et al. [2018] or Pliszka [2021].

[3] Effective from 1 January 2014, the SSM Regulation includes a broad set of macroprudential instruments and grants the ECB the power to use macroprudential instruments in addition to the national regulation, if necessary, to address macroprudential risks in the SSM countries. In addition to CRR/CRD IV, referring to Directive 2013/36/EU and Regulation (EU) N° 575/2013, the SSM Regulation refers to Council Regulation (EU) No. 1024/2013 of 15 October 2013 conferring specific tasks on the European Central Bank concerning policies relating to the prudential supervision of credit institutions (OJ L 287, 29.10.2013, p. 63). In particular, Article 5 of the SSM Regulation provides that the ECB may, if deemed necessary, apply higher requirements for capital buffers than those applied by the national competent authorities or national designated authorities of participating Member States. These capital buffers are to be held by credit institutions at the relevant level in addition to own funds requirements. The ECB may also apply more stringent measures aimed at addressing macroprudential risks at the level of credit institutions subject to the procedures set out in Regulation (EU) No 575/2013 and Directive 2013/36/EU in the cases specifically set out in relevant Union law.

havioural equations are estimated with the use of macroeconomic and bank-level data, and all the equations are solved simultaneously to efficiently incorporate the desired feedback loops. In this manner, the BEAST model significantly enhances the methodological toolkit of the ECB, allowing it to conduct sophisticated analyses of the banking sector without direct involvement from financial institutions.

The model employs a semi-structural approach that combines data-driven and structural elements. Most macrofinancial and bank responses are estimated with transaction-, bank-, or country-level data. This concerns bank loan adjustments in terms of price and volumes or funding costs. Other predominantly data-driven elements include multiple calibrated parameters reflecting the structures of bank balance sheets and profit and loss accounts. Theoretical foundations inform all empirical specifications of behavioural equations, thereby ensuring robust long-term properties of the model. It anchors mechanisms governing banks' liability structure adjustments or profit distribution restrictions. Other structural elements are the explicit incorporation of regulatory limits (such as for the Maximum Distributable Amount (MDA)), accounting rules, and the aggregation of the impact on individual banks' into economy-wide outcomes.

The model provides projections for various categories relevant to financial stability considerations. This concerns lending to the non-financial private sector, different bank liability components, loan loss provisioning, bank solvency, and maturity mismatches. For all categories, it combines the ability to preserve the heterogeneity of individual banks with an aggregate and temporal perspective.

The model is well suited to support regulatory and prudential policy assessments, considering their intricate interactions with each other and other policies. It captures a wide range of micro- and macroprudential capital- and liquidity-based instruments, as well as conventional and unconventional monetary policy. Moreover, the policy impact assessment benefits from the comprehensive treatment of intrabank and interbank transmission channels and the incorporation of macrofinancial feedback loops.

The construction of the model was kicked-started in the context of the preparations for the 2018 macroprudential stress test (Budnik et al. [2019]). Since 2016, the ECB has prepared what was initially called a "top-down macroprudential extension" of the supervisory bank stress test to quantify second-round effects not directly observed from the use of the static balance sheet bottom-up stress test coordinated by the European Banking Authority (EBA) and the Single Supervisory Mechanism (SSM).[4][5] The macroprudential stress test aimed to evaluate bank reactions, acknowledge that they can act as shock amplifiers, and remedy other shortcomings of the EBA/SSM exercise that might limit its realism, such as methodologically imposed caps and floors. Its less emphasised ambition was to increase the independence from the bottom-up approaches, which could also provide banks with substantial leeway for strategic under-reporting of vulnerabilities,[6], are often deemed too resource intensive, require a strenuous effort of both banks and supervisors, and lack the flexibility for running the analysis in an ad hoc manner (de Guindos [2019], Kok et al. [2021]). Since 2018, the BEAST model has succeeded its predecessor, the Stress Test Analytics for Macroprudential Purposes in the euro area STAMP€ (Dees et al. [2017]) as the main tool for macroprudential and top-down stress testing.[7]

[4]For a motivation and exposition, see Dees et al. [2016].

[5]Bottom-up stress tests are performed by banks as part of a system-wide exercise, where supervisory authorities provide banks with common scenarios and assumptions (Baudino et al. [2018]). The EBA/SSM EU-wide stress testing exercise has been conducted biennially since 2009 in a constrained bottom-up manner.

[6]For empirical evidence of the "gaming" behaviour of banks participating in the stress test, see Philippon et al. [2017], Niepmann and Stebunovs [2018] or Quagliariello [2019].

[7]Top-down stress tests are performed by supervisory authorities directly using their own stress test frameworks including data, scenarios, assumptions and models (Baudino et al. [2018]).

The BEAST model has gradually evolved into a workhorse model applied to a wide range of financial stability issues. Since its birth, the model has consistently supported risk assessment. The risk assessment works covered identifying vulnerabilities to different macroeconomic shocks, such as in the euro area macroprudential stress test of the banking sector at the start of the coronavirus pandemic[8], climate stress testing and bank interest rate risk sensitivity analysis (Budnik et al. [2022d]). Furthermore, it has supported multiple policy evaluation projects, including the impact evaluation of the Basel III finalisation reforms (Budnik et al. [2021b]), the ECB guidance on non-performing loans (Budnik et al. [2022c]), and tracking the evolution of macroprudential policy stance over time (Budnik et al. [2022a]). The model has also been used for the calibration of macroprudential buffers and the identification of optimal macroprudential policy responses (Budnik et al. [2022b]), to support ECB communication (Enria [2020]), and to understand the interaction between macroprudential and monetary policy.

To place the BEAST model in the literature, it is important to note that it represents a brand-new approach to stress testing. Its predecessor, the Stress-Test Analytics for Macroprudential Purposes in the euro area (STAMP€) model (Dees et al. [2017]), belongs to the family of so-called modular approaches. The STAMP€ model is a rich platform of interconnected models that leverages the infrastructures built for providing benchmark risk parameters in regular EU-wide stress tests. It operates as a hybrid environment, utilising the results of the supervisory stress test with constant bank balance sheets as input, and assessing the amplification mechanism by sequentially applying different models. However, such an approach inherently suffers from inconsistency and a limited ability to describe the amplification mechanisms. Other large-scale models used by supervisory institutions, such as FLARE (Federal Reserve Board of the USA) (Correia et al. [2022]), MFRAF (Bank of Canada) (Fique [2017]), DELFI (De Nederlandsche Bank) (Berben et al. [2018]), or Arnie (Bank of Austria) (Feldkricher et al. [2013]), also rely on a modular design and share similar weaknesses.

The BEAST diverges from the fragmented piecemeal or suite-of-models approach. The BEAST model combines behavioural assumptions, the mapping of economic conditions into bank risk parameters, and accounting identities, and solves them as a simultaneous system. This approach strives to encapsulate all relevant elements of an amplification mechanism in each solution, thus preserving internal consistency of feedback mechanisms, and resembling the proposal of Krznar and Matheson [2017].[9]

The BEAST introduces various methodological innovations in the realm of bank stress testing and policy assessment. For example, it experiments with parametric and bootstrapped stochastic shocks to inject and assess macrofinancial uncertainty or learn about the evolution of at-risk measures. The latter can then inform about the resilience-building benefits of policy measures. The stochastic simulations of the model, facilitated by its semi-structural design, allow for a new approach to scenario design, where the relevant scenario is sourced from a family of statistically plausible scenarios and remains consistent with the desired narrative. Additionally, the BEAST model can evaluate the uncertainty of the parameters and map it to the uncertainty of the model results in policy exercises.

This paper describes a mature model that is fully phased-in into the policy process. Budnik et al. [2020] documented the infant version of the model, providing a snapshot of its design and mechanisms around a year from its inception. Since its last publication, the model has been

[8] For more details on the top-down macroprudential stress test, see the ECB's report Macroprudential stress test of the euro area banking system amid the coronavirus (COVID-19) pandemic.

[9] Alternative approaches, such as agent-based network models that can specifically address interconnectedness and spill-overs (see e.g. Grzegorz [2018] or Laliotis et al. [2019]), or DSGE models with financial frictions (see e.g. Foroni et al. [2022]) offer other possibilities but come with their own challenges in terms of calibration and incorporating non-linear behaviour.

enriched with new blocks, including detailed modelling of bank liabilities, funding costs, and liquidity management, endogenous risk weights, and new mechanisms such as the feedback loop between solvency and funding costs, endogenous write-offs, and the interplay between management buffers and dividend payouts. The model has undergone a comprehensive validation using both qualitative and quantitative criteria. It has also evolved and matured through its involvement in analytical projects, leading to the incorporation of new supervisory tools (e.g. loan moratoria or NPL coverage expectations) and policies (e.g. public guarantees, profit distribution restrictions, or ECB unconventional monetary policy measures). Many of its equations have been further fine-tuned and empirically validated.[10] The growing experience with the model and the increase in the numerical efficiency of its solution have expanded its use to stochastic applications.

Regular applications of the model led to the development of a rich model infrastructure. The infrastructure consists of many modules that facilitate model updates with new information, support model adaptations, ensure its stability, e.g. via regular backups, minimise the time needed to derive, and help analysing model outcomes. Its relevant role is to update the dynamic absorption and the model with various sources of available information, including the most recent realisation of macroeconomic data and detailed information on bank balance sheets and profit and loss accounts obtained from supervisory reporting sources. The model also accommodates forward-looking information, such as macroeconomic projections of ECB staff (ECB [2022c]), and information about already announced macroprudential and supervisory policies. Accordingly, the information from ECB and non-ECB sources can be automatically uploaded, integrated, and validated.

The paper marks the end of the conceptual development of the model and serves as testament to the capabilities and limitations of semi-structural models in the field of financial stability. The construction of a semi-structural model with individual banks has demonstrated that such large frameworks can be effectively created and utilised within a policy institution, and numerical challenges can be overcome. Additionally, it has highlighted the unique advantages of these models, including their ability to capture the heterogeneity of the system, exploit rich information, and provide narratives despite their size. The implementation of the BEAST model in the financial stability sphere has demonstrated its ability to address numerous questions in the field and serve as an anchor for policy discussions over time and across analyses. Furthermore, the phased implementation of the BEAST model demonstrated advantages in developing a policy model in conjunction with its regular policy implementation. However, the creation of models of this type and size requires a significant investment of resources.

The model has provided new evidence regarding the relevance and mechanisms of the real economy - banking sector and funding-solvency feedback loops. Amplification can arise from the combination of bank heterogeneity, regulatory and accounting constraints, and the resulting asymmetries in bank responses that are more likely to emerge under stressed economic or financial conditions. It can contribute to the deepening of recessions and financial strains, as illustrated by an additional reduction in GDP by 2.6% under very severe economic conditions and by 1. 6% under severe economic conditions, in 3-year stress test scenarios. The asymmetries of bank responses can also be reflected in the propagation of large-scale monetary policy shocks.

This paper is structured as follows. Chapter 2 provides a high-level overview of the model.

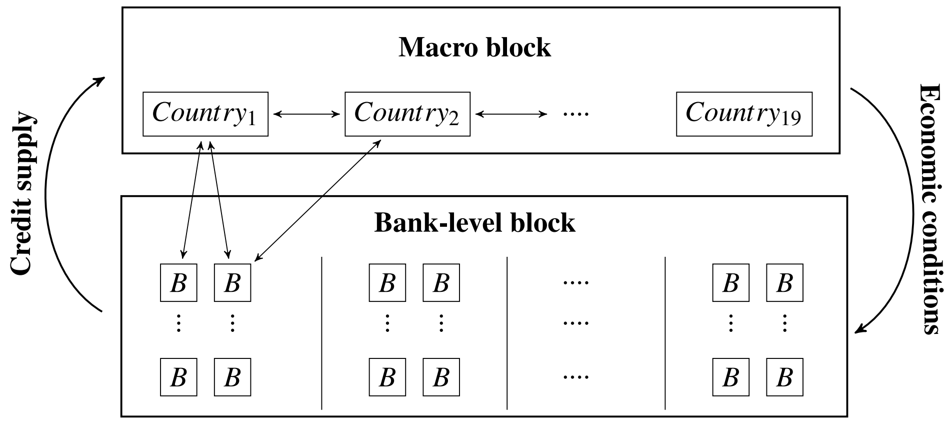
[10]The macro-micro workstream of the Working Group on Stress Testing (WGST) has played an important role in this process, as it has discussed and developed the model as one of its core toolboxes. In doing so, the WGST followed its ECB Financial Stability Committee's (FSC) mandate to operationalise methodologies and academic research on risk analysis as well as counterfactual risk assessment and policy impact assessment.

Chapter 3 describes the modelling approach used for the macroeconomy, while Chapter 4 delves into the assumptions used to model banks' behaviour, their balance sheets, and profit and loss accounts. Chapter 5 discusses the feedback loop between the banking sector and the real economy. Chapter 6 presents different approaches to solving the model, including stochastic simulations and their applications. Chapter 7 documents the most important model properties and selected validation analysis. Chapter 8 presents past and current applications of the model in the policy domain. Finally, Chapter 9 concludes the paper. Several annexes at the end of the paper provide estimation details for the model's empirical equations.

2 Overview

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

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



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

Figure 1: Basic model structure

Each economy is represented by a set of macrofinancial variables, including GDP, inflation, house prices, and government bond yields. The dynamics of economies are modelled in a simplified manner using equations derived from country-level Vector Autoregression (VAR), as discussed in chapter 3. These equations are further augmented with additional equations that capture trade spillovers and the effects of a common monetary policy environment.

The bank's assets consist of holdings in both the banking and trading books, including interest-bearing securities that may be classified in either book (see Table 1). In the banking book, the model specifically tracks loan exposures to different sectors, such as the non-financial corporate sector (NFC), household loans backed by real estate ($HHHP$), and household credit for consumption purposes ($HHCC$). It also considers exposures to sovereigns (SOV), the financial sector (FIN), and central banks (CB). The bank's exposures to the non-financial private sector can exhibit significantly different dynamics depending on the geographical location. However, for other exposures in both the banking and trading books, banks have the ability to adjust the amounts of asset holdings without changing their geographical composition (see Chapter 4).

On the liability side, a bank's balance sheet comprises equity, sight and term deposits from corporates (NFC) and households (HH), secured funding through repos, issued collateralised debt securities, and unsecured wholesale funding including inter-bank liabilities and debt securities. Banks have the ability to adjust private sector deposits separately for different geographical regions, while the geographical composition of other liabilities remains constant (see Chapter 4.2).

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

Table 1: Schematic illustration of bank's balance sheet

Bank net profits take into account impairments resulting from credit risk, net interest income, asset revaluation, and net trading and fee-commission income. Within the model, the flows between the three IFRS9 asset impairment stages – performing, with increased credit risk since initial recognition, and credit-impaired – are monitored for each distinct banking book portfolio (see Section 4.1.3). Changes in asset quality are reflected in the corresponding loan loss provisions, which, when aggregated, are included in the profit and loss statement. A comprehensive description of the impairment stages and loan loss provisioning can be found in Sections 4.1.3 and 4.1.4.

Banks are subject to capital and liquidity regulation. Each banking book portfolio has its assigned risk weight based on an internal model-based approach (IRB) or a standardised approach (STA) (see Section 4.1.7.1). Total risk-weighted amounts are obtained by combining the amounts of credit risk exposure in the banking book with capital charges associated with market and operational risk (see Section 4.1.7.5 and 4.1.7.6). These risk-weighted amounts serve as the denominator for calculating the Common Equity Tier 1 (CET1) capital ratio (see Section 4.3.1). The actual CET1 capital ratio can then be compared to the bank's individual capital targets. Additionally, banks are required to adhere to liquidity requirements that ensure their ability to meet debt obligations as they mature (see Section 4.3). The model incorporates two regulatory limits: the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), which were introduced under Basel III.

Banks respond to macroeconomic and market conditions, as well as regulatory requirements, by adjusting their balance sheets. They make changes to their lending by modifying loan volumes (Section 4.1.2) and interest rates (Section 4.1.5). They also adjust the composition and structure of their liabilities (Section 4.2.3) and determine dividend payouts (Section 4.4.5). The difference between the actual and target CET1 ratio plays a role in guiding banks' behavioral responses, influencing decisions regarding profit distribution and lending. Additionally, the deviation from liquidity coverage ratio (LCR) and net stable funding ratio (NSFR) requirements affects the composition of bank wholesale funding.

In closing the model, bank lending decisions have an impact on the real economy. This impact is achieved through two alternative feedback loops. The first feedback loop involves the aggregation of non-linear bank credit supply elements at the country level, which is interpreted as excessive deleveraging. This aggregated response is subsequently transformed into a credit supply shock that directly influences the real economy. The visualization of this mechanism can be observed in Figure 11. The second feedback loop functions by superseding the dynamics of country-level lending volumes and interest rates with their aggregated bank-level counterparts. Section 5 elaborates in greater detail on both feedback loops.

2.1 Zooming into selected model mechanisms

Banks in the BEAST operate in a monopolistic competition in lending markets, while acting as price-takers in funding markets. This framework is inspired by the Monti-Klein banking industry model (see Klein [1971] and Monti [1972]). In line with this model, banks face a downward-sloping demand curve for lending and adjust loan price and volumes accordingly. They have the ability to discriminate between different lending markets in which they operate.

2.1.1 Bank lending

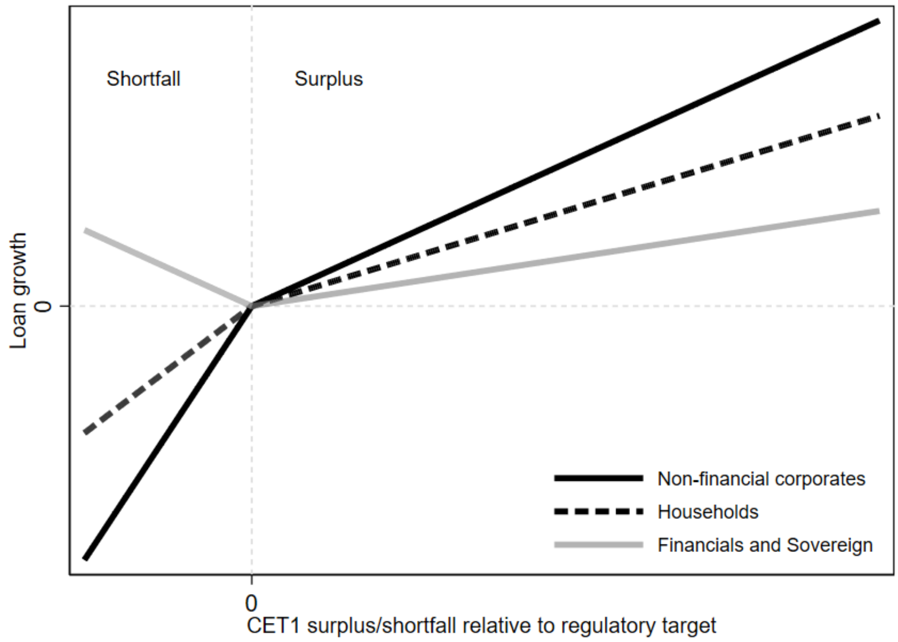
Bank lending volumes and pricing are determined by the interplay of loan demand and supply factors. Loan demand primarily depends on macro-financial variables, including the business cycle, GDP, unemployment, inflation dynamics, and market interest rates. On the other hand, the supply of loans is influenced by the specific circumstances of each individual bank, such as its solvency, leverage, profitability, asset quality, and funding costs.

A significant factor that influences bank loan volumes is the surplus or shortfall in the CET1 ratio relative to its regulatory target. The regulatory target represents the cumulative capital requirements and buffers imposed by the supervisory authority (refer to Section 4.3). In Figure 2, banks with a surplus of capital (located to the right of the vertical line) tend to lend more to the non-financial private sector compared to banks with a shortfall (located to the left of the vertical line). Moreover, corporate lending volumes are generally more sensitive to a bank's solvency position compared to household lending volumes.

There is an important non-linearity in bank responses to a capital shortfall as compared to surplus. This non-linearity is reflected in the different slopes of loan growth observed to the left and right of the vertical line, and it is supported by empirical evidence.[11] When a bank faces a CET1 capital shortfall, it tends to significantly reduce its lending to the non-financial private

[11] This non-linear adjustment emerges in the empirical regressions of loan supply as reported in Appendix C.2.

sector, particularly to corporates. This adjustment is particularly pronounced for higher-risk corporate loans, which carry higher risk weights and consume more capital. Additionally, these loans often have shorter maturities, making them a more straightforward target for deleveraging purposes. [12]



Notes: $0X$-axis reports the value of the difference between the bank actual CET1 capital ratio and its regulatory target. Banks to the right of point 0 report CET1 ratio surplus, and those to the left, CET1 ratio shortfall. $0Y$-axis reports the (stylised) marginal impact of bank solvency position on its loan growth.

Figure 2: Bank solvency and loan supply

Banks that experience a capital shortage may still demonstrate a tendency to increase their lending to the least risky segments of the market, including financial institutions and sovereigns. Interestingly, the marginal impact of being below the regulatory CET1 target is even greater than that of being above the target by the same absolute magnitude. This empirically observed behavior among European banks can be justified by their intention to restore profitability by engaging in lending activities in low-risk markets, where loans are associated with close to zero risk weights.[13]

Bank adjustments of loan volumes and interest rates are summarised in Figure 3, which illustrates the various channels through which macrofinancial conditions impact bank lending. These conditions can directly influence credit demand or indirectly affect asset quality. In addition, banks face changing funding costs that are influenced by their own economic situation and evolving market conditions. Banks closely monitor these conditions along with regulatory requirements, including regulatory CET1 and leverage ratios.[14] Banks adjust their loan supply

[12]The size of a bank's management buffer indirectly affects its lending decisions. Banks that maintain robust management buffers above regulatory capital thresholds and refrain from using them to pay dividends effectively reduce the risk of experiencing a regulatory capital shortfall and having to deleverage in the face of unexpected future shocks.

[13]Additionally, the model incorporates the consideration of relative risk weights in bank lending to different market segments. This additional factor complements the impact of CET1 capital shortfall or surplus on sector-specific lending, and enables the model to capture significant changes in risk weights imposed by the regulator. For more information, please refer to Section 4 and the corresponding Appendix.

[14]The deviation of a bank's actual leverage ratio from its regulatory target has a positive and linear impact on

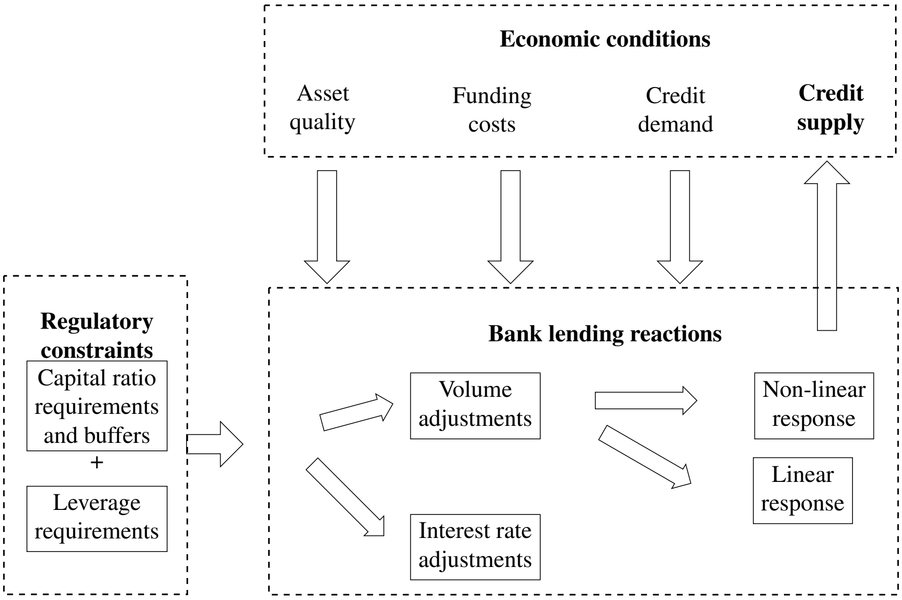


Figure 3: Schematic illustration of model dynamics focusing on bank lending

and interest rates accordingly, with the former response involving a non-linear reaction to a CET1 capital shortfall realisation and changes in asset quality (see Chapter 4.1.2). The lending response of banks, or specifically the non-linear component of their loan supply response, directly influences loan supply at the country level.

2.1.2 Capital accumulation

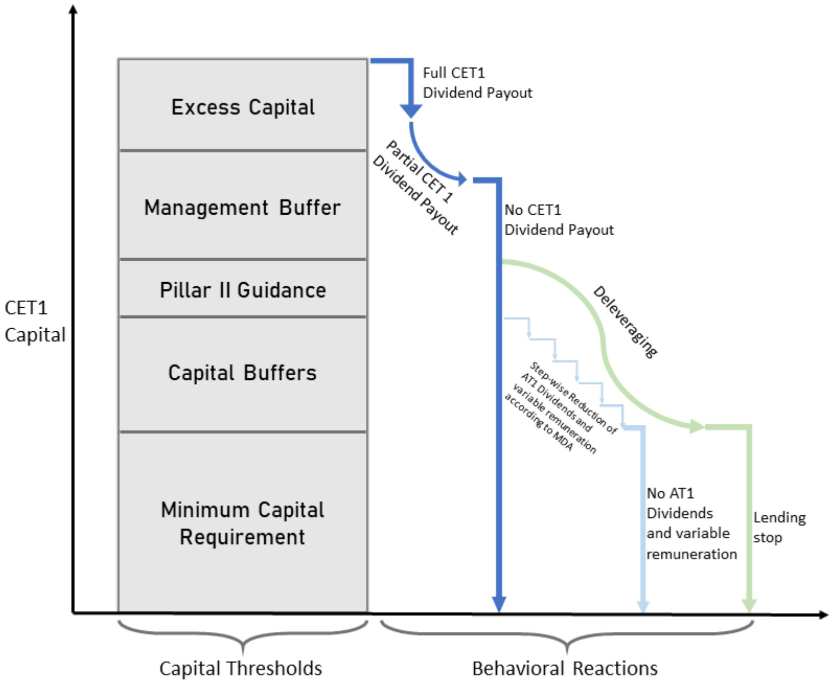
Banks can most directly adjust their capitalisation through profit retention. Profit retention policies implemented by profitable banks serve as the primary safeguard against declining capital and leverage ratios. In the model, banks are assumed to be unable to recapitalise or issue new shares. Therefore, profit retention policies represent the fastest overall mechanism for preserving healthy capitalisation in profitable banks, while the effects of other mechanisms, therein bank deleveraging, unfold over a longer time frame.

Profit retention is based on a straightforward rule: a bank distributes profits as long as it can maintain its internal target capital ratio. This internal target is determined by a combination of regulatory requirements, buffers, and bank management decisions. Bank management buffers are contingent on the bank's business model and balance sheet characteristics. For instance, banks that rely heavily on wholesale funding may opt for a higher management buffer to mitigate related risks effectively.

Figure 4 provides an overview of how banks manage their payouts based on their hypothetical CET1 ratio with full profit retention. Banks that have excess capital above their internal target will pay out the full amount of excess capital or a corresponding share of their previous period profits. Banks that are below their internal capital target, but still meet all their capital requirements and Combined Buffers, will cease to payout CET1 dividends. However, banks that do not meet their internal capital target but remain safely above their Pillar II Guidance level will not engage in deleveraging, while those closer to the Combined Buffers will begin to deleverage.

both loan volumes and interest rates, in contrast to the non-linear response of the former observed for the CET1 ratio.

When banks reach the Maximum Distributable Amount (MDA) limits, their discretion in payouts is overridden by regulatory rules. The MDA limit comes into effect when banks utilise their Combined Buffers. Under these circumstances, banks are obligated to continue paying all scheduled variable remuneration, minority interests, and fixed-schedule dividends to their Additional Tier 1 (AT1) capital. However, if banks completely deplete their Combined Buffers, they will stop paying variable remuneration, minority interests, and fixed-schedule dividends to AT1 capital. Additionally, they will halt the issuance of any new loans. Finally, when the CET1 ratio reaches the threshold of 5.125%, AT1 capital is transformed into CET1 capital.



Notes: Hypothetical CET1 capital corresponds with the level of capital with full retention of profits.

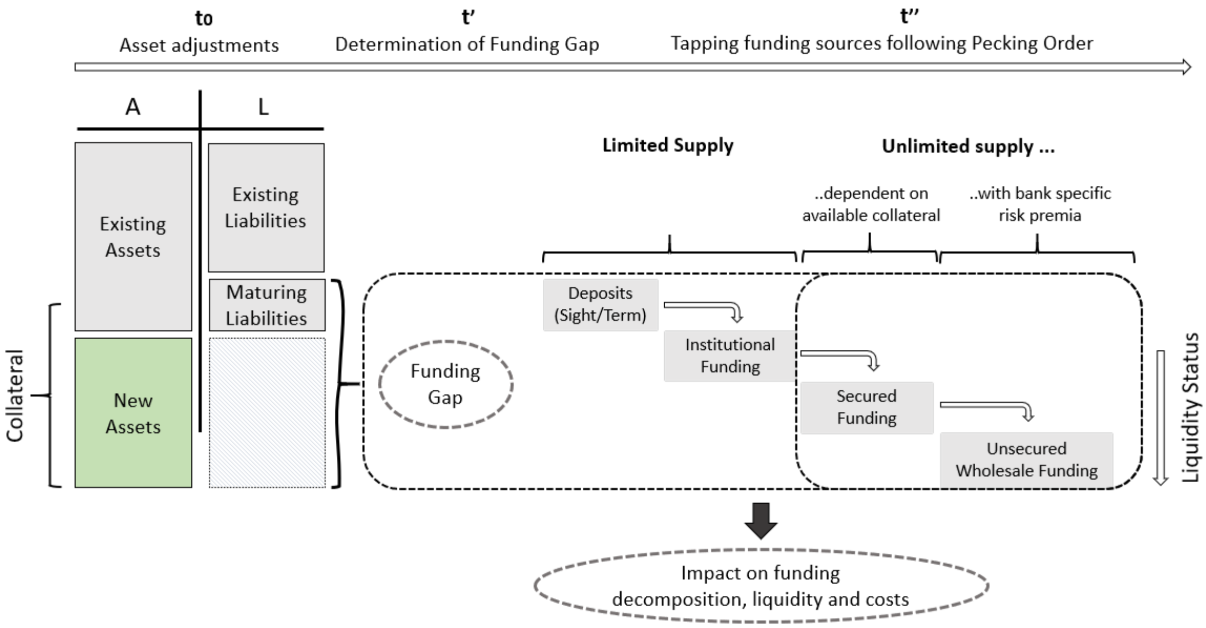
Figure 4: Behavioral reactions to the level of capital relative to thresholds

2.1.3 Bank funding

Banks finance their assets through a combination of their own funds and debt funding. The structure of banks' debt funding depends on their historical and current decisions regarding retained earnings and their liquidity management policy. Additionally, the average funding costs incurred by banks are influenced by their internal risk profile, which affects the risk margins applied to wholesale funding in the market.

When a bank needs to finance newly issued assets or replace maturing liabilities, it requires fresh funding. The composition of this new funding follows a pecking order, as shown in Figure 5. The funding gap between assets, own funds, and debt funding typically arises after certain liabilities mature or when there is an expansion of assets. It can also occur following a negative shock to the bank's own funds. Initially, the gap is filled by retail, sovereign, and central bank funding, which are relatively low-cost sources of funding but have limited availability. If these sources are not sufficient, banks turn to the wholesale market. Although wholesale funding is unlimited, it comes at a higher cost.

In the wholesale market, a bank can choose to secure funding by posting collateral, accessing funds close to the risk-free rate, or it can issue unsecured debt, which carries an additional credit spread. The final composition of wholesale funding is influenced by the availability of collateral and the requirement for the bank to maintain liquidity ratios such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NFCR) at all times.



Notes: Institutional funding sums up sovereigns and central bank deposits.

Figure 5: Funding adjustments

Banks are exposed to the risk of a funding-solvency feedback loop due to their dependence on wholesale funding. If a bank's solvency deteriorates, it leads to a higher credit spread on unsecured wholesale funding. This decline in solvency can also result in an increased reliance on wholesale funding overall. The combination of higher marginal costs and composition effect contributes to a higher average cost of funding. This, in turn, increases interest expenses and reduces bank profitability. When profitability is insufficient, it limits the bank's ability to retain earnings and may even further deplete its existing capital, intensifying the negative feedback loop.

To mitigate the negative spiral, banks can increase their use of secured funding. They can collateralise high-quality liquid assets or pools of loans to generate short-term repos or long-term covered bonds and asset-backed securities, respectively, both of which incur no credit spread. Consequently, by maintaining a stock of collateralizable assets, banks can partially shield themselves from the adverse effects of the funding-solvency feedback loop.

A solvency-funding costs feedback loop is most likely to emerge in adverse macroeconomic conditions. In such circumstances, the supply of stable private deposits tends to be constrained, while the likelihood of capital depletion rises. Consequently, there is an increased demand for wholesale funding. Simultaneously, risk margins in wholesale markets are typically elevated. The combination of these factors creates challenges for banks in obtaining affordable funding and sows seeds for risk amplification.

3 Macroeconomy

The macroeconomic block includes the representation of individual economies within the euro area[15] and the international environment of the rest of the world. Each of these euro area countries can be subject to different macrofinancial shocks, and countries are interconnected through trade linkages.

3.1 Representation of a single euro area economy

The dynamics of an individual euro area economy is captured by equations derived from a structural vector autoregressive model (SVAR).[16] Each country, denoted as C, is characterised by the following:

$$Y_t^C = a_Y^C + \sum_L A_{Y,L}^{Y,C} Y_{t-L}^C + \sum_L B_L^{Y,C} M_{t-L}^{EA} + \sum_L E_L^{Y,C} X_{t-L}^C + \sum_L F_L^{Y,C} Z_{t-L}^C + v_t^{Y,C} \tag{1}$$

$$M_t^C = a_M^C + \sum_L A_{M,L}^{M,C} Y_{t-L}^C + \sum_L B_L^{M,C} M_{t-L}^{EA} + \sum_L E_L^{M,C} X_{t-L}^C + \sum_L F_L^{M,C} Z_{t-L}^C + v_t^{M,C} \tag{2}$$

where Y_t^C is a vector of 10 country-specific endogenous variables, including real GDP, HICP, unemployment rate, the spread between 10-year government bond yield and 3-month EURIBOR, import volume, export price, residential property price, bank loan volumes and lending rate for the non-financial private sector, and equity price index (see Table 2). Vectors M_t^C and M_t^{EA} are related to the monetary policy framework, each including the EURIBOR 3-month rate, STN, and a measure of unconventional monetary policy denoted as UMP. The specific country indexing of M_t in the equations is explained in Section 3.3.1. Vectors X_t^C represent country-specific measures of foreign demand and competitors' export prices, and Z_t^C includes an additional set of variables, including dummies related to the episode of the COVID-19 pandemic and the index of energy prices and its L lags.[17] The number of lags, L, is set at 2, and t represents the time period. The vectors v consist of reduced-form residuals, assumed to be independent and identically distributed with a mean of zero and a covariance matrix Σ. Vectors a and matrices A, B, E, and F contain the estimated coefficients of the model.

The structural representation of the reduced-form residuals at the country level is as follows:

$$v_t^C = D^C \varepsilon_t^C \text{ with } \varepsilon_t^C \sim \mathcal{N}(0, 1) \tag{3}$$

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

[16] A simplified approach to modelling macroeconomies was a deliberate choice during the setup of the model. The new model was intended to focus on representing the dynamics of a heterogeneous banking sector, rather than attempting to directly compete with or replicate the existing semi-structural and structural macroeconomic models within the institution. However, it remained essential to ensure that each country represented in the model included a comprehensive range of macrofinancial variables that had a significant ex ante impact on the banking sector, including their interactions. Furthermore, it was important for the country representation to effectively capture the time dynamics of macrofinancial variables and reflect the feedback loop between the banking sector and the real economy. The VAR-type specification was found to meet all these criteria.

[17] For a detailed explanation of the methodology used to address the impact of the COVID-19 episode, refer to Appendix **??**.

	Variable name	Variable transformation	Definition
Y_t	YER	log difference	Real GDP (level, constant prices, SACA)
	HIC	log difference	Harmonised Index of Consumer Prices (quarterly average)
	URX	level	Unemployment rate (percent)
	IHX	log difference	Residential property price (new and existing dwellings)
	SPR	level	Spread between the long-term (10-year benchmark government bond yield) and the short-term interest rate
	ESX	log difference	Equity price (index level, quarterly average)
	MTR	log difference	Import volume
	XTD	log difference	Export price
	BLR	level	Bank loan rate (weighted average of NFC and HH rates, new business coverage)
	CPN	log difference	Bank loan volume (sum of NFC and HH loan volume, outstanding amount at the end of period)
M_t	STN	level	Short-term interest rate (Euribor)
	UMP	log difference	Consolidated Eurosystem's total assets, excluding intra-Eurosystem assets and liabilities
X_t	FDR	log difference	Foreign demand
	CXD	log difference	Competitors' export price
Z_t	EPR	log difference	Country-specific fossil energy price index
	DU	level	COVID-19 pandemic Dummies

Notes: [a] The fossil energy price index is a weighted average of gas, oil, and solid fossil fuel. The weights for gas, oil, and solid fossil fuel are proportional to the specific countries reliance of gas, oil and solid fossil fuel to fossil energy according to the International Energy Agency (IEA).

Table 2: Definition of macroeconomic variables

where D^C is the matrix that provides the mapping between the vector of reduced-form residuals ν_t^C and the orthogonal structural shocks ε_t^C.

The structural representation identifies and constrains nine shocks through a combination of sign and zero restrictions, as outlined in Table 3. The three remaining structural shocks are left unrestricted.

	Credit Supply	Credit Demand	Monetary Policy	Unconventional Monetary Policy	Stock Price	Yield	Resident. Price	Aggregate Demand	Aggregate Supply
Real GDP	0	0	+	+	0			+	+
HICP	0	0	+	0	0	0	0	+	-
Unemp. rate	0	0							
Short-term rate	0	0	-	0	0	0		+	
Interest rate spread	0	0		-		+	0		
Import volume	0	0							
Export price	0	0							
Residential prop. price	0	0					+		
Bank lending rate	-	+							
Bank loan volume	+	+							
Equity price index	0	0	+		+				
Eurosystem's assets	0	0	0	+	0	0			

Table 3: Summary of identifying restrictions in SVAR

Identifying a credit supply shock follows the approach of Barnett and Thomas [2013] and Hristov et al. [2012]. It is based on the assumption that an innovation in credit supply leads to an opposite movement in lending volumes and rates. A shock specified in this way is consistent with a decrease in bank capital (Gerali et al. [2010]), a deterioration in bank asset quality (Gertler and Karadi [2011]), or an increase in investor risk aversion that is not directly linked to credit defaults (Gilchrist et al. [2009]). Conversely, an exogenous increase in credit demand is expected to cause bank lending volumes and rates to move in the same direction. These sign restrictions are complemented by a set of zero restrictions on the impact of credit supply and demand shocks on other variables in the system.[18]

[18]The high saturation of credit supply and demand shocks with zero restrictions is directly related to the subsequent use of the SVAR-based equations in the specification of the feedback loop between the banking sector and

We distinguish between two types of monetary policy shocks. An expansionary standard monetary policy shock causes an immediate decrease in the short-term interest rate and an increase in the equity price index. An expansionary unconventional monetary policy shock is characterised by an immediate increase in the Eurosystem's total assets and a reduction in the spread between bond yields and the EURIBOR 3M rate. The effects of the shock of expansionary standard monetary policy on output and inflation follow the findings of Christiano et al. [1996] and Uhlig [2005], where it is expected to have a positive impact on output and inflation. For the unconventional monetary policy shock, we impose impact restrictions based on studies by Boeckx et al. [2017], Hesse et al. [2018], and Hristov et al. [2020].[19]

A positive stock price shock is characterised by an immediate increase in the equity price index without contemporaneous spillover effects on other variables. Zero impact restrictions are imposed on the Eurosystem's total assets, interest rate spreads, real GDP growth, and inflation. The impact restrictions on a positive bond yield shock are inspired by the concept of a shock to the excess bond premium as considered by Gilchrist and Zakrajšek [2012]. These restrictions include a positive change in the interest rate spread and the Eurosystem's total assets, no contemporaneous reaction of inflation, and the response of stock prices to this shock is left unrestricted. The identification of a residential property price shock follows Buch et al. [2014].

A standard set of restrictions, as described in Hristov et al. [2012], is applied to differentiate between aggregate demand and aggregate supply shocks. A positive aggregate demand shock is characterised by the parallel movement of inflation and GDP, both increasing, and also triggers an increase in short-term interest rates. On the other hand, an aggregate supply shock leads to inflation and GDP moving in opposite directions.

The forecast error variance decomposition supports a strong impact on credit supply shocks on lending interest rates and volumes (compare table 21 in Appendix **??**). Notably, it reveals a strong influence of these shocks on residential house prices. Additionally, credit supply shocks have substantial impacts on real GDP, inflation, and equity prices. Monetary policy shocks demonstrate relatively weak impacts on macrofinancial variables. Residential property and aggregate demand shocks play a substantial role in driving fluctuations in different dimensions of the economy, including economic activity and market prices.

3.2 Rest of the world

The rest of the world comprises 18 international economies that have the strongest financial links to the euro area. The selection of these countries is based on an analysis of asset exposures of euro area banks to non-euro area counterparts. Specifically, the model includes all non euro area European Union economies as of 2020, such as Bulgaria, Czech Republic, Denmark, Croatia, Hungary, Poland, Romania, Sweden, as well as two European Free Trade Association

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the real economy. The restrictions ensure that only loan volumes and interest rates are contemporaneously affected by credit supply and demand shocks. Consequently, the introduction of the feedback loop by augmenting the credit supply shock (as discussed in Section 5.2) or replacing SVAR-derived equations with aggregate measures of bank-level lending volumes and interest rates (as described in Section 5.2) does not require changes in the remaining equations representing a national economy. These adjustments can be made without altering the structure of the other equations that capture the dynamics of the economy. Despite these considerations, the restrictiveness of zero-impact restrictions has been tested against alternative approaches. It has been found that loosing restrictions, such as allowing for contemporaneous impacts of credit-related shocks on stock prices, did not have a significant impact on the responses of the SVAR model to credit-related structural shocks.

[19] We impose a positive sign restriction on impact on output for the unconventional monetary policy shock. While for the conventional monetary policy shock this restriction is needed for the shock identification, for the unconventional monetary policy shock it was imposed only as a feature to allow for a more intuitive shape of the impulse response function.

(EFTA) economies, Switzerland and Norway. Furthermore, other regions included in the model are Brazil, China, Japan, Mexico, Russia, Sweden, Turkey, the United Kingdom, and the United States.

Each country in the rest of the world segment is represented by equations of a reduced-form VAR:

$$\tilde{Y}_t^C = \tilde{a}_{\tilde{Y}}^C + \sum_L \tilde{A}_L^C \tilde{Y}_{t-L}^C + \tilde{v}_t^C \tag{4}$$

with representing a K^C-dimensional white noise process characterised by a time-invariant positive definite covariance matrix. Vector $\tilde{Y}$ comprises K^C variables, including real GDP, import volumes, and export prices for each country. Depending on data availability, other variables such as inflation, unemployment rate, equity prices, and residential property prices are added to the specification (see Annex B.2 for details).

3.3 Linking individual economies

The use of VAR-type equations in the model deviates from a closed-form VAR representation. The first deviation pertains to the modelling of common euro area monetary policy and the second to the modelling of cross-border spillovers.

3.3.1 Common euro area monetary policy

The common euro area monetary policy is accounted for by imposing the condition of a single euro area short-term interest rate and a measure of unconventional monetary policy. The dynamic formula for the short-term interest rate of the euro area, denoted as STN^{EA}, is derived by aggregating the predictions from country-specific equations in 2, STN^C, using nominal GDP weights. Additionally, STN^{EA} is subject to a floor level of -1.5%.[20]

$$STN_t^{EA} = \max\left(-1.5\%, \sum_C w^C \times STN_t^C\right) \tag{5}$$

where w^C represent the individual country nominal GDP share in the euro area nominal GDP (in 2021).

Unconventional monetary policy is approximated by the consolidated balance sheet of the Eurosystem, which has been directly impacted by the ECB's asset purchase programme (APP) and the pandemic emergency purchase programme (PEPP).[21] The consolidated balance sheet of the Eurosystem, denoted UMP^{EA}, is defined in a way similar to the short-term interest rate, taking into account the weighted average of country-specific equations in 2 UMP^C:

$$UMP_t^{EA} = \sum_C w^C \times UMP_t^C \tag{6}$$

[20] Setting a floor on the short-term interest rate significantly below zero is supported by the analysis conducted in Altavilla et al. [2021], which demonstrates that the risk-neutral density of the EONIA (Euro Overnight Index Average) forward curve extends significantly below zero following the implementation of negative interest rate policies.

[21] It will also include targeted longer-term refinancing operations (TLTROs).

with country weights defined as w^C.

3.3.2 Cross-border spillovers

The dynamics of individual euro area economies are influenced by cross-country trade spillovers through foreign demand and competitors' export prices contained in X_t. The foreign demand variable reflects the import volumes of a country's trading partners, while the foreign price variable captures the export prices of other countries, as shown in Figure 6. In both cases, the foreign demand and price variables are weighted by the counterparty's export/import shares.[22]

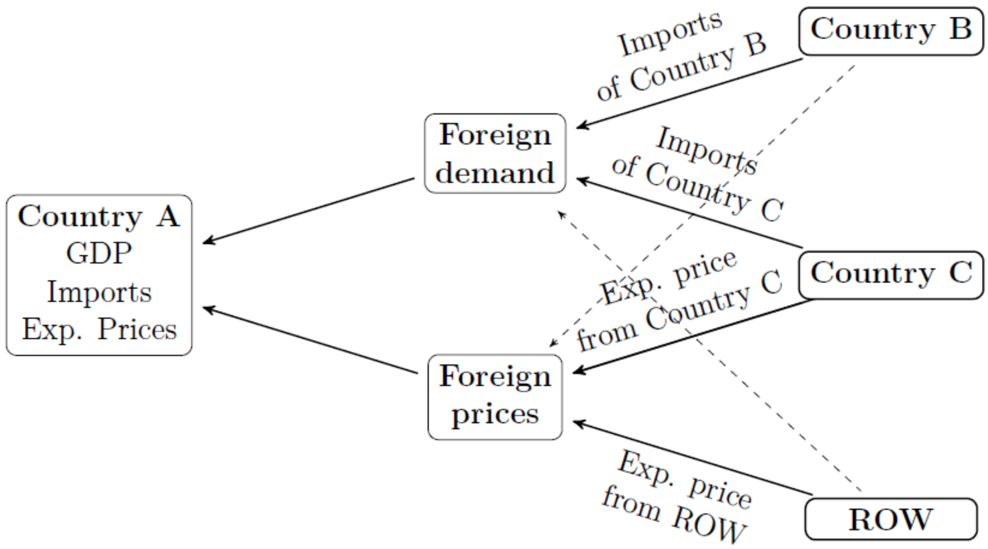


Figure 6: Cross-country trade spill overs

The foreign demand of a euro area country C is determined by calculating the weighted sum of the changes in import volumes from its trading partners within the euro area and from the rest of the world:

$$FDR_t^C = \sum_{T \in \{EA \setminus C, RoW\}} w_{FDR}^T \times MTR_t^T \tag{7}$$

where w_{FDR}^T represent the share of exports from country C to country T in the total exports of country C.

The competitor prices of country C are calculated by taking the weighted sum of the changes in export prices of all its trading partners from which it imports:

$$CXD_t^C = \sum_{T \in \{EA \setminus, RoW\}} w_{CXD}^T \times XTD_t^T \tag{8}$$

where w_{CXD}^C represent the share of imports from country T in the total imports of country C.

The trade interactions between euro area countries are bidirectional. On the contrary, the trade interactions between the euro area and other countries of the world are unidirectional. A

[22] The methodology for introducing trade spillovers in the model is inspired by the Stress Test Elasticities utilised in the EBA/SSM stress test exercises since 2011. All trade shares are assumed to remain constant throughout the simulation horizon.

shock affecting one euro area economy propagates to other economies within the euro area, and their response is transmitted back to the source economy, creating a feedback loop among euro area countries. Shocks originating from the rest of the world can affect multiple euro area countries simultaneously. However, the response of euro area economies does not feed back into the dynamics of third countries.

3.4 Yield curve

Banks hold a variety of financial instruments with different maturities in their banking and trading books. Information on EURIBOR 3M and 10-year yields $LTN = STN + SPR$ for euro area countries, the euro area as a whole and the United States (discussed in Sections 3.1 and 3.2) is projected onto the full yield curve using a three-factor representation as proposed by Nelson and Siegel [1987].

The yields of country-specific bonds $Yield_t^C$ with a maturity of τ are derived as follows:

$$Yield_t^C(\tau) = \beta_{1,t}^C + \beta_{2,t}^C \left(\frac{1 - e^{-\lambda_t^C \tau}}{\lambda_t^C \tau} \right) + \beta_{3,t}^C \left(\frac{1 - e^{-\lambda_t^C \tau}}{\lambda_t^C \tau} - e^{-\lambda_t^C \tau^C} \right) \tag{9}$$
$$\text{with } Yield_t^C(3 \text{ month}) = STN_t^C \text{ and } Yield_t^C(10 \text{ year}) = STN_t^C + SPR_t^C$$

where λ_t^C is the exponential rate of decay, $\beta_{1,t}^C$, $\beta_{2,t}^C$, and $\beta_{3,t}^C$ can be interpreted as the level, the slope, and the curvature, respectively (see Diebold and Li [2002]).

To ensure full identification of each yield curve, the model assumes that the level and slope of the curve are influenced by changes in EURIBOR 3M and 10-year yields, while the curvatures and discount rates remain fixed. The exponential decay rate and curvature of the yield curves are determined based on estimated values derived from the most recent quarterly data (see Annex B.3 for details).

4 Banking system

The banking block contains the representation of around 90 individual banks. Each bank is pictured by its balance sheet, profit and loss accounts, and a set of equations that describe its behavioural reactions. The model places most emphasis on modelling banking book assets, the evolution of credit risk and interest income, with less sophisticated modelling of banks' trading books and market risk.

The timing of the bank adjustment mechanisms is illustrated in Figure 7. Each period starts with changes in asset quality. A share of performing loans defaults and a share of defaulted loans is cured. Following changes in asset quality, banks adjust interest rates on loans along with the original provisions in lending contracts, and update flexible interest rate contracts along with the prevailing interest rates in the money market. Analogous interest rate updates apply to banks' debt funding instruments. A proportion of performing loans and liabilities maturing in the period is then removed from banks' balance sheet. Finally, banks can decide to write off some of their new or legacy defaulted exposures.

In the next step, banks decide on the issuance and pricing of new loans balancing out credit demand considerations and their financial situation. Subsequently, they adjust their loan-loss provisions taking into account the updated stock of performing and defaulted assets. They also adjust holdings of other assets, therein assets held for trading. This closes the cycle of adjustments on the asset side of banks. In the following, banks can update the risk weights and other capital charges to better reflect changes in the economic environment and arrive at the estimate of their risk weighted amounts.

Banks' liability volumes and structure are adapted once their asset holdings are known. Banks first collect new private sector deposits, and later close the remaining funding gap with financial and sovereign sector deposits and last with central bank and wholesale funding. At this stage, both sides of banks' balance sheets are known, and banks realise their profits. A share of profits is paid out in the form of dividends, and the remaining amounts are added to capital holdings. Adjustments of own funds close the period and the next period starts with the update of asset quality.

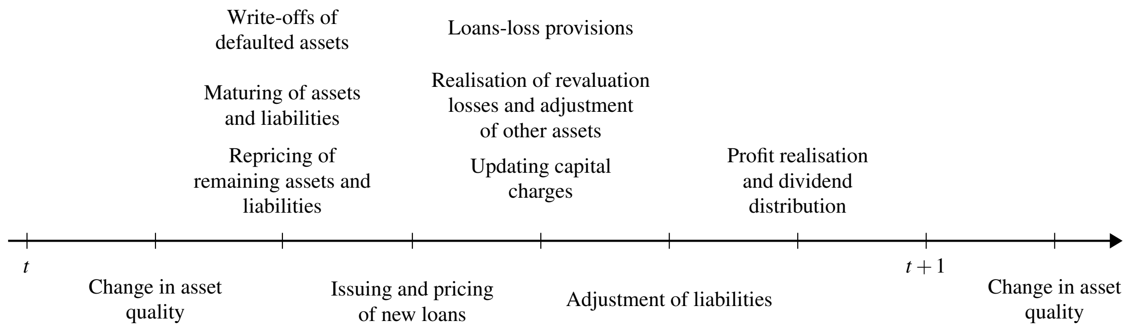


Figure 7: Timing of bank adjustments

This section is divided into four parts. The first part discusses bank assets and capital charges. The second part looks at the evolution of own funds and bank liabilities. The third part introduces capital and liquidity requirements and measures of bank compliance. The last part explains the dynamics of profit and loss accounts and the distribution of profits.

4.1 Bank assets

4.1.1 Structure of banks' asset side

Banks hold assets in a banking or trading book. Assets in the banking book are recorded at historical cost and are expected to be held to maturity. Trading book assets are mostly valued at mark-to-market.

Loans to the non-financial private sector make up the largest share of banking book assets. They sum up to the average of 63.1% of the total euro area banks' banking book assets.[23] They are further broken down into loans to euro area non-financial corporates NFC, loans to euro area households for housing purposes $HHHP$, loans to euro area households for consumption $HHCC$ and loans to the rest of the world non-financial private sector (RoW). Loans to the euro area non-financial private sector are further broken down by the country of exposure and are referred to as bank sector country loan portfolios.

Other loans in the banking book include loans to the sovereign sector SOV, loans to the financial sector FIN and to the central bank CB. The three types of exposure are modelled at the bank level, without an additional country breakdown, and are referred to as bank-sector loan portfolios.[24] The banking book also includes relatively small bank sector portfolios of

[23] As reported in 2020Q4 by all banks participating in the 2021 EU-wide stress test exercise.

[24] Although loans to financial and public sector are modelled in aggregate, their geographical composition is acknowledged by linking bank-level variables to macro-financial developments in countries of exposure weighted by the share of each country exposure in the total bank-sector amount. See, e.g., Section 4.1.2.

equity EQ, derivatives $DERIV$, securitised portfolios SEC and other holdings $OTHER$, jointly corresponding to 6.7% of the banking book.

For each asset portfolio in the banking book, the model calculates the evolution of the volumes (Section 4.1.2) and quality of assets (Section 4.1.3), loan-loss provisions (Section 4.1.4) and credit risk weights (Section 4.1.7).

The model projects effective interest rates (Section 4.1.5) for all assets bearing interest. Types of interest-bearing assets are most of the time synonymous with banking book portfolios, with the exception of security holdings that can be classified either in the banking or trading book.[25] Security holdings are aggregated in three bank sector portfolios of financial $SFIN$, non-financial corporates $SNFC$, and government and central bank counterparties $SGOV$. The latter category constitutes the largest, 65.9%, share of the euro area banks' security holdings.

Assets in banks' trading books are classified along with their accounting classes. They include trading assets reported through amortised costs or fair value $ACFVPL$, assets reported through fair value and other comprehensive income $FVOCI$ and trading assets reported through other comprehensive income or profit and loss $FVOCIPL$. Additional items in the trading book are net assets (combining assets and liabilities) with a trading intend TI, hedging instruments EH and $HEDGES$, and non-trading assets $NONT$. The dynamics of trading assets is related to changes in the size of the banking book and revaluation gains or losses (Section 4.1.6).

Different types of bank asset exposure are summarised in Table 4.

Abbreviation	Description	Accounting book	Granularity	Decomposition
Banking book				
NFC	Loans: Non-financial corporates	Banking book	Sector-Country-Bank	16.3
HHCC	Loans: Household consumption and other Loans	Banking book	Sector-Country-Bank	8.6
HHHP	Loans: Household mortgages	Banking book	Sector-Country-Bank	20.4
RoW	Loans: Rest of the world non-financial private sector	Banking book	Sector-Bank	17.8
SOV	Loans: Government, public sector entities	Banking book	Sector-Bank	13
CB	Loans: Central banks	Banking book	Sector-Bank	13.9
FIN	Loans: Credit institutions and other financial corporations	Banking book	Sector-Bank	5.6
OTHER	Loans: Other loan exposures	Banking book	Sector-Bank	3.9
EQ	Other: Equity exposures	Banking book	Sector-Bank	0.4
SEC	Other: Securitized portfolios	Banking book	Sector-Bank	2.4
DERIV	Other: Derivatives	Banking book	Sector-Bank	-
Security holdings				
SFIN	Securities: Financial institutions	Banking or trading book	Sector-Bank	28.1
SNFC	Securities: Non-financial corporates	Banking or trading book	Sector-Bank	6.0
SGOV	Securities: Central banks and governments	Banking or trading book	Sector-Bank	65.9
Trading book				
ACFVPL	Trading assets: Amortised costs or fair value via P&L	Trading book	Sector-Bank	71.5
FVOCI	Trading assets: Fair value via other comprehensive income	Trading book	Sector-Bank	12.8
FVOCIPL	Trading assets: Fair value via other comprehensive income or P&L	Trading book	Sector-Bank	15.7
TI	Net assets: Held with trading intent	Trading book	Sector-Bank	-
EH	Net assets: Economic hedges	Trading book	Sector-Bank	-
HEDGES	Net assets: Hedging instruments	Trading book	Sector-Bank	-
NONT	Net assets: Non trading mandatory or optional at FVPL	Trading book	Sector-Bank	-
LACFVPL	Liabilities: via amortised costs or fair value via P&L	Trading book	Sector-Bank	-

Notes: The share of individual asset classes is calculated relative to the size of the banking book excluding derivatives $DERIV$, the total interest-bearing securities, and the trading book excluding net assets TI,EH,$HEDGES$,$NONT$ and liabilities $LACFVPL$, respectively. P&L stands for profit and loss accounts, and FVPL for fair value through profit and loss. Securities under $FVOCI$ and $FVOCIPL$ which are reported at fair value and the changes in their value between accounting periods are included in other comprehensive income are otherwise referred to as available-for-sale securities.

Table 4: Asset sectors

[25] The distinction of interest rate bearing assets follows the convention of the EU-wide stress test reporting standards.

4.1.2 Loan volume dynamics and new loans

Bank lending volumes are influenced by changes in both loan demand and loan supply. The growth rate of the loan volumes,[26] $TotalLoans\_gr$, for sectors $S \in \{NFC, HHCC, HHHP, RoW, FIN, SOV, CB\}$, can be decomposed into the impacts of loan demand, $LoanDemand$, which includes macroeconomic conditions in the country of exposure and captures the inertia in lending volumes, and loan supply, $LoanSupply$, which represents the willingness of banks to extend lending.

$$TotalLoans\_gr_{i,t}^{S,C} = LoanDemand_{i,t}^{S,C} + LoanSupply_{i,t}^{S,C} \tag{10}$$

where the country superscript C is relevant for $S \in \{NFC, HHCC, HHHP\}$ and can be withdrawn for $S \in \{FIN, SOV, CB, RoW\}$.

The marginal impact of the loan demand and loan supply components of the loan volume dynamics is identified separately due to data challenges. Impacts are derived from the estimated loan demand and supply equations, which are estimated separately for sectors $S \in \{NFC, HHCC, HHHP, FIN, SOV\}$. The coefficients for the volumes of loans to central banks CB are borrowed from the corresponding estimates for sovereign exposures.

The loan demand equation is a function of country-specific macrofinancial variables such as GDP growth quarter-on-quarter $YERgr$, quarterly inflation rate $HICgr$, change in unemployment rate ΔURX and short-term rate STN and the spread between long- and short-term rate $SPREAD$ that are included with up to two lags $p = 2$. Additionally, the equation includes the change in the effective rate of country-specific bank sector lending $\Delta EIRAssetNew$ and the past growth rate of loan volumes $TotalLoans\_gr$. Sector-specific coefficients β^S are estimated in a two-step estimation approach explained in more detail in the Appendix C.1.

$$\begin{aligned} LoanDemand_{i,t}^{S,C} = \sum_p (&\beta_{1,p}^S \Delta log(TotalLoans\_gr_{i,t-p}^{S,C}) + \beta_{2,p}^S YERgr_{t-p}^C \\ &+ \beta_{3,p}^S HICgr_{t-p}^C + \beta_{4,p}^S \Delta URX_{t-p}^C + \beta_{5,p}^S \Delta STN_{t-p}^{EA} \\ &+ \beta_{6,p}^S SPR_{t-p} + \beta_{7,p}^S \Delta EIRAssetNew_{i,t-p}^{S,C}) \end{aligned} \tag{11}$$

Measurements of economic activity $YERgr$ and $HICgr$ enter equation (11) with a positive sign. Changes in market and bank interest rates reduce loan demand.

The loan supply equation is divided into a linear component $LoanSupplyLin$ and a non-linear component $LoanSupplyNonLin$. The two components are estimated jointly (see Appendix C.2) but on occasions play a different role in the model (see Section 5.3 describing the alternative feedback loop mechanisms).

$$LoanSupply_{i,t}^S = LoanSupplyLin_{i,t}^S + LoanSupplyNonLin_{i,t}^S \tag{12}$$

An important driver of loan supply dynamics is bank capitalisation. It is captured by the surplus or shortfall of CET1 capital over the regulatory requirements of the CET1 ratio $CET1SurShortfall$, and the Tier1 leverage ratio relative to its regulatory target value $LEVRSurShortfall$.[27] The coefficients on $CET1SurShortfall$ and $LEVRSurShortfall$ are allowed to differ for $Type = 0$ banks, including most of the banks in the sample, and $Type = 1$ banks, grouping banks that due to the nature of their business model (special lenders) or ownership

[26] Bank lending does not distinguish between new credit lines and drawing from existing credit lines with a bank. This distinction is not present in either of the datasets regularly used to inform the model.

[27] See Section 4.3 for the exact definitions of the two bank capitalisation variables.

structure (state owned) exhibit significantly lower elasticities of lending to bank capitalisation.[28] Further, the effect of $CET1SurShortfall$ is different for domestic (indicator variable $Home = 1$) and foreign exposures ($Home = 0$), capturing a potential home bias. Last, the specification allows for the non-linearity of the relationship between bank capitalisation and lending by introducing the interaction variable $CET1SurShortfall \times I(CET1SurShortfall < 0)$.

Other supply-side drivers of loan volumes include profitability, funding costs, asset quality, and relative sector-specific risk weights. Bank profitability is measured with *ROA* on an annual basis. Funding costs are captured by the average costs of all liabilities of a bank *EIRLiab*. Asset quality is measured with the granular country sector bank (sector bank for FIN and SOV) net NPL ratio *netNPLR*, which accounts for provisions made already for defaulted exposures. The effect of the net NPL ratio differs in cases where the (gross) NPL ratio increased ($\Delta_4 NPLR > 0$) in the last year and in cases where it decreased ($\Delta_4 NPLR < 0$). This is another source of non-linearity in bank adjustments of loan volumes. Finally, the relative risk weight is defined as the sector-country-specific risk weight relative to the average risk weight of a bank $RRW^{S,C} = RW^{S,C}/RW$. The relative risk weight is interacted with a capital shortfall realisation to accommodate the non-linearity in the substitution of loans between high- and lower-risk weight sectors that can emerge when banks fall below their regulatory capital target.

$$\begin{aligned}
LoanSupplyLin_{i,t}^{S,C} = {} & \beta_1^S\, CET1SurShortfall_{i,t} \times I(Type_i = 0) \times I(HomeForeign_i^{S,C} = 0) \\
& + \beta_2^S\, CET1SurShortfall_{i,t} \times I(Type_i = 0) \times I(Home_i^{S,C} = 1) \\
& + \beta_3^S\, CET1SurShortfall_{i,t} \times I(Type_i = 1) \times I(Home_i^{S,C} = 0) \\
& + \beta_4^S\, CET1SurShortfall_{i,t} \times I(Type_i = 1) \times I(Home_i^{S,C} = 1) \\
& + \beta_5^S\, LEVRSurShortfall_{i,t} \times I(Type_i = 0) \\
& + \beta_6^S\, LEVRSurShortfall_{i,t} \times I(Type_i = 1) \\
& + \beta_7^S\, netNPLR_{i,t}^{S,C} \times I(\Delta_4 NPLR_{i,t}^{S,C} < 0) \\
& + \beta_8^S\, ROA_{i,t} + \beta_9^S\, EIRLiab_{i,t} \\
& + \beta_{10}^S\, RRW_{i,t}^{S,C}
\end{aligned} \tag{13}$$

$$\begin{aligned}
LoanSupplyNonLin_{i,t}^{S,C} = {} & \beta_{11}^S\, CET1SurShortfall_{i,t} \times I(CET1SurShortfall_{i,t} < 0) \\
& + \beta_{12}^S\, netNPLR_{i,t}^{S,C} \times I(\Delta_4 NPLR_{i,t}^{S,C} > 0) \\
& + \beta_{13}^S\, RRW_{i,t}^{S,C} \times I(CET1SurShortfall_{i,t} \geq 0)
\end{aligned} \tag{14}$$

Along with the convention taken in this paper, the coefficients β represent any estimated model parameter in the banking block and are indexed independently in each equation, with β_0 casually representing a constant term (therein, also sector- or bank-specific) and β indexed from 1 above the marginal effect of different explanatory variables.

Banks cut their loan growth by 0.94% for NFC and 0.55% for the $HHHP$ and $HHCC$ sectors with a capital ratio shortfall of 1 pp CET1 capital ratio shortfall (see equation (C.2)). Banks in trouble tend to lower the most exposures with higher risk weights, mainly loans to $NFCs$, to a lesser extent loans to households, and substitute them with exposures with lowest risk weights,

[28] More information on the bank sample can be found in Appendix A, Table 18.

such as loans to sovereigns and the financial sector. Moreover, banks cut their loan supply more in response to increases in net NPL ratios, when their share of defaulted exposures is on an upward path.

The dynamics of loan volumes to the non-financial private sector of the rest of the world RoW is derived using coefficient estimates for $S \in \{NFC, HHHP, HHCC\}$. The coefficients sourced from the equations (11), (13), and (14) are transformed into the corresponding coefficients RoW using the exposure shares of the bank i $shareRoW$ to the sectors $S \in \{NFC, HHHP, HHCC\}$ in all countries outside the euro area:

$$\beta_i^{RoW} = \sum_S shareRoW_i^S \beta^S \tag{15}$$

Furthermore, macrofinancial variables $Var^{RoW} \in \{YERgr, HICgr, URX, LTN, STN\}$ entering the RoW loan growth equation also take into account the bank-specific exposure shares to the non-financial private sector in individual countries outside the euro area $C \in RoW$:

$$Var_{i,t}^{RoW} = \sum_{C \in RoW_i} shareRoW_{C,i} Var_{i,t}^C \tag{16}$$

The loan volume growth equations introduce a degree of substitutability of loans between banks. The most direct channel is the discrepancy of loan volume dynamics between banks in trouble, due to their profitability, capitalisation, or NPLs, and banks successfully circumventing these. Over time, the differences in the growth rate of loan volumes between banks cumulate into changes in their market shares in relevant loan segments. Another channel is the pricing of loans. Other things being equal, banks offering lower interest rates attract higher loan demand. At the same time, banks offering lower interest on loans tend to be banks with curtailed funding costs, and therefore banks that are soundly capitalised (see Section 4.1.5). Finally, there are adjustments for the entire economy. A dropout of a bank from a market segment in a country affects the country's economic activity. This in turn permeates the loan demand of other banks.

The different factors that influence the lending dynamics in the model are summarised in Figure 8. The macrofinancial environment, economic growth, changes in interest rates, and consumer price inflation directly affect the demand for loans in all economic sectors S. The macroeconomic conditions impact, as well, bank loan supply by ultimately affecting asset quality and funding costs, and then banks' profitability and solvency. Especially loan supply adjustments can be highly heterogeneous for banks with sound and troubled solvency levels, with the latter expected to react in a non-linear fashion with strong deleveraging.

The new lending $NewLoans$ is derived as:

$$\begin{aligned} NewLoans_{i,t}^{S,C} = (1 - Insolvent_{i,t-1}) \times max(0, TotalLoans_{i,t-1}^{S,C} \times TotalLoans\_gr_{i,t}^{S,C} \\ + Outflows_{i,t}^{S,C}) \end{aligned} \tag{17}$$

where $TotalLoans$ is the total amount of bank loans to a sector at the end of the reference period. $Outflows$ is the amount of loans due in the reference period. $Insolvent$ is a discreet variable taking the value of 1 if the bank does not meet the minimum capital requirements and 0 otherwise (see equation (203)).[29]

[29] Accordingly, banks can deleverage only by limiting the issuance of new loans. Approaches to incorporate other mechanisms, such as sales of existing assets, failed due to the poor quality of the corresponding supervisory data.

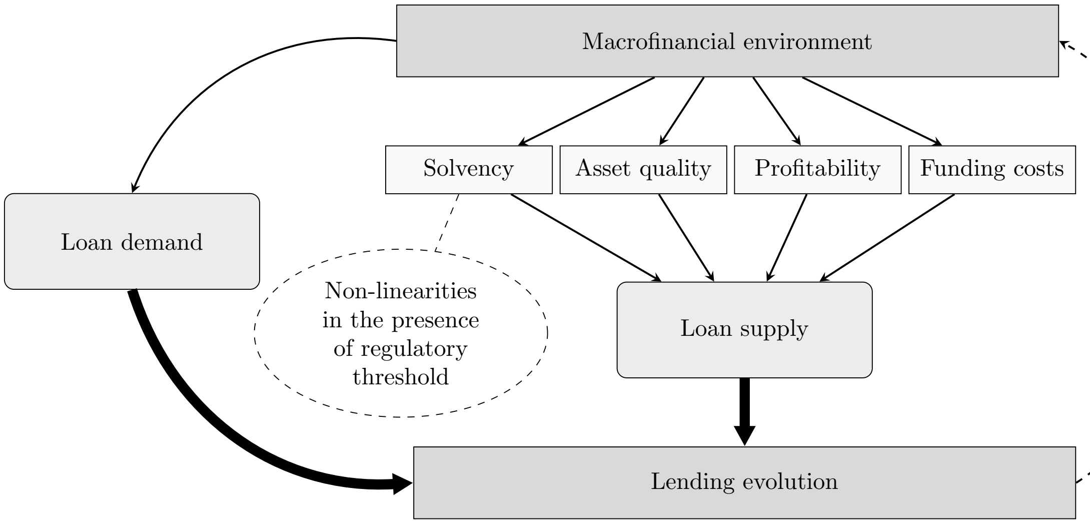


Figure 8: Conceptual representation of the lending evolution

Bank exposures to sectors $S \in \{OTHER, EQ\}$ follow a simplified dynamics that grows proportionally to the nominal GDP of the domestic country of a bank C_i:

$$Exp_{i,t}^{S} = Exp_{i,t-1}^{S} \times \left(YERgr_t^{C_i} + HICgr_t^{C_i} + 1\right) \tag{18}$$

Finally, bank exposures to the remaining sectors $S \in \{SEC, DERIV\}$ remain constant over time:

$$Exp_{i,t}^{S} = Exp_{i,t-1}^{S} \tag{19}$$

The total assets in the banking book $TotalExposure$ include all country-specific exposures to the non-financial private sectors and those broken down by sector only $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$, along with the remaining sectors $S^{OTH} \in \{OTHER, EQ, SEC\}$:

$$TotalExposure_{i,t} = \sum_{S}\sum_{C} TotalLoans_{i,t}^{S,C} + \sum_{S^{OTH}} Exp_{i,t}^{S^{OTH}} \tag{20}$$

where the sum operation and the superscript C apply only to $S \in \{NFC, HHCC, HHHP\}$. The same consideration applies to all analogous sum operations throughout the paper.

The total assets of a bank TA are then scaled by the growth of the assets in the banking book:[30]

$$TA_{i,t} = TA_{i,t-1} \times \frac{TotalExposure_{i,t}}{TotalExposure_{i,t-1}} \tag{21}$$

4.1.3 Evolution of asset quality in the banking book

The assessment of asset quality in the banking book aligns with the IRFS9 accounting standards. Following the IFRS9 framework for the classification and measurement of financial

[30]The total assets include additional items not specifically covered by the banks submissions for the EU-wide stress test templates and cannot be derived only by summing up assets tracked in the model.

instruments and the provisioning of loan losses based on the expected credit loss (ECL) framework, financial assets are categorized into three stages of credit impairment. The stages of credit impairment comprise stage 1 (S1), with the corresponding asset volume denoted as $NonDefExpS1$, with a stable risk profile, stage 2 (S2), $NonDefExpS2$, with a significant increase in credit risk, and stage 3 (S3), $DefExp$, where the corresponding assets are credit-impaired. The variable $TotalLoans$ from equation (17) representing exposures in sector $S \in \{NFC, HHHP, HHCC, FIN, SOV, CB, RoW\}$ and for a specific country C, can be decomposed as follows:

$$TotalLoans_{i,t}^{S,C} = NonDefExp_{i,t}^{S,C} + DefExp_{i,t-1}^{S,C} \tag{22}$$

and further as:

$$NonDefExp_{i,t}^{S,C} = NonDefExpS1_{i,t}^{S,C} + NonDefExpS2_{i,t-1}^{S,C} \tag{23}$$

The dynamics of asset credit quality are governed by a transition probability matrix. The transition rate matrix TR for sector S and country C comprises diagonal elements representing the probability of staying within the original credit impairment stage. Conversely, the off-diagonal elements of the matrix denote the probabilities of transitioning to other stages. TR provided below exemplifies a stochastic matrix, and thus, the sum of elements in each row must equal one:

$$TR_{i,t}^{S,C} = \begin{bmatrix} TR11_{i,t}^{S,C} & TR12_{i,t}^{S,C} & TR13_{i,t}^{S,C} \\ TR21_{i,t}^{S,C} & TR22_{i,t}^{S,C} & TR23_{i,t}^{S,C} \\ TR31_{i,t}^{S,C} & TR32_{i,t}^{S,C} & TR33_{i,t}^{S,C} \end{bmatrix} \tag{24}$$

Performing exposures evolve along with the new loans issuance,[31] shifts in asset quality and expiration of maturing loans. The estimation of loan outflow is deduced from the inverse of the portfolio's average annual duration $AvgDuration$, which is assumed to be constant over the simulation horizon and adjusted to align with quarterly time steps by multiplying it by a factor of 0.25. Furthermore, the model assumes that only performing exposures can mature. Therefore, the outflow of maturing loans in period t is adjusted for exposures that are transitioning to stage 3, determined by the transition rates $TR23$ and $TR13$:

$$\begin{aligned} NonDefExpS1_{i,t}^{S,C} = (1 - 0.25 \times (AvgDuration_{i}^{S,C})^{-1}) \times (& \\ (1 - TR12_{i,t}^{S,C} - TR13_{i,t}^{S,C}) \times NonDefExpS1_{i,t-1}^{S,C} & \\ + TR21_{i,t}^{S,C} \times NonDefExpS2_{i,t-1}^{S,C} + TR31_{i,t}^{S,C} \times DefExp_{i,t-1}^{S,C}) & \\ + NewLoans_{i,t}^{S,C} & \end{aligned} \tag{25}$$

$$\begin{aligned} NonDefExpS2_{i,t}^{S,C} = (1 - 0.25 \times (AvgDuration_{i}^{S,C})^{-1}) \times (& \\ (1 - TR21_{i,t}^{S,C} - TR23_{i,t}^{S,C}) \times NonDefExpS2_{i,t-1}^{S,C} & \\ + TR12_{i,t}^{S,C} \times NonDefExpS1_{i,t-1}^{S,C} + TR32_{i,t}^{S,C} \times DefExp_{i,t-1}^{S,C}) & \end{aligned} \tag{26}$$

[31] New loans are always classified as S1 at the origination.

Consequently, the outflows in equation (17) amount to:

$$
\begin{aligned}
Outflows_{i,t}^{S,C} = 0.25 \times (AvgDuration_{i}^{S,C})^{-1} \times (\\
(1 - TR13_{i,t}^{S,C}) \times NonDefExpS1_{i,t-1}^{S,C} \\
+ (1 - TR23_{i,t}^{S,C}) \times NonDefExpS2_{i,t-1}^{S,C} \\
+ (1 - TR31_{i,t}^{S,C} - TR32_{i,t}^{S,C}) \times DefExp_{i,t-1}^{S,C}) + WriOff_{i,t}^{S,C}
\end{aligned} \tag{27}
$$

Defaulted exposures increase with the inflows of newly defaulted assets and decrease with the cure rates $TR31$ and $TR32$ and the write-off rate $WriOff_{i,t}^{S,C}$:

$$
\begin{aligned}
DefExp_{i,t}^{S,C} &= (1 - TR31_{i,t}^{S,C} - TR32_{i,t}^{S,C} - WriOff_{i,t}^{S,C}) \times DefExp_{i,t-1}^{S,C} \\
&+ TR13_{i,t}^{S,C} \times NonDefExpS1_{i,t-1}^{S,C} + TR23_{i,t}^{S,C} \times NonDefExpS2_{i,t-1}^{S,C}
\end{aligned} \tag{28}
$$

Consequently, the gross NPL ratio in equation (13), denoted as $NPLR$, is defined as the share of defaulted exposures $DefExp$ relative to the total outstanding amount:

$$
NPLR_{i,t}^{S,C} = \frac{DefExp_{i,t}^{S,C}}{TotalLoans_{i,t}^{S,C}} \tag{29}
$$

Transition rates are projected in a logit space to ensure that each element of the transition probability matrix remains between 0 and 1[32]. The empirical specification of transition rates for sectors $S \in \{NFC, HHHP, HHCC, FIN, SOV\}$ employs a seemingly unrelated regression model (SUR) (more details can be found in Appendix D.1.1). For $K = \{13, 12, 21, 23, 31, 32\}$, a transition rate $TR[K]$ equals:

$$
\begin{aligned}
TR[K]_{i,t}^{S,C} = invlogit\Big(& \beta_0^S + \sum_K \beta_1^{S,K} \, logit(TR[K]_{i,t-1}^{S,C}) \\
&+ \beta_2^S \, ExpRel_{t-1}^{S,C} + \beta_3^S \, YERgr_{t-1}^C + \beta_4^S \, MTRgr_{t-1}^C + \beta_5^S \, IHXgr_{t-1}^C \\
&+ \beta_6^S \, HICgr_{t-1}^C + \beta_7^S \, XTDgr_{t-1}^C + \beta_8^S \, ESXgr_{t-4}^C + \beta_9^S \, \Delta URX_{t-2}^C \\
&+ \beta_{10}^S \, LTN_{t-1}^C + \beta_{11}^S \, STN_{t-1}^C + \beta_{12}^S \, SPR_{t-1}^C \Big)
\end{aligned} \tag{30}
$$

Transition rates generally depend on the lags of all non-diagonal elements of the matrix TR and a set of macrofinancial variables. Among the latter, there are country-level real GDP growth $YERgr$, HICP inflation rate $HICgr$, growth rates of imports of goods and services $MTRgr$, of residential property prices $IHXgr$, of prices of exports of goods and services $XTDgr$, and of equity index $ESXgr$, unemployment rate URX, long-term LTN and short-term STN interest rates and interest rate spread SPR. Additionally, all equations include the relative amount of exposures in the relevant impairment stage $ExpRel$:[33]

[32]Logit function is defined as **logit**$(p) = ln(p/(1-p))$. Therefore, the inverse logit function is defined as **invlogit**$(p) = 1/(1+exp(-p))$.

[33] The relative amounts of exposures in the individual impairment stages capture empirical patterns observed in the data. For example, a higher percentage of S3 exposures cure to S1 or S2 when the relative amount of S3 exposures increases. On the flip side, a higher percentage of S2 exposures tends to remain in S2 when the relative amount of S2 exposures increases.

$$ExpRel^{S,C}_{i,t} = \begin{cases} NonDefExpS1Rel^{S,C}_{i,t} = \frac{NonDefExpS1^{S,C}_{i,t}}{TotalLoans^{S,C}_{i,t}} & \text{if } K = \{13,12\} \\ NonDefExpS2Rel^{S,C}_{i,t} = \frac{NonDefExpS2^{S,C}_{i,t}}{TotalLoans^{S,C}_{i,t}} & \text{if } K = \{21,23\} \\ DefExpRel^{S,C}_{i,t} = \frac{DefExp^{S,C}_{i,t}}{TotalLoans^{S,C}_{i,t}} & \text{if } K = \{31,32\} \end{cases} \tag{31}$$

The probability of default $PDpit$ is defined as a weighted average of the default transition rates $TR13$ and $TR23$:

$$PDpit^{S,C}_{i,t} = \frac{TR13^{S,C}_{i,t} \times NonDefExpS1^{S,C}_{i} + TR23^{S,C}_{i,t} \times NonDefExpS2^{S,C}_{i}}{NonDefExpS1^{S,C}_{i,t} + NonDefExpS2^{S,C}_{i,t}} \tag{32}$$

The evolution of defaulted exposures is furthermore influenced by write-offs. Write-offs take place each quarter after the realisation of new defaults, but before the building up of loan loss provisions. Every period, banks write off the share $WriOffr$ of their defaulted exposures:

$$WriOff^{S,C}_{i,t} = WriOffr^{S,C}_{i,t} \times DefExp^{S,C}_{i,t-1} \tag{33}$$

where $WriOff$ is the quarterly value of write-offs. The projection of $WriOffr$ follows from a tobit function, which accounts for its non-linear nature:

$$WriOffr^{S,C}_{i,t} = \Phi\Big(\frac{WriOffrLin^{S,C}_{i,t}}{\sigma}\Big) \times \left[WriOffrLin^{S,C}_{i,t} + \sigma * \frac{\phi(\frac{WriOffrLin^{S,C}_{i,t}}{\sigma})}{\Phi(\frac{WriOffrLin^{S,C}_{i,t}}{\sigma})}\right] \tag{34}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, $\phi(\cdot)$ is the standard normal density function, σ is the estimated standard error of the tobit regression, and $WriOffrLin$ is the underlying linear function (more details can be found in Appendix C.3) of the following form:

$$\begin{aligned} WriOffrLin^{S,C}_{i,t} = \beta^S_0 + \beta^S_1 NPLR^{S,C}_{i,t-1} + \beta^S_2 NPLR1Y^{S,C}_{i,t-1} + \beta^S_3 ProvCovDefR^{S,C}_{i,t-1} \\ \beta^S_4 ColCovDefR^{S,C}_{i,t-1} + \beta^S_5 ROA_{i,t-1} + \beta^S_6 NPLR1Y^{S,C}_{i,t-1} \times ProvCovDefR^{S,C}_{i,t-1} \\ \beta^S_7 ProvCovDefR^{S,C}_{i,t-1} \times ROA_{i,t-1} + \beta^S_8 ProvCovDefR^{S,C}_{i,t-1} \times NPLR^{S,C}_{i,t-1} \\ \beta^S_9 ColCovDefR^{S,C}_{i,t-1} \times ROA_{i,t-1} \end{aligned} \tag{35}$$

where $NPLR1Y$ is the share of exposures that had defaulted at least one year earlier. $ProvCovDefR$ is coverage of defaulted exposure with provisions defined as:

$$ProvCovDefR^{S,C}_{i,t} = \frac{ProvStockDef^{S,C}_{i,t}}{DefExp^{S,C}_{i,t}} \tag{36}$$

Banks tend to write off defaulted exposures when defaulted loans have a relatively high coverage with loan loss provisions and they are long past due. They also write off a higher share of defaulted loans when the overall NPL burden on their balance sheet is larger, but their profitability remains robust.

The estimated regression coefficients for the sector SOV are used to project the transition and write-off rates for the sector CB. For the sector RoW transition and write-off rates, the regression coefficients are derived as a linear combination of coefficients for $S \in \{NFC, HHHP, HHCC\}$ with bank-specific weights similar to those of equation (15). The macrofinancial variables in RoW transition rate and write-off rate equations are derived as a weighted average of the variables in the rest of the world countries following the same approach as in equation (16).

The total write-offs $TotWriOff$ are later deduced from the profits of continuing operations:[34]

$$TotWriOff_{i,t} = \sum_S \sum_C WriOffR_{i,t}^{S,C} \times DefExp_{i,t}^{S,C} \tag{37}$$

The model attributes simplified asset quality dynamics to exposures to sectors $S^{OTH} \in \{OTHER, EQ, SEC\}$. For these sectors, the model distinguishes only between performing and defaulted exposures, and the share of each is assumed to be constant:

$$NonDefExp_{i,t}^S = NonDefExp_{i,t-1}^S \frac{Exp_{i,t}^S}{Exp_{i,t-1}^S} \tag{38}$$

$$DefExp_{i,t}^S = DefExp_{i,t-1}^S \frac{Exp_{i,t}^S}{Exp_{i,t-1}^S} \tag{39}$$

On aggregate, for $S \in \{NFC, HHHP, HHCC, FIN, SOV, CB, RoW\}$, the total stock of non-defaulted exposures amounts to:

$$\begin{aligned} NonDefExp_{i,t} = &\sum_S \sum_C \left(NonDefExpS1_{i,t}^{S,C} + NonDefExpS2_{i,t}^{S,C} \right) \\ &+ \sum_{S^{OTH}} NonDefExp_{i,t}^S \end{aligned} \tag{40}$$

and of defaulted exposures amounts to:

$$DefExp_{i,t} = \sum_S \sum_C DefExp_{i,t}^{S,C} + \sum_{S^{OTH}} DefExp_{i,t}^S \tag{41}$$

4.1.4 Loan-loss provisioning

Banks create loan loss provisions for performing and non-performing exposures according to IFRS9 accounting standards, where the lifetime expected credit loss (ECL) is the present value of the expected loss incurred if the borrower defaults at any time before the loan maturity.[35] 1-year ECL is recognised for loans in stage 1 and the lifetime ECL is recognised for loans in stages 2 and 3.

For exposures classified as stage 1, loan loss provisions $ProvStockNonDefS1$ are calculated according to the 1-year ahead transition probability to stage 3, $TR1Y13$, and the corresponding forward-looking LGD value, $LGD1Y13$:

[34] Total write offs can be also corrected for the collateral recovery rate, which in selected model simulations is assumed to equal 20% for secured exposures, and 0% for unsecured exposures. Data on collateral recovery rates for euro area banks are scarce, and the calibration is based on an ad hoc data collection by the SSM involving high-NPL banks.

[35] The model also incorporates the SSM's NPL coverage expectations for defaulted equations which overwrite the IRFS9 provisioning rules in this section for defaulted assets. A detailed description of the two alternative implementations of the NPL coverage expectations can be found in Budnik et al. [2022c].

$$ProvStockNonDefS1_{i,t}^{S,C} = NonDefExpS1_{i,t}^{S,C} \times TR1Y13_{i,t}^{S,C} \times LGD1Y13_{i,t}^{S,C} \tag{42}$$

The loan loss provisions for stage 2 exposures, $ProvStockNonDefS2$, are composed of two parts. The first part is calculated for exposures that stay in stage 2 between quarters $t-1$ and t and accounts for a loss according to the lifetime loss rate $LR2X$. The second part corresponds to assets that migrate to stage 2 from stage 1 or 3 and accounts for a loss according to the loss rate $LR12$:

$$\begin{aligned} ProvStockNonDefS2_{i,t}^{S,C} = {} & (1 - 0.25 \times (AvgDuration_i^{S,C})^{-1}) \\ & \times (1 - TR23_{i,t}^{S,C} - TR21_{i,t}^{S,C}) \times LR2X_{i,t}^{S,C} \times NonDefExpS2_{i,t-1}^{S,C} \\ & + TR12_{i,t}^{S,C} \times LR12_{i,t}^{S,C} \times NonDefExpS1_{i,t-1}^{S,C} \\ & + TR32_{i,t}^{S,C} \times LR12_{i,t}^{S,C} \times DefExp_{i,t-1}^{S,C} \end{aligned} \tag{43}$$

The loan loss provisions for defaulted exposures, $ProvStockDef$, are split similarly into two parts, depending on the stage from which an exposure migrated to stage 3. The exposure in default already in $t-1$ can cure or be written off. Correspondigly, in the absence of the supervisory coverage expectations, loans that are written off are assumed to have had earlier been provisioned on the average level of the defaulted portfolio. The remaining part $(1 - TR31_{i,t}^{S,C} - TR32_{i,t}^{S,C} - WriOffr_{i,t}^{S,C})$ remains in default and accounts for a loss according to the lifetime loss rate $LR33$.

An additional conservative assumption in the model is that the provisioning coverage ratio for the existing defaulted exposures staying in stage 3 is not allowed to drop between two consecutive periods. That is, if $LR33$ is lower in time t than in $t-1$ a bank would need to account for this difference, which is proportional to $ProvStockDef - LR33 \times DefExp$. The second component of $ProvStockDef$ is the provision created for exposures that migrated to stage 3 from stage 1 or stage 2. The first represents a loss according to the parameter of loss given default $LGD13$, while the latter is provisioned according to the parameter $LGD23$.

$$\begin{aligned} ProvStockDef_{i,t}^{S,C} = {} & (1 - TR31_{i,t}^{S,C} - TR32_{i,t}^{S,C} - WriOffr_{i,t}^{S,C}) \times LR33_{i,t}^{S,C} \times DefExp_{i,t-1}^{S,C} \\ & + (1 - TR31_{i,t}^{S,C} - TR32_{i,t}^{S,C} - WriOffr_{i,t}^{S,C}) \\ & \times I(ProvStockDef_{i,t-1}^{S,C} > LR33_{i,t}^{S,C} \times DefExp_{i,t-1}^{S,C}) \\ & \times (ProvStockDef_{i,t-1}^{S,C} - LR33_{i,t}^{S,C} \times DefExp_{i,t-1}^{S,C}) \\ & + TR13_{i,t}^{S,C} \times LGD13_{i,t}^{S,C} \times NonDefExpS1_{i,t-1}^{S,C} \\ & + TR23_{i,t}^{S,C} \times LGD23_{i,t}^{S,C} \times NonDefExpS2_{i,t-1}^{S,C} \end{aligned} \tag{44}$$

The aggregation of loan loss provisions per bank takes the stock of provisions for non-defaulted and defaulted exposures for $S \in \{NFC, HHHP, HHCC, FIN, SOV, CB, RoW\}$:

$$ProvStockNonDef_{i,t} = \sum_S \sum_C (ProvStockNonDefS1_{i,t}^{S,C} + ProvStockNonDefS2_{i,t}^{S,C}) \tag{45}$$

$$ProvStockDef_{i,t} = \sum_S \sum_C ProvStockDef_{i,t}^{S,C} \tag{46}$$

Provisions for equity EQ and other $OTHER$ sectors are assumed to evolve in constant proportions to the corresponding bank exposures:

$$ProvStock_{i,t}^{S,C} = ProvStock_{i,t-1}^{S,C} \frac{Exp_{i,t}^{S}}{Exp_{i,t-1}^{S}} \tag{47}$$

Then, the total volume loan loss provisions is given by:

$$\begin{aligned} ProvStock_{i,t} &= ProvStockNonDef_{i,t} + ProvStockDef_{i,t} \\ &+ ProvStock_{i,t}^{OTHER} + ProvStock_{i,t}^{EQ} + ProvStock_{i,t}^{IFRS9Adj} \end{aligned} \tag{48}$$

where a bank-specific IFRS9 adjustment term $IFRS9Adj$ stays constant over time.[36]

4.1.4.1 IFRS9 loss parameters

LGD represents the share of expected loss on exposures that transition from a performing stage (i.e., stage 1 or stage 2) to a non-performing stage, i.e., to stage 3. The loan loss provisioning model differentiates between $LGD13$, which is the loss given default on exposures that migrate from stage 1 to stage 3, and $LGD23$, which is the loss given default for exposures that migrate from stage 2 to stage 3.

Analogically to the transition rates (see Section 4.1.3), the parameters LGD are projected in the logit space to ensure the estimations remain between 0 and 1. Parameters $LGD13$ and $LGD23$ are modelled jointly in a seemingly unrelated regression (SUR) framework, though separately for each sector $S \in \{NFC, HHHP, HHCC, FIN, SOV\}$ (for details, see Appendix D.1.2). For $K = \{13, 23\}$, a loss given default $LGD[K]$ equals:

$$\begin{aligned} LGD[K]_{i,t}^{S,C} = invlogit\Big(&\beta_0^S + \sum_K \beta_1^{S,K}\, logit(LGD[K]_{i,t-1}^{S,C}) + \beta_2^S\, ExpRel_{t-1}^{S,C} + \beta_3^S\, logit(CureRateLT_{t-1}^{S,C}) \\ &+ \beta_4^S\, YERgr_{t-1}^C + \beta_5^S\, MTRgr_{t-1}^C + \beta_6^S\, IHXgr_{t-1}^C + \beta_7^S\, HICgr_{t-1}^C + \beta_8^S\, XTDgr_{t-1}^C \\ &+ \beta_9^S\, ESXgr_{t-4}^C + \beta_{10}^S\, \Delta URX_{t-1}^C + \beta_{11}^S\, LTN_{t-1}^C + \beta_{12}^S\, STN_{t-1}^{EA} + \beta_{13}^S\, SPR_{t-1}^C\Big) \end{aligned} \tag{49}$$

Each LGD depends on the lags of both $LGDs$ in the system and a set of macroeconomic variables, including country-level real GDP growth $YERgr$, HICP inflation rate $HICgr$, growth rates of imports of goods and services $MTRgr$, of residential property $IHXgr$, the prices of exports of goods and services $XTDgr$, and the equity index $ESXgr$, unemployment rate URX, long-term LTN and short-term STN interest rates and interest rate spread SPR

In addition, the specification accounts for the relative amount of exposures in the individual stages of impairment (see equation (4.1.5.3)) and the lifetime cure rates, $CureRateLT$. The parameter $CureRateLT$ approximates the component of LGD that relates to the estimated cumulative proportion of defaulted exposures that cure through zero loss repayment during a workout period. The lifetime cure rate is the average expected share of cures during the lifetime of an exposure updated by the transition probabilities $TR31$ and $TR32$ and averaged by the expectation adjustment parameter $\beta_{EXP}^{Cure} = 0.8$:

[36] It is sourced from the EU-wide stress test submissions.

$$CureRateLT_{i,t}^{S,C} = \beta_{EXP}^{Cure} CureRateLT_{i,t-1}^{S,C} + (1-\beta_{EXP}^{Cure}) \times (1-(1-TR31_{i,t}^{S,C} - TR32_{i,t}^{S,C})^{4\times AvgDuration_i^{S,C}} \tag{50}$$

Parameters $LGD13$ and $LGD23$ are aggregated to the point in time $LGDPiT$, which is an average loss on newly defaulted exposure:

$$\begin{aligned} LGDPiT_{i,t}^{S,C} = &(TR13_{i,t}^{S,C} \times NonDefExpS1_{i,t}^{S,C} \times LGD13_{i,t}^{S,C} \\ &+ TR23_{i,t}^{S,C} \times NonDefExpS2_{i,t}^{S,C} \times LGD23_{i,t}^{S,C}) \\ &/(TR13_{i,t}^{S,C} \times NonDefExpS1_{i,t}^{S,C} + TR23_{i,t}^{S,C} \times NonDefExpS2_{i,t}^{S,C}) \end{aligned} \tag{51}$$

Loss rates LR represent the expected lifetime loss on exposures in stage 2 and stage 3. The IRFS9 loan loss provisioning rules distinguish three lifetime loss rates: the expected loss rate for exposures that migrate from stage 1 to stage 2 $LR12$, the expected loss rate for exposures that migrate from stage 2 to any other stage $LR2X$, and the lifetime expected loss rate for exposures that remain in stage 3 $LR33$.

The three loss rate parameters are projected in logit space and in a seemingly unrelated regression (SUR) framework (see Appendix D.1.2). SUR regressions are considered separately for each sector $S \in \{NFC, HHHP, HHCC, FIN, SOV\}$. For $K = \{12, 2X, 33\}$, a loss rate $LR[K]$ equals:

$$\begin{aligned} LR[K]_{i,t}^{S,C} = invlogit\Big(&\beta_0^S + \sum_K \beta_1^{S,K} logit(LR[K]_{i,t-1}^{S,C}) + \beta_2^S ExpRel_{t-1}^{S,C} + \beta_3^S logit(LGDPiT_{t-1}^{S,C}) \\ &+ \sum_L \beta_4^{S,L} logit(TR[L]_{i,t-1}^{S,C}) + \beta_5^S YERgr_{t-1}^C + \beta_6^S MTRgr_{t-1}^C + \beta_7^S IHXgr_{t-1}^C + \beta_8^S HICgr_{t-1}^C \\ &+ \beta_9^S XTDgr_{t-1}^C + \beta_{10}^S ESXgr_{t-4}^C + \beta_{11}^S \Delta URX_{t-1}^C + \beta_{12}^S LTN_{t-1}^C + \beta_{13}^S STN_{t-1}^{EA} + \beta_{14}^S SPR_{t-1}^C\Big) \end{aligned} \tag{52}$$

where $L = \{13, 12, 21, 23, 31, 32\}$. Therefore, each LR depends on the lags of all LRs in the system and the same set of macroeconomic variables as $LGDs$ in equation (49). The specification also considers the relative amount of exposures in the individual impairment stages, the point-in-time $LGDpit$ and transition rates.[37]

The estimated regression coefficients for the sector SOV are also used to project $LGDs$ and LRs for the sector CB. For the sector ROW the regression coefficients and macrofinancial variables are derived as a linear combination of sector-specific coefficients and country variables from the rest of the world, correspondingly, as in equations (15) and (16).

The 1-year ahead transition probability to stage 3 $TR1Y13$, which is applied in the projections of $ProvStockNonDefS1$ in equation (42), is a naive one-period ahead forecast of annualised $TR13$ assuming a simple scheme of banks' adaptive expectations. $TR1Y13$ becomes a function of $TR13$ in the current and previous period with an adaptive expectation parameter $\beta_{EXP} = 0.5$:

[37] $LGDPiT$ and transition rates are a natural choice as LRs represent lifetime expected loss expressed as percentage of the current exposure and thus intuitively should be affected by the likelihood of transiting up or down between the impairment stages or by the loss rates associated with default events.

$$TR1Y13_{i,t}^{S,C} = 1-(1-(1+\beta_{EXP})\,TR13_{i,t}^{S,C} - \beta_{EXP}\,TR13_{i,t-1}^{S,C})^4 \tag{53}$$

Analogically, we also derive $LGD1Y13$, which is the corresponding forward-looking loss given default parameter for exposures in stage 1 based on the values of $LGD13$ in the current and previous period:

$$LGD1Y13_{i,t}^{S,C} = (1+\beta_{EXP})\,LGD13_{i,t}^{S,C} - \beta_{EXP}\,LGD13_{i,t-1}^{S,C} \tag{54}$$

4.1.5 Pricing of loans

4.1.5.1 Pricing of new loans

The pricing of new loans to the non-financial private sector takes into account bank funding costs and differs for short- and long-term maturity loans $D = \{Short, Long\}$. Effective interest rate margins $EIRmargin$ for $S \in \{NFC, HHCC, HHHP, RoW\}$ are defined as the spread between the respective lending rate $EIRAssetNew$ and the average bank funding costs $EIRLiab$ both expressed in quarterly terms:[38]

$$EIRmargin_{i,t}^{S,C} = EIRAssetNew_{i,t}^{S,C} - EIRLiab_{i,t} \tag{55}$$

And further:

$$\begin{aligned}
\Delta EIRmargin_{i,t}^{S,C} = \sum_D Share_i^{S,C,D} \times (&\beta_1^{S,D}\,\Delta EIRmargin_{i,t-1}^{S,C} \\
&+ \beta_2^{S,D}\,\Delta STN_{i,t-1}^{EA} + \beta_3^{S,D}\,\Delta LTN_{i,t-1}^{C} \\
&+ \beta_4^{S,D}\,\Delta YERgr_{i,t-1}^{C} + \beta_5^{S,D}\,\Delta HICgr_{i,t-1}^{C} \\
&+ \beta_6^{S,D}\,CET1SurShortfall_{i,t-1} + \beta_7^{S,D}\,\Delta LevRaT_{i,t-1})
\end{aligned} \tag{56}$$

where $Share^{S,C,D}$ is a bank-specific share of loans in each maturity bucket D.

The estimated equations for $S \in \{NFC, HHCC, HHHP\}$ link the interest rates on new bank loans to short- STN and long-term LTN market rates and general macroeconomic conditions in the country of exposure C. The latter account for fluctuations in loan demand and credit risk within the business cycle and include GDP growth $YERgr$, inflation $HICgr$ and the unemployment rate URX. Additionally, the pricing equation includes the solvency distance to regulatory requirements $CET1SurShortfall$ as defined in equation (201) and the change in the banks' leverage ratio $LevRaT$. A positive estimated coefficient on banks' leverage ratio captures the cost of equity effect on bank lending. A detailed description of the estimation methodology and results can be found in the Appendix C.4.

The share of loans in a maturity bucket is approximated according to a $Gamma(k, x, \theta)$ distribution with $k = 1$, $\theta = AvgDuration$, and x that denotes the threshold value distinguishing

[38]Banks use an average funding cost to price loans rather than an internal transfer price that might vary but sector. This choice is related to the inaccessibility of historical information on bank internal transfer prices that prevented empirical identification of accordingly derived loan interest rate equations.

between short- and long-term loans any sector.[39] The share of loans in a portfolio with average maturity θ which mature not earlier than after x years, but before y years is then provided by the function:

$$F(x,y,\theta) = e^{-\frac{x}{\theta}} - e^{-\frac{y}{\theta}}, \text{ where } 0 \leq x \leq y \tag{57}$$

The maturity cut-off values to distinguish between short- and long-term maturity loans are one year for NFC and household consumption $HHCC$ loans and 5 years for household mortgages $HHHP$:

$$Share_i^{S,C,D} = \begin{cases} F(0,1,AvgDuration_i^{S,C}) & \text{if } D = Short, S = \{NFC, HHCC\} \\ F(0,5,AvgDuration_i^{S,C}) & \text{if } D = Short, S = HHHP \\ 1 - F(0,1,AvgDuration_i^{S,C}) & \text{if } D = Long, S = \{NFC, HHCC\} \\ 1 - F(0,5,AvgDuration_i^{S,C}) & \text{otherwise} \end{cases} \tag{58}$$

The new lending margins for banks' RoW exposures are obtained by averaging the coefficients estimated for sectors $S \in \{NFC, HHCC, HHHP\}$ with weights proportional to their shares in RoW exposures. Additionally, the macrofinancial variables in equation (56) are substituted with their weighted average counterparts RoW as in equation (16).

Banks are price-takers for new loans to sovereign SOV and financial loans FIN. Sovereign and financial exposures are divided into domestic exposures, with their share of $Share^{S,Home}$ and foreign exposures, with their share of $1 - Share^{S,Home}$. The interest rates on these exposures are then linked to the domestic country C's ($Yield^C$) and the euro area yield curves ($Yield^{EA}$) taking into account the average maturity of loans.

$$\begin{aligned} EIRAssetNew_{i,t}^{S} = {} & EIRAssetNew_{i,t-1}^{S} + 0.25 \\ & \times (Share_i^{S,Home} \times \Delta Yield_t^C (AvgDuration_i^S) \\ & + (1 - Share_i^{S,Home}) \times \Delta Yield_t^{EA} (AvgDuration_i^S)) \end{aligned} \tag{59}$$

Banks are also price-takers for central bank loans CB, for which interest rates are directly linked to the euro area yield curve:

$$EIRAssetNew_{i,t}^{CB} = EIRAssetNew_{i,t-1}^{CB} + 0.25 \times \Delta Yield_t^{EA} (AvgDuration_{i,t}^{CB}) \tag{60}$$

Interests on newly acquired debt securities issued by non-financial corporations $SNFC$ and sovereigns $SGOV$ are derived from bank and sector-specific yield curves $Yield^S$:

$$EIRAssetNew_{i,t}^{S} = EIRAssetNew_{i,t-1}^{S} + 0.25 \times \Delta Yield_{i,t}^{S} \tag{61}$$

The annualized yields on bank security holdings are decomposed into a credit spread and the risk-free market interest rate in the euro area for the relevant maturity. The latter is approximated by the euro area yield curve $Yield^{EA}$:

[39] This distribution has sensible properties (positive support, strong positive skew) and a computationally efficient cumulative density function in $1 - e^{-x/\theta}$.

$$Yield_{i,t}^{S} = CreditSpread_{i,t}^{S} + Yield_{t}^{EA}(AvgDuration_{i}^{S}) \tag{62}$$

The credit spread expresses the risk of counterparty default[40] and follows a log-multiplicative specification that captures the empirical non-linearity in risk margins. A change in risk factors has a larger impact on risk margins when these are already elevated and ensures that the yields on bonds never decrease below the risk-free rate.

$$CreditSpread_{i,t}^{S} = e^{LinSpread_{i,t}^{S}} \tag{63}$$

$LinSpread$ for $SNFC$ and $SGOV$ is related to macrofinancial variables of the country of exposure that include real GDP YER, inflation $HICgr$, stock market growth ESX, and the spread SPR between long- and short-term rates in the country of exposure C (see Appendix C.6). For corporate debt securities, the linear component of the risk margin also depends on the maturity of the assets held.

The linear component of the credit spread on newly acquired sovereign bonds $LinSpread^{SGOV}$ that aggregates information on market conditions in all countries in the euro area is described by:

$$\begin{aligned} LinSpread_{i,t}^{SGOV} &= \beta_1\, LinSpread_{i,t-1}^{SGOV} \\ &+ \sum_{C} Share_{i}^{SGOV,C} \times \Big(\beta_2\, YERgr_{t}^{C} + \beta_3\, ESXgr_{t}^{C} \\ &+ \beta_4\, \Delta SPR_{t}^{C}\Big) + \beta_5\, \Delta STN_{t}^{EA} \end{aligned} \tag{64}$$

where $Share^{SGOV,C}$ is the share of sovereign country bonds C in all sovereign bonds acquired by a bank. While, the linear component of the credit spread on newly acquired corporate bonds $LinSpread^{SNFC}$ is described by:

$$\begin{aligned} LinSpread_{i,t}^{SNFC} &= \beta_1\, log(AvgDuration_{i,t}^{SNFC}) \\ &+ \sum_{C} Share_{i}^{SNFC,C} \times \Big(\beta_2\, YERgr_{t}^{C} + \beta_3\, YERgr_{t-1}^{C} + \beta_4\, YERgr_{t-2}^{C} \\ &+ \beta_5\, ESXgr_{t}^{C} + \beta_6\, ESXgr_{t-1}^{C} + \beta_7\, \Delta URX_{t}^{C} \\ &+ \beta_8\, \log(AvgDuration_{i,t-1}^{SNFC}) \times \Delta LTN_{t-1}^{C}\Big) \end{aligned} \tag{65}$$

where $Share^{SNFC,C}$ is the share of corporate country bonds C in all corporate bonds acquired by a bank.

The interest rates on securities issued by financial companies $SFIN$ are based on the assumption of a common financial market for this type of securities in the euro area. The interest rate formula takes into account the bank-specific share of securities issued by counterparts in the euro area $Share^{SFIN,EA}$ and those issued outside the euro area $1 - Share^{SFIN,EA}$. For the former, changes in interest rates on securities are approximated by changes in the euro area yield curve, and for the latter by changes in the US yield curve (see Section 3.4).

[40]Other factors such as tax or liquidity effects that can contribute to the credit spread but are not included in the model. For a discussion of the validity of focusing on default risk, see C.9.

$$
\begin{aligned}
EIRAssetNew_{i,t}^{SFIN} = {} & EIRAssetNew_{i,t-1}^{SFIN} + 0.25 \\
& \times (Share_i^{SFIN,EA} \times \Delta Yield_t^{EA}(AvgDuration_i^{SFIN}) \\
& + (1 - Share_i^{SFIN,EA}) \times \Delta Yield_t^{US}(AvgDuration_i^{SFIN}))
\end{aligned} \tag{66}
$$

4.1.5.2 Pricing of existing, maturing and non-performing loans

The interest rates for existing and performing assets that carry interest $EIRAssetExist$ are updated taking into account the issuance of new loans in the previous quarter and considering the share of floating interest rate loans $ShareFloat$. For the latter, the model assumes a direct pass-through of changes in the EURIBOR 3-month rate STN^{EA}. For $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB, OTHER, DERIV, SNFC, SGOV, SFIN\}$ the interest rate on the maturing and performing assets is equal to:

$$
\begin{aligned}
EIRAssetExist_{i,t}^{S,C} = {} & (EIRAssetNew_{i,t-1}^{S,C} \times VolAssetNew_{i,t-1}^{S,C} \\
& + EIRAssetExist_{i,t-1}^{S,C} \times VolAssetExist_{i,t-1}^{S,C})/ \\
& (VolAssetNew_{i,t-1}^{S,C} + VolAssetExist_{i,t-1}^{S,C}) \\
& + 0.25 \times (RefDuration_i^{S,C})^{-1} \, ShareFloat_i^{S,C} \, \Delta STN_t^{EA}
\end{aligned} \tag{67}
$$

where $VolAssetNew$ are the period average volumes of new and $VolAssetExist$ of existing and performing assets bearing interest. $RefDuration$ is the average annualized duration of the reference rate.

The interest rates for maturing assets $EIRAssetMat$ are updated with the change in $EIRAssetExist$ and assume a gradual convergence of interest rates between maturing and existing assets which depends on the average duration of the portfolio $AvgDuration$:

$$
\begin{aligned}
EIRAssetMat_{i,t}^{S,C} = {} & EIRAssetMat_{i,t-1}^{S,C} + \Delta EIRAssetExist_{i,t}^{S,C} \\
& - 0.25 \times (AvgDuration_i^{S,C})^{-1} \, (EIRAssetMat_{i,t-1}^{S,C} - EIRAssetExist_{i,t-1}^{S,C})
\end{aligned} \tag{68}
$$

The effective interest rate on non-performing interest bearing assets $EIRAssetNPE$ is assumed to remain constant for all sectors:

$$
EIRAssetNPE_{i,t}^{S,C} = EIRAssetNPE_{i,t-1}^{S,C} \tag{69}
$$

4.1.5.3 The period average volumes of new, existing and maturing interest-bearing assets

The total period average assets $VolAssetTotal$ for $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$ are projected along with the dynamics of the corresponding banking book assets $TotalLoans$ outlined in Section 4.1.2:

$$
VolAssetTotal_{i,t}^{S,C} = VolAssetTotal_{i,t-1}^{S,C} \times \frac{TotalLoans_{i,t}^{S,C}}{TotalLoans_{i,t-1}^{S,C}} \tag{70}
$$

The dynamics of the volumes of bank security holdings for $S \in \{SNFC, SGOV, SFIN\}$ follows instead:

$$\begin{aligned} VolAssetTotal^{S,C}_{i,t} = &(1 - 0.25 \times (AvgDuration^{S,C}_{i})^{-1}) \\ &\times (VolAssetTotal^{S,C}_{i,t-1} - VolNPE^{S,C}_{i,t-1}) + VolNPE^{S,C}_{i,t-1} \\ &+ (1 - Insolvent_{i,t-1}) \times max(0, VolAssetTotal\_gr^{S}_{i,t} \times VolAssetTotal^{S,C}_{i,t-1} \\ &+ 0.25 \times (AvgDuration^{S,C}_{i})^{-1} \times (VolAssetTotal^{S,C}_{i,t-1} - VolNPE^{S,C}_{i,t-1})) \end{aligned} \tag{71}$$

where $VolNPE$ is the volume of non-performing securities and $VolAssetTotal\_gr$ is derived by combining the corresponding considerations of security demand $VolAssetDemand$ and supply $VolAssetSupply$:

$$VolAssetTotal\_gr^{S}_{i,t} = VolAssetDemand^{S}_{i,t} + VolAssetSupply^{S}_{i,t} \tag{72}$$

The demand for debt securities $VolAssetDemand$ is derived applying the estimated parameters and the same explanatory variables as in equation (73). This reflects the assumption that the credit needs of a debt security issuing counterpart are proportionately reflected in their bank loan take-up and market debt issuance:[41]

$$\begin{aligned} VolAssetDemand^{S}_{i,t} = \sum_{p} &(\beta^{S'}_{1,p} \Delta log(VolAssetTotal^{S}_{i,t-p}) \\ &+ \beta^{S'}_{2,p} YERgr^{C}_{t-p} + \beta^{S'}_{3,p} HICgr^{C}_{t-p} \\ &+ \beta^{S'}_{4,p} URX^{C}_{t-p} + \beta^{S'}_{5,p} LTN^{C}_{t-p} \\ &+ \beta^{S'}_{6,p} STN^{EA}_{t-p} + \beta^{S'}_{7,p} EIRAssetNew^{S}_{i,t-p}) \end{aligned} \tag{73}$$

where $p = 2$ and:

$$S' = \begin{cases} NFC & \text{if } S = SNFC \\ SOV & \text{if } S = SGOV \\ FIN & \text{if } S = SFIN \end{cases}$$

The motivation of banks to hold debt securities compared to loans on their balance sheet could differ. Accordingly, the credit supply function for the debt security holdings of banks is estimated separately from that of loan supply (more information can be found in Appendix C.5):

$$\begin{aligned} VolAssetSupply^{S,C}_{i,t} = &\beta^{S}_{1} CET1SurShortfall_{i,t} \\ &+ \beta^{S}_{2} CET1SurShortfall_{i,t} \times I(Type_{i} = 1) \\ &+ \beta^{S}_{3} LEVRSurShortfall_{i,t} \\ &+ \beta^{S}_{4} LEVRSurShortfall_{i,t} \times I(Type_{i} = 1) \\ &+ \beta^{S}_{5} netNPLR_{i,t} + \beta^{S}_{5} ROA_{i,t} + \beta^{S}_{6} EIRLiabWhsl_{i,t} \end{aligned} \tag{74}$$

[41] This assumption allows circumventing the the lack of granular counter-party level security data that would allow estimating the corresponding demand equations directly.

Compared to the analogous specification of bank loan supply in equations (13) and (14) the supply function of bank debt security holdings excludes the relative risk weights and non-linear adjustments, replaces the bank and sector-specific net NPL rate with its bank-level counterpart $netNPLR$ and the average debt funding costs with the average wholesale funding costs $EIRLiabWhsl$.

Last, the model simplifies the dynamics for other $OTHER$ interest-bearing assets linking them directly to the nominal GDP growth in a country where the banks are headquartered:

$$VolAssetTotal_{i,t}^{OTHER} = VolAssetTotal_{i,t-1}^{OTHER} \times \left(YERgr_t^C + HICgr_t^C + 1\right) \tag{75}$$

and that of the derivatives holdings $DERIV$ that remain constant over time:

$$VolAssetTotal_{i,t}^{DERIV} = VolAssetTotal_{i,t-1}^{DERIV} \tag{76}$$

The total average volumes of the interest-bearing assets of a bank $VolAssetTotal$ sum up the volumes of assets for $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB, SNFC, SGOV, SFIN, OTHER\}$, but exclude derivative holdings:

$$VolAssetTotal_{i,t} = \sum_S \sum_C VolTotalAsset_{i,t}^{S,C} \tag{77}$$

The total period average volumes of interest-bearing assets for $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB, SNFC, SGOV, SFIN\}$ are broken down into:

$$VolAssetTotal_{i,t}^{S,C} = VolAssetNew_{i,t}^{S,C} + VolAssetExist_{i,t}^{S,C} + VolAssetMat_{i,t}^{S,C} + VolNPE_{i,t}^{S,C} \tag{78}$$

where $VolAssetMat$ are the average volumes of the maturing assets during the period and $VolNPE$ the average volumes of non-performing assets.

The new lending volumes are denoted by $VolAssetNew$ and defined by the overall lending growth net of maturing volumes:

$$\begin{aligned} VolAssetNew_{i,t}^{S,C} = {} & (1 - PomAsset_i^{S,C})\,(\Delta VolAssetTotal_{i,t}^{S,C} \\ & + VolAssetMat_{i,t}^{S,C}\,(PomAsset_i^{S,C})^{-1}) \end{aligned} \tag{79}$$

where $PomAsset$ stands for the point of maturity. The point of maturity informs about the time point in a year when the average loan matures and serves as a measure of asset turnover.

The existing volumes $VolAssetExist$ are then defined by:

$$\begin{aligned} VolAssetExist_{i,t}^{S,C} = {} & (1 - 0.25 \times (AvgDuration_i^{S,C})^{-1}) \times (VolAssetTotal_{i,t-1}^{S,C} \\ & - VolNPE_{i,t}^{S,C}) \end{aligned} \tag{80}$$

where the volumes of non-performing exposures $VolNPE$ are deducted from existing assets since only performing exposures can mature.

The law of motion for maturing assets is given by:

$$VolAssetMat^{S,C}_{i,t} = PomAsset^{S,C}_{i} \times 0.25 \times (AvgDuration^{S,C}_{i})^{-1} \times (VolAssetTotal^{S,C}_{i,t-1} - VolNPE^{S,C}_{i,t}) \tag{81}$$

The average volumes of non-performing assets $VolNPE$ for $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$ are projected in line with the corresponding stock of non-performing loans in the banking book $DefExp$ outlined in equation (28):

$$VolNPE^{S,C}_{i,t} = VolAssetTotal^{S,C}_{i,t-1} \times \left(\frac{VolNPE^{S,C}_{i,t-1}}{VolAssetTotal^{S,C}_{i,t-2}} + \Delta\frac{DefExp^{S,C}_{i,t}}{TotalLoans^{S,C}_{i,t}}\right) \tag{82}$$

The average volumes of non-performing security holdings for $S = \{SNFC, SGOV, SFIN\}$ follow the simplified dynamics with the constant share of non-performing exposures:

$$VolNPE^{S}_{i,t} = VolAssetTotal^{S}_{i,t} \times \frac{VolNPE^{S}_{i,t-1}}{VolAssetTotal^{S}_{i,t-1}} \tag{83}$$

Furthermore, the volumes of performing assets $VolPE$ for any $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB, SNFC, SGOV, SFIN\}$ can be derived as:

$$VolPe^{S,C}_{i,t} = VolAssetTotal^{S,C}_{i,t} - VolNPe^{S,C}_{i,t} \tag{84}$$

4.1.5.4 Interest income

Interest income is calculated by applying the IRFS9 standards. For performing loans (in stage 1 and 2) the interest revenue is calculated on the gross carrying amount, while for non-performing loans (in stage 3) it is calculated on the net carrying amount. The net carrying amount involves the estimate of loan loss provisions for defaulted assets $VolProvNPE$, which for sectors $S = \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$ are projected along with the dynamics of $ProvStockDef$ described in equation (47):

$$VolProvNPE^{S,C}_{i,t} = VolNPE^{S,C}_{i,t} \times \left(\frac{VolProvNPE^{S,C}_{i,t-1}}{VolNPE^{S,C}_{i,t-1}} + \Delta\frac{ProvStockDef^{S,C}_{i,t}}{DefExp^{S,C}_{i,t}}\right) \tag{85}$$

For sectors $S = \{SNFC, SGOV, SFIN\}$ the loan loss provisions for defaulted assets assume the constant coverage ratio for such exposures over time:

$$VolProvNPE^{S}_{i,t} = VolNPE^{S}_{i,t} \times \frac{VolProvNPE^{S}_{i,t-1}}{VolNPE^{S}_{i,t-1}} \tag{86}$$

The total interest income of a bank $TotalIntInc$ amounts to:

$$\begin{aligned} TotalIntInc_{i,t} = \sum_S \sum_C (&VolAssetExist^{S,C}_{i,t} \times EIRAssetExist^{S,C}_{i,t} \\ &+ VolAssetMat^{S,C}_{i,t} \times EIRAssetMat^{S,C}_{i,t} \\ &+ VolAssetNew^{S,C}_{i,t} \times EIRAssetNew^{S,C}_{i,t} \\ &+ (VolNPE^{S,C}_{i,t} - VolProvNPE^{S,C}_{i,t}) \times EIRAssetNPE^{S,C}_{i,t}) \\ &+ IntInc^{DERIV}_{i,t} + IntInc^{OTHER}_{i,t} \end{aligned} \tag{87}$$

The modelling of interest income for sectors $S = \{DERIV, OTHER\}$ follows simplified formulas without the breakdown into interest income from new, existing, maturing, and defaulted exposures. Interest income on $OTHER$ interest-bearing assets is linked to the nominal GDP in a home country of a bank, and that of $DERIV$ stays constant over time:

$$IntInc^{OTHER}_{i,t} = IntInc^{OTHER}_{i,t-1} \times \left(YERgr^C_t + HICgr^C_t - 1\right) \tag{88}$$

$$IntInc^{DERIV}_{i,t} = IntInc^{DERIV}_{i,t-1} \tag{89}$$

4.1.6 Trading book assets

Banks' trading books evolve with buying and selling of assets and the revaluation gains and losses resulting from market price corrections. Banks buy or sell assets so that their exposures in the trading book are approximately in a constant proportion with respect to the total assets in the banking book $TotalExposure$ from equation (20). This assumption reflects the stability of banks' business model over time. Changes in the mark-to-market value of trading book assets are captured by revaluation rates, $RevalRate$. The trading assets $MRAsset$ for $S \in \{ACFVPL, FVOCI, FVOCIPL\}$ evolve along with:

$$\begin{aligned} MRAsset^S_{i,t} = &MRAsset^S_{i,t-1} \times (RevalRate^S_{i,t} + 1) \\ &+ (1 - Insolvent_{i,t-1}) \times (\frac{TotalExposure_{i,t}}{TotalExposure_{i,t-1}} - 1) \end{aligned} \tag{90}$$

Net trading assets $MRNetAsset$ for $S \in \{TI, EH, NONT, HEDGES\}$:

$$\begin{aligned} MRNetAsset^S_{i,t} = &MRNetAsset^S_{i,t-1} \times (RevalRate^S_{i,t} + 1) \\ &+ (1 - Insolvent_{i,t-1}) \times (\frac{TotalExposure_{i,t}}{TotalExposure_{i,t-1}} - 1) \end{aligned} \tag{91}$$

And finally trading liabilities $MRLiab^{ACFVPL}$[42]:

$$\begin{aligned} MRLiab^{LACFVPL}_{i,t} = &MRLiab^{LACFVPL}_{i,t-1} \times (RevalRate^{LACFVPL}_{i,t} + 1) \\ &+ (1 - Insolvent_{i,t-1}) \times (\frac{TotalExposure_{i,t}}{TotalExposure_{i,t-1}} - 1) \end{aligned} \tag{92}$$

[42]The model follows the EBA methodology by including here financial liabilities under IFRS9 measured at ACFVPL including among others financial guarantee contracts, commitments to provide a loan at a below-market interest rate and contingent consideration.

Consequently, the full gains and losses *Reval* are as follows:

$$Reval_{i,t}^{S} = MRAsset_{i,t-1}^{S} \times RevalRate_{i,t}^{S} \tag{93}$$

$$Reval_{i,t}^{S} = MRNetAsset_{i,t-1}^{S} \times RevalRate_{i,t}^{S} \tag{94}$$

Changes related to mark-to-market gains and losses for each asset, net asset, and liability category are limited to two risk factors: the yield curve and equity prices.[43] Furthermore, revaluation gains and losses are based only on the delta sensitivity of the trading portfolio to market prices.[44]

Revaluation gains or losses for all sectors $S \in \{ACFVPL, FVOCI, FVOCIPL, TI, EH, NONT, HEDGES, LACFVPL\}$ evolve along with:

$$RevalRate_{i,t}^{S} = max(RevalSovSpread_{i,t}^{S} + RevalEquity_{i,t}^{S}, -1) \tag{95}$$

where the revaluation rate of $RevalSovSpread$ is derived from changes in the yield curve, and $RevalEquity$ is derived from changes in the prices of the shares. The overall gains or losses on each asset, net asset, and liability class are capped at 100%.

Revaluation gains and losses related to changes in the yield curve take into account the changes in the yield curves of all individual countries in the euro area and the United States at maturity points $\tau = \{0.25Y, 1Y, 3Y, 5Y, 10Y, 15Y\}$.[45] The resulting $RevalSovSpread$ follows the formula:

$$RevalSovSpread_{i,t}^{S} = \sum_{C \in \{EA,US\}} \sum_{M} SovSpreadDelta_{i}^{M,S,C} \times 10000 \times \Delta Yield_{t}^{C}(\tau) \tag{96}$$

Elasticities $SovSpreadDelta$ refer to the estimated sensitivity of an asset, net asset or liability class to a 1bp increase in a credit spread (the multiplication by 10000 in the formula is introduced accordingly). They are constant over a simulation horizon, but regularly updated with quarterly supervisory information that complements banks' submissions in EBA/SSM stress tests.[46]

The gains and losses related to changes in equity prices, $ESXgr^{C}$, are derived applying banks' equity risk deltas, i.e. elasticities with respect to a 1pp change in equity prices in country C, $EquityDelta$:

$$RevalEquity_{i,t}^{S} = \sum_{C \in \{EA,US\}} EquityDelta_{i}^{S,C} \times 100 \times (e^{ESXgr_{t}^{C}} - 1) \tag{97}$$

[43] The modelling of revaluation gains and losses has so far been limited to variables most relevant for the pass-though of monetary policy. Other risk categories such as commodity, including energy instruments and foreign exchange risk, are not captured.

[44] It excludes other first sensitives such as sensitivity to volatility (vega) or passage of time (theta), and higher order sensitivities, such as the rate of change in the delta (gamma).

[45] For simplicity, there is no distinction make between changes in nominal yields related to changes in credit spreads and risk-free interest rates. Changes in yields are fully attributed to the evolution of credit spreads.

[46] Bank deltas are additive and take account of the composition of trading book instruments, such that assuming a constant portfolio structure they can be summed up without additional exposure weighting. They are capture-all multipliers which take full account of the use of derivatives or other instruments and techniques to hedge banks' positions, e.g., interest rate swaps.

Additional impacts of market risk factors for banks come from changes in credit valuation adjustment $CVARes$ and liquidity and model uncertainty reserves $LiqRes$. Credit valuation adjustment changes in response to movements in counterparty credit spreads, derivative prices, and securities financing transactions.

Reserves for credit valuation adjustments are aggregated at the bank level, while for liquidity and model uncertainty, they are considered separately for assets held for trading HFT, mandatory or optional at fair value through profit or loss $FVPL$, and through other comprehensive income $FVOCI$. In the absence of exogenous shocks $cCVARes$, $CVARes$ remains constant over time:

$$CVARes_{i,t} = CVARes_{i,t-1} \times cCVARes_{i,t} \tag{98}$$

Analogously, liquidity and model uncertainty reserves for $S \in \{HFT, FVPL, FVOCI\}$ follow:

$$LiqRes^{S}_{i,t} = LiqRes^{S}_{i,t-1} \times cLiqRes^{S}_{i,t} \tag{99}$$

The value of the total trading book of a bank is derived by summing up assets, net assets, and liabilities in the relevant classes:

$$MRAsset_{i,t} = \sum_{S} MRAsset^{S}_{i,t} + \sum_{S} MRNetAsset^{S}_{i,t} + MRLiab^{LACFVPL}_{i,t} \tag{100}$$

4.1.7 Risk Weighted Amounts

For the purpose of calculating bank solvency ratios, banks in the model calculate risk-weighted assets (RWA). These are made up of capital charges for credit, market, and operational risk. The methodology of calculating risk weighted amounts is based on Basel III.[47] This section first details the methodology for calculating credit risk weights and then for calculating market and operational risk capital charges.

4.1.7.1 Capital charges for credit risk

The total capital charge for credit risk is derived as a sum of risk weighted bank sector country or bank sector level exposures in sectors $S = \{NFC, HHCC, HHHP,$ ROW, SOV, FIN, CB and other sectors $S^{OTH} = \{EQ, OTHER, SEC\}$:

$$\begin{aligned} CRREA_{i,t} = & \sum_{S}\sum_{C}(CRREA\_ND^{S,C}_{i,t} + CRREA\_D^{S,C}_{i,t}) \\ & + \sum_{S^{OTH}} CRREA^{S,}_{i,t} \end{aligned} \tag{101}$$

[47] Additionally, the model enables a calculation of RWA under the revised Basel III framework which increases the sensitivity of risk weights under the standardised approach and limits the scope to which the internal modelling approach can be applied. Furthermore, it also introduces the output floor, which requires that the RWA under the IRB approach be at least 72 5% of the RWA under the standardised approach.

The corresponding risk-weighted assets for non-defaulted $CRREA\_ND$ and defaulted exposures $CRREA\_D$ for sectors $S = \{NFC, HHCC, HHHP, RoW, SOV,$
$FIN, CB\}$ are calculated as:

$$\begin{aligned} CRREA\_ND_{i,t}^{S,C} &= 12.5 \times CRRW\_ND_{i,t}^{S,C} \times NonDefExp\_REA_{i,t}^{S,C} \\ CRREA\_D_{i,t}^{S,C} &= 12.5 \times CRRW\_D_{i,t}^{S,C} \times DefExp\_REA_{i,t}^{S,C} \end{aligned} \tag{102}$$

where 12.5 is the reciprocal of the minimum capital ratio of 8% as prescribed by the Basel II capital adequacy rules. $NonDefExp\_REA$ and $DefExp\_REA$ correspond to performing and non-performing exposures at default amount (EAD) respectively. $CRRW\_ND$ and $CRRW\_D$ stands for the average portfolio-specific effective risk weight on performing and non-performing exposures.

EAD amounts for $S = \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$ move in line with $TotalLoans$ as described in Section 4.1.2, taking into account the asset quality evolution as described in Section 4.1.3:

$$\begin{aligned} NonDefExp\_REA_{i,t}^{S,C} &= (NonDefExp\_REA_{i,t-1}^{S,C} + DefExp\_REA_{i,t-1}^{S,C}) \frac{TotalLoans_{i,t}^{S,C}}{TotalLoans_{i,t-1}^{S,C}} \\ &- DefExp\_REA_{i,t}^{S,C} \end{aligned} \tag{103}$$

$$\begin{aligned} DefExp\_REA_{i,t}^{S,C} = &\left(\frac{DefExp\_REA_{i,t-1}^{S,C}}{NonDefExp\_REA_{i,t-1}^{S,C} + DefExp\_REA_{i,t-1}^{S,C}} + \Delta \frac{DefExp_{i,t}^{S,C}}{TotalLoans_{i,t}^{S,C}} \right) \\ &\left(NonDefExp\_REA_{i,t-1}^{S,C} + DefExp\_REA_{i,t-1}^{S,C} \right) \times \frac{TotalLoans_{i,t}^{S,C}}{TotalLoans_{i,t-1}^{S,C}} \end{aligned} \tag{104}$$

For the remaining sectors $S = \{OTHER, EQ, SEC\}$ in the banking book, the model scales their risk weighted exposure amount by the corresponding exposure growth, without explicitly modelling their underlying effective risk weights.

$$CRREA_{i,t}^{S} = CRREA_{i,t}^{S} \frac{Exp_{i,t}^{S}}{Exp_{i,t-1}^{S}} \tag{105}$$

Banks can choose between three methodologies to calculate capital charges for credit risk. The standardised approach (STA) is the simplest of the approaches and is based on predefined risk weights that are linked to credit ratings assigned by external rating institutions or have a fixed level for unrated exposures.[48] The internal rating-based (IRB) approach establishes a more granular link between capital charges and individual asset risk than the standardised approach. Under the internal rating-based approach, there is an additional distinction between Foundation IRB (F-IRB) and Advanced IRB (A-IRB).

[48] The STA has been introduced already in Basel I standards. The revision of the STA approach under Basel II aimed to increase the risk sensitivity of the approach by introducing a wider differentiation of risk weights while avoiding excessive complexity. Although Basel II increased the sensitivity of STA risk weights to economic conditions, asset migrations under the STA approach tend to be still lower compared to the IRB approach.

Abbreviation	Methodological approach	Estimated bank parameters
STA	Standardized approach	-
F-IRB	Internal rating based approach - Foundation	PDreg
A-IRB	Internal rating based approach - Advanced	PDreg, LGDreg, EAD, MAT

Table 5: Methodological approaches for credit risk capital requirements

The model accommodates the application of three methodologies by defining the effective risk weights $CRRW\_ND$ and $CRRW\_D$ as a weighted average of the risk weights calculated along with each of the methodologies. The share of exposures in each portfolio $S = \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$ that are under the standardised methodology is denoted by $sMethod^{STA}$, and the IRB methodologies jointly by $sMethod^{IRB} = 1 - sMethod^{STA}$. The respective exposure shares for $sMethod^{M}$ where $M \in \{STA, IRB\}$ are assumed to stay constant throughout the simulation horizon:

$$\begin{aligned} CRRW\_ND_{i,t}^{S,C} &= \sum_{M} sMethod_{i}^{M,S,C} \times CRRW\_ND_{i,t}^{M,S,C} \\ CRRW\_D_{i,t}^{S,C} &= \sum_{M} sMethod_{i}^{M,S,C} \times CRRW\_D_{i,t}^{M,S,C} \end{aligned} \tag{106}$$

The exposures under IRB approaches will be further broken down in the share under the A-IRB methodology denoted by $sMethod^{AIRB}$, and the share under the F-IRB $sMethod^{FIRB}$, where $sMethod^{AIRB} + sMethod^{FIRB} = 1$. Accordingly:

$$\begin{aligned} sMethod_{i}^{STA,S,C} + sMethod_{i}^{IRB,S,C} \times sMethod_{i}^{AIRB,S,C} + \\ sMethod_{i}^{IRB,S,C} \times sMethod_{i}^{FIRB,S,C} = 1 \end{aligned} \tag{107}$$

4.1.7.2 Capital charges for credit risk non-defaulted exposures

The effective risk weights for non-defaulted exposures under the standardized approach STA for the sectors $S = \{HHCC, HHHP, SOV, CB, RoW\}$ are assumed to remain constant over time:[49]

$$CRRW\_ND_{i,t}^{STA,S,C} = CRRW\_ND_{i,t-1}^{STA,S,C} \tag{108}$$

The STA risk weights for the non-financial corporate sector NFC are derived separately for the exposures of small and medium enterprises SME and non-SME exposures $NSME$ and then weighted with the respective shares of the exposures to the segments SME and non-SMEs $sShare^{STA,SME}$ and $sShare^{STA,NSME}$ (with $sShare^{STA,SME} + sShare^{STA,NSME} = 1$).

$$CRRW\_ND_{i,t}^{STA,NFC,C} = \sum_{B} sShare_{i}^{STA,B} \times CRRW\_ND_{i,t-1}^{B,STA,NFC,C} \tag{109}$$

[49]Treating the risk weights to sovereigns and central banks constant relates to Article 114 of CRR stating that banks exposure to member states' central government and domestic central banks shall be assigned a risk weight of 0% irrespective of economic situation. For the rest of the world exposures, the constancy of risk weights is a simplifying assumption.

The risk weights are assumed to remain within a corridor derived directly from the regulation, with lower $STA^{NFC}_{Low} = 0.2$, and upper $STA^{NFC}_{High} = 1.5$ limits. Additionally, for the SME sector, the model takes into account the effective supporting factor SF^{SME} applicable to each bank exposure, which amounts to:

$$SF^{SME,C}_{i,t} = \begin{cases} 1-(1-0.7619)\times Share15^{SME,C}_i \text{ until the end 2020} \\ 0.85-(0.85-0.7619)\times Share25^{SME,C}_i \text{ from 2021 onwards} \end{cases} \tag{110}$$

The parameters $Share15^{SME,C}$ and $Share25^{SME,C}$ correspond to the share of corporate loans in the portfolios of individual banks with a value below 1.5 million and a value below 2.5 million, respectively. Changes in the supporting factor in 2021 relate to the introduction of CRR2.

Consequently, the applicable effective limits for $L \in \{Low, High\}$ in the corporate risk weights are equal:

$$STA^{B,NFC}_{L} = \begin{cases} STA^{NFC}_{L} \times SF^{SME,C}_{i,t} \text{ if } B = SME STA^{NFC}_{L} \text{ if } B = NSME \end{cases} \tag{111}$$

The risk weights for the corporate segments $B = \{SME, NSME\}$ meet the following:

$$CRRW\_ND^{B,STA,NFC,C}_{i,t} = 0.08 \times \begin{cases} STA^{B,NFC}_{Low} \text{ if } \Xi^{B,STA,NFC,C}_{i,t} \leq STA^{NFC}_{B,Low} \\ STA^{B,NFC}_{High} \text{ if } \Xi^{B,STA,NFC,C}_{i,t} \geq STA^{NFC}_{B,High} \\ \Xi^{B,STA,NFC,C}_{i,t} \text{ otherwise} \end{cases} \tag{112}$$

and otherwise the evolution of risk weights is linked to macroeconomic conditions:

$$\begin{aligned} \Xi^{B,STA,NFC,C}_{i,t} = {} & 12.5 \times CRRW\_ND^{B,STA,NFC,C}_{i,t-1} + \\ & (STA^{B,NFC}_{High} - STA^{B,NFC}_{Low}) \times \\ & \Delta\Phi \Big(\beta^B_0 + \beta^B_1 \widehat{CRRW\_ND}^{B,STA,NFC,C}_{i,t-1} + \\ & \beta^B_2 YERgr^C_{i,t-1} + \beta^B_3 IHXgr^C_{t-1} \\ & + \beta^B_4 SPR^C_{t-1} + \beta^B_5 \Delta STN^{EA}_{t-1} \\ & + \beta^B_6 PDpit^{NFC,C}_{i,t} + \beta^B_7 log(TA_{i,t_0}) \end{aligned} \tag{113}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. TA_0 are total bank assets in the last historical period available, serve here as a proxy for the bank's expertise in risk management, and enter with a negative sign. Finally:

$$\widehat{CRRW\_ND}^{B,STA,NFC,C}_{i,t} = \frac{12.5 \times CRRW\_ND^{B,STA,NFC,C}_{i,t} - STA^{B,NFC}_{Low}}{STA^{B,NFC}_{High} - STA^{B,NFC}_{Low}} \tag{114}$$

$\widehat{CRRW\_ND}$ is a transformed risk weight that remains in the $[0, 1]$ interval.

The risk weights for the financial sector are assumed to also remain within a corridor derived from the regulation and $STA^{FIN}_{Low} = 0$ and $STA^{FIN}_{High} = 1.5$. Furthermore:

$$CRRW\_ND^{STA,FIN}_{i,t} = 0.08 \times \begin{cases} STA^{FIN}_{Low} \text{ if } \Xi^{STA,FIN}_{i,t} \leq STA^{FIN}_{Low} \\ STA^{FIN}_{High} \text{ if } \Xi^{STA,FIN}_{i,t} \geq STA^{FIN}_{High} \\ \Xi^{STA,FIN}_{i,t} \text{ otherwise} \end{cases} \tag{115}$$

Within the limits prescribed by the regulation, the standardised risk weights for financial exposures FIN follow a logit specification.

$$\begin{aligned}
\Xi_{i,t}^{STA,FIN} =& 12.5 \times CRRW_ND_{i,t-1}^{STA,FIN} + (STA_{High}^{FIN} - STA_{Low}^{FIN}) \times \\
& \Delta invlogit \Big(\beta_0 + \beta_1\, logit(\widehat{CRRW_ND}_{i,t-1}^{STA,FIN}) \\
& + \beta_2\, YERgr_{t-1}^{C} + \beta_3\, IHXgr_{t-1}^{C} \\
& + \beta_4\, SPR_{t-1}^{C} + \beta_5\, \Delta STN_{t-1}^{EA} \\
& + \beta_6\, \Delta PDpit_{i,t}^{FIN} + \beta_7\, ProvCovNonDefR_{i,t}^{FIN} \\
& + \beta_8\, log(TA_{i,0})
\end{aligned} \tag{116}$$

where as for NFC exposures, $\widehat{CRRW\_ND}^{STA,FIN}$ is defined as:

$$\widehat{CRRW\_ND}_{i,t}^{STA,FIN} = \frac{12.5 \times CRRW\_ND_{i,t}^{STA,FIN} - STA_{Low}^{FIN}}{STA_{High}^{FIN} - STA_{Low}^{FIN}} \tag{117}$$

The standardised risk weights for the financial sector depend on changes in macrofinancial environment, therein interest rates, point-in-time probability of default $PDpit$ for financial exposures, and the coverage ratio of non-defaulted exposures with provisions $ProvCovNonDefR$:

$$ProvCovNonDefR_{i,t}^{FIN} = \frac{(ProvStockNonDefS1_{i,t}^{FIN} + ProvStockNonDefS2_{i,t}^{FIN})}{NonDefExp_{i,t}^{FIN}} \tag{118}$$

See Appendix D.2.5 for more information on the estimation of the standardised risk weights for NFC and FIN sectors.

The risk weights for non-defaulted exposures under the internal rating based approaches for sectors $S = \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$ are functions of the regulatory probability of default $PDreg$ and loss given default $LGDreg\_ND$. More precisely:

$$CRRW\_ND_{i,t}^{IRB,S,C} = \underbrace{SF_{i,t}^{S,C} \times LGDreg\_ND_{i,t}^{S,C} \times (F(PDreg_{i,t}^{S,C})}_{\text{Basel III formula}} + RWWedge_{i,t}^{S,C} \tag{119}$$

where $CRRW\_ND^{IRB}$ is an effective IRB risk weight, $F(PDreg)$ and $RWWedge$ are both functions of $PDreg$. SF is defined as:

$$SF_{i,t}^{S,C} = 1.06 \times \begin{cases} 1 - sShare^{IRB,SME} + sShare^{IRB,SME} \times \frac{1-(1-0.7619)\times Share15_i^{SME,C}}{0.85-(0.85-0.7619)\times Share25_i^{SME,C}} \\ \qquad \text{if S=NFC and from 2021 onwards} \\ 1 \text{ otherwise} \end{cases} \tag{120}$$

Namely, it equals an IRB scaling factor from Basel III standards for all risk weights, but for those for corporate exposures. There, it accounts for changes in the SME supporting factor in 2021, recognising that IRB risk weights for corporate exposures are modelled assuming the constancy of CRR, in contrast to the CRR2, regime (see equation (110)). $sShare^{IRB,SME}$ is share of SME lending of corporate IRB exposures of a bank.

$F(PDreg)$ is a product of a default threshold $\Omega(PDreg)$ and the maturity adjustment term $MAT(PDreg)$:

$$F(PDreg_{i,t}^{S,C}) = \Omega\left(PDreg_{i,t}^{S,C}\right) \times MAT\left(PDreg_{i,t}^{S,C}\right) \tag{121}$$

The default threshold $\Omega(PDreg)$ is derived under the assumption that systematic and idiosyncratic risk factors follow a normal distribution.[50] It is derived from $PDreg$ by applying the inverse normal distribution function $G(.)$ and taking into account the degree of the systemic risk exposure of the obligor captured by the sector-specific asset correlation term R^S.

$$\Omega\left(PDreg_{i,t}^{S,C}\right) = N\left(\left(\left(\frac{1}{1-R_{i,t}^{S,C}}\right)^{0.5} \times G(PDreg_{i,t}^{S,C}) + \left(\frac{R_{i,t}^{S,C}}{1-R_{i,t}^{S,C}}\right)^{0.5} \times G(0.999)\right) - PDreg_{i,t}^{S,C}\right) \tag{122}$$

where $N(.)$ is the standard normal distribution function. The sector-specific asset correlation coefficient R^S is defined by the regulation (see BCBS [2005]) as:

$$\begin{aligned} R_{i,t}^{S,C} &= \alpha_1^S \times \left(\frac{1-\exp^{-\gamma^S \times PDreg_{i,t}^{S,C}}}{1-\exp^{-\gamma^S}}\right) + \alpha_2^S \times \left(1 - \frac{1-\exp^{-\gamma^S \times PDreg_{i,t}^{S,C}}}{1-\exp^{-\gamma^S}}\right) \\ &+ sShare_i^{IRB,REV,C} \times 0.04 \times (S = HHCC) - sShare_i^{IRB,SME,C} \times 0.04 \times (S = NFC) \end{aligned} \tag{123}$$

The asset correlation term for each household consumption loan portfolio $HHCC$ is adjusted for the share of revolving loans $sShare^{IRB,REV}$ within the portfolio. Analogously, the asset correlation term for the NFC sector takes into account the share of SME lending $sShare^{IRB,SME}$. The household real estate exposures $HHHP$ receive a fixed asset correlation coefficient $R = 0.15$. Other sector-specific input parameters are sourced from BCBS [2019] and summarised in Table 6.

Sector α_1^S	α_2^S	γ^S	
NFC	0.12	0.24	50
HHCC	0.03	0.16	35
SOV	0.12	0.24	50
FIN	1.25	0.24	50

Table 6: Input parameters for credit risk asset correlation

The maturity-dependent term MAT of the Basel capital requirement formula is a function of the regulatory probability of default, and it is given by:

$$MAT\left(PDreg_{i,t}^{S,C}\right) = \frac{1 + (M_{i,t}^{S,C} - 2.5) \times b(PDreg_{i,t}^{S,C})}{1 - 1.5 \times b(PDreg_{i,t}^{S,C}))} \tag{124}$$

[50] The Basel formula for capital requirements follows from the work of Merton [1974] and Vasicek [2015] which enabled the application of an Asymptotic Single Risk Factor (ASRF) model for credit portfolio losses.

where M stands for the effective sector-specific maturity and the maturity adjustment term $b()$ is given by $b(PDreg_{i,t}^{S,C}) = (0.11852 - 0.05478 \times log(PDreg_{i,t}^{S,C}))^2$ for $S = \{NFC, SOV, FIN\}$ and set to $b = 0$ for retail loans $HHCC$ and $HHHP$ (see BCBS [2019]).

The dynamic evolution of $PDreg$ follows a simple autoregressive process and for sectors $S = \{NFC, HHCC, HHHP, SOV, FIN, CB$ depends on its past changes and the point in time probability of default $PDpit$ defined equation (32):

$$\begin{aligned} PDreg_{i,t}^{S,C} = max\Big(0, min\Big(1, \\ PDreg_{i,t-1}^{S,C} + \beta_1^S \left(PDreg_{i,t-1}^{S,C} - PDreg_{i,t-2}^{S,C}\right) \\ \beta_2^S \left(-(1 - PDpit_t^{S,C})^4 + (1 - PDpit_{t-1}^{S,C})^4\right)\Big)\Big) \end{aligned} \tag{125}$$

where the formula indicates that $PDreg$ is an annual concept, whereas $PDpit$ is a quarterly quantity. See Appendix D.2.1 for estimation details.

The regulatory LGD for the IRB methodologies $LGDreg\_ND^{IRB}$ is obtained by applying the weighted average of $AIRB$ and $FIRB$ for LGDs using the exposure share of each of the methodologies $M = \{FIRB, AIRB\}$ in the general exposures under IRB:

$$LGDreg\_ND_{i,t}^{IRB,S,C} = \sum_M sMethod_i^{M,S,C} \times LGDreg\_ND_{i,t}^{M,S,C} \tag{126}$$

Under the F-IRB approach, the regulatory loss given default $LGDreg\_ND$ is stated by the regulator and remains constant for all sectors $S \in \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$:[51]

$$LGDreg\_ND_{i,t}^{FIRB,S,C} = LGDreg\_ND_{i,t-1}^{FIRB,S,C} \tag{127}$$

In the A-IRB approach instead, banks are free to apply their own methodology when calculating $LGDreg\_ND$. This choice is reflected in the following estimated formula for sectors $S = \{NFC, HHCC, HHHP, SOV, FIN, CB\}$:

$$LGDreg\_ND_{i,t}^{AIRB,S,C} = LGDreg\_ND_{i,t-1}^{AIRB,S,C} + 0.25 \times \Delta\widehat{LGDreg\_ND}_{i,t}^{AIRB,S,C} \tag{128}$$

$$\begin{aligned} \widehat{LGDreg\_ND}_{i,t}^{AIRB,S,C} = \textbf{logistic}\Big(\beta_0^S + \beta_1^S LGDreg\_ND_{i,t-1}^{AIRB,S,C} + \beta_2^S LGDpit_{i,t-1}^{S,C} \\ + \beta_3^S YERgr_{t-1}^C + \beta_4^S IHXgr_{t-1}^C \\ + \beta_5^S URX_{t-1}^C + \beta_6^S LTN_{t-1}^C\Big) \end{aligned} \tag{129}$$

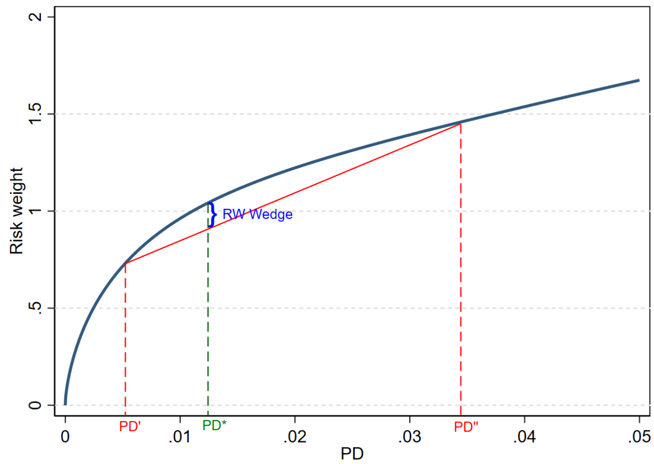
where point in time $LGDpit$ is defined in equation (51). See Appendix D.2.2 for estimation details.

For aggregated non-euro area exposures RoW, a simplifying assumption is taken and $PDreg$ and $LGDreg\_ND^{AIRB}$ stay constant:

[51] The prescribed loss-given default values corresponds to 45% for senior claims on corporates, sovereigns and financials secured by collateral and 75% in absence of collateral (see Basel framework CRE32).

$$
\begin{aligned}
PDReg_{i,t}^{RoW} &= PDReg_{i,t-1}^{RoW} \\
LGDreg\_ND_{i,t}^{AIRB,RoW} &= LGDreg\_ND_{i,t-1}^{AIRB,RoW}
\end{aligned} \tag{130}
$$

The Basel IRB risk weight function is concave. Figure 9 plots the projected risk weight as a function of $PDreg$. This concavity implies that when the formula is applied on aggregated values $PDreg$ of individual exposures, it results in a wedge between the risk weight calculated this way and the correct risk weight, which would apply the formula on each individual exposure and aggregate the result. To account for this fact, the model introduces an estimated risk weight add-on $RWWedge$ in equation (119).



Notes: The plotted line illustrates how estimated PDs map into regulatory risk weights for corporate sector loans with turnover larger than €50 million, assuming a standard value for loss given default (45%) and effective maturity (2.5 years). The red lines in the plot illustrate individual portfolio level probability of defaults (PDs), while the green line represents the aggregated PD combining the two portfolios. The resulting difference between the actual risk weight for the aggregated portfolio and the one obtained by the linear combination of the input parameters is mapped into $RWWedge$.

Figure 9: Schematic illustration IRB risk weight function

The definition of $RWWedge$ refers to the local curvature of the risk weight function and uses the first derivative of $F(PDreg)$:

$$
\begin{aligned}
F'(PDreg_{i,t}^{S,C}) = \Omega'\left(PDreg_{i,t}^{S,C}\right) \times MAT\left(PDreg_{i,t}^{S,C}\right) \\
+\Omega\left(PDreg_{i,t}^{S,C}\right) \times MAT'\left(PDreg_{i,t}^{S,C}\right)
\end{aligned} \tag{131}
$$

The correction term $RWWedge$ is then projected based on the estimated regression coefficients:

$$
RWWedge_{i,t}^{S,C} = \beta_1^S F'(PDreg_{i,t}^{S,C}) + RWAddon_i^{S,C} \tag{132}
$$

where $RWAddon$ (a constant of the corresponding regression at the sector level) translates into a constant add-on. For the estimation methodology and sector-specific estimates, see Appendix D.2.4.

4.1.7.3 Capital charges for credit risk defaulted exposures

The methodology of the standardised approach simplifies the dynamics of capital charges for defaulted exposures and prescribes constant risk weights for all sectors $S = NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$:

$$CRRW\_D_{i,t}^{STA,S,C} = CRRW\_D_{i}^{STA,S,C} \tag{133}$$

The evolution of capital charges for defaulted exposures for IRB approaches $CRRW\_D^{IRB,S,C}$ follows:

$$CRRW\_D_{i,t}^{IRB,S,C} = sMethod_{i}^{AIRB,S,C} \times max(0, LGDreg\_D_{i,t}^{AIRB,S,C} - ELBE_{i,t}^{AIRB,S,C}) \tag{134}$$

which recognises that the risk weights on the defaulted exposures under FIRB are equal to zero, that is, $CRRW\_D^{FIRB} = 0$. $LGDreg\_D^{AIRB,S,C}$ stands for the bank estimate of the loss given default using the A-IRB methodology, and $ELBE^{AIRB,S,C}$ is the expected loss best estimate. The loss given default for AIRB exposures is projected for $S = \{NFC, HHCC, HHHP, SOV, FIN, CB\}$on the basis of the estimated equation. $LGDreg\_D$ is linked to the growth rate of GDP $YERgr$, stock markets $ESXgr$ and real estate prices $IHXgr$, as well as the short STN and long-term interest rate LTN for the country of exposure. :

$$LGDreg\_D_{i,t}^{AIRB,S,C} = LGDreg\_D_{i,t-1}^{AIRB,S,C} + \Delta\widehat{LGDreg\_D}_{i,t}^{AIRB,S,C}/4 \tag{135}$$

$$\begin{aligned} \widehat{LGDreg\_D}_{i,t}^{AIRB,S,C} = \mathbf{logistic}\Big(&\beta_0^S + \beta_1^S\,\mathbf{logit}\Big(LGDreg\_D_{i,t-1}^{AIRB,S,C}\Big) \\ &+ \beta_2^S\,LGDreg\_ND_{i,t-1}^{AIRB,S,C} \\ &+ \beta_3^S\,YERgr_{t-1}^C + \beta_4^S\,IHXgr_{t-1}^C \\ &+ \beta_5^S\,\Delta URX_{t-1}^C + \beta_6^S\,SPR_{t-1}^C\Big) \end{aligned} \tag{136}$$

The expected loss best estimate $ELBE$ depends on the same set of explanatory variables as $LGDreg$:

$$ELBE_{i,t}^{AIRB,S,C} = ELBE_{i,t-1}^{AIRB,S,C} + \Delta\widehat{ELBE}_{i,t}^{AIRB,S,C}/4 \tag{137}$$

$$\begin{aligned} \widehat{ELBE}_{i,t}^{AIRB,S,C} = \mathbf{logistic}\Big(&\beta_0^S + \beta_1^S\,\mathbf{logit}\Big(ELBE_{i,t-1}^{AIRB,S,C}\Big) \\ &+ \beta_2^S\,LGDpit_{i,t-1}^{S,C} \\ &+ \beta_3^S\,YERgr_{t-1}^C + \beta_4^S\,IHXgr_{t-1}^C \\ &+ \beta_5^S\,\Delta URX_{t-1}^C + \beta_6^S\,SPR_{t-1}^C\Big) \end{aligned} \tag{138}$$

See Appendix D.2.3 for estimation details for both $AIRB$ parameters. For the RoW sector, both regulatory parameters are assumed to remain constant over time:

$$\begin{aligned} LGDreg\_D_{i,t}^{AIRB,RoW} &= LGDreg\_D_{i,t-1}^{AIRB,RoW} \\ ELBE_{i,t}^{AIRB,RoW} &= ELBE_{i,t-1}^{AIRB,RoW} \end{aligned} \tag{139}$$

4.1.7.4 Expected regulatory IRB losses

In IRB approaches, banks are asked to calculate the potential shortfalls between the total eligible provisions and the expected regulatory losses (see Section 4.2.2). Banks total expected regulatory losses under IRB $ELREG^{IRB}$ are defined by the weighted sum of expected losses for defaulted and non-defaulted IRB exposures for $S = \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$:

$$\begin{aligned} ELREG_{i,t}^{IRB} = \sum_{S}\sum_{C}(&NonDefExp\_REA_{i,t}^{S,C} \times PDreg\_IRB_{i,t}^{S,C} \times LGDreg\_ND_{i,t}^{S,C} \\ &+ DefExp\_REA_{i,t}^{S,C} \times LGDreg\_D_{i,t}^{S,C}) \times sMethod_{i}^{IRB,S,C} \end{aligned} \tag{140}$$

4.1.7.5 Capital charges for market risk

The market risk capital charges are composed of standardised method $STAMRREA$ and internal model method $IMMRREA$ risk exposure amount, All Price Risk component APR and Credit Valuation Adjustments CVA:

$$MRREA_{i,t} = STAMRREA_{i,t} + IMMRREA_{i,t} + APR_{i,t} + CVA_{i,t} \tag{141}$$

The model applies a simplified formula to calculate market risk charges by setting them proportional to total trading book exposures $MRAsset$ as defined in equation (100):

$$\begin{aligned} STAMRREA_{i,t} &= STAMRREA_{i,t-1} \times \frac{MRAsset_{i,t}}{MRAsset_{i,t-1}} \\ IMMRREA_{i,t} &= IMMRREA_{i,t-1} \times \frac{MRAsset_{i,t}}{MRAsset_{i,t-1}} \\ APR_{i,t} &= APR_{i,t-1} \times \frac{MRAsset_{i,t}}{MRAsset_{i,t-1}} \\ CVA_{i,t} &= CVA_{i,t-1} \times \frac{MRAsset_{i,t}}{MRAsset_{i,t-1}} \end{aligned} \tag{142}$$

4.1.7.6 Capital charges for operational risk

A simplified methodology is also applied for the operational risk capital charges. Here, capital charges $OPREA$ consist of charges calculated along with the basic indicator and standardised approach $BIASTAOR$ and the operational risk advanced approach $AMAOR$.

$$OPREA_{i,t} = BIASTAOR_{i,t} + AMAOR_{i,t} \tag{143}$$

The model assumes that operational risk is proportional to banks' total assets, and the two operational risk charges are scaled accordingly by the assets of the banks TA:

$$\begin{aligned} BIASTAOR_{i,t} &= BIASTAOR_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \\ AMAOR_{i,t} &= AMAOR_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \end{aligned} \tag{144}$$

4.1.7.7 Total risk weighted amount

The total risk weighted amount of banks sums up the credit risk weighted amount $CRREA$, the market risk weighted amount $MRREA$ and the operational risk weighted amount $OPREA$. Other risk weighted amounts $OtherREA$ not classified in any of these categories are assumed to remain constant.

$$TotREA_{i,t} = MRREA_{i,t} + CRREA_{i,t} + OPRREA_{i,t} + OtherREA_{i,t} \tag{145}$$

4.2 Bank liabilities and own funds

4.2.1 Structure of bank liabilities and own funds

To raise funding for income-generating assets and activities, a bank accumulates its own funds and issues debt. In the model, the own funds comprise Common Equity Tier 1 $CET1TR$ (transitional value), additional Tier 1 $AT1CAP$, and Tier 2 $T2CAP$ capital. Together, capital instruments make up 7.5% of the total liabilities of the banks and their own funds (see Table 7).

The largest type of bank liabilities are retail deposits. Retail deposits, composed of sight deposits to households HHS and non-financial corporations $NFCS$, term deposits $DEPT$ and deposits to the rest of the world RoW (including sight and term deposition of non-financial private sector counterparts in the non-euro area) and sum up to 51.1 % of total liabilities and own funds on average. The retail deposits to the non-financial private sector in the euro area are additionally broken down by the source country.

Another type of debt financing is institutional funding, which comprises funding by central banks NCB and governments SOV. These collectively amount to 9% of the total liabilities and own funds. The fourth source of funding is the wholesale debt, which can be further broken down into secured SEC and unsecured funding $UNSEC$. Secured wholesale funding makes up 9.1% of total liabilities and own funds on average and consists of short-term repurchase agreements $SECST$ and collaterized debt securities issued by banks $SECLT$. Unsecured funding accounts for 20.9% of total liabilities and own funds and consists of sight $FINS$ and term FIN deposits from financial corporations, bonds, other securities, or hybrid instruments $OTHSEC$. Finally, the last funding type distinguished in the model are derivatives $DERIV$ and other liabilities $OTHER$.

In order to describe bank funding and liquidity management, debt instruments are classified as slow and fast moving. Slow-moving funding sources are in short supply, and banks cannot influence their supply, especially in the short term. The slowest moving category is sight $SIGHT$, term $TERM$, and deposits from the rest of the world RoW. Fast-moving funding sources generally are in abundant supply, though they also have higher costs. These include institutional deposits $INST$ and wholesale funding SEC and $UNSEC$. Banks' liquidity management focuses on steering their LCR and NSFR, which they achieve by adjusting the duration and collateralization of issued wholesale funding.

Abbreviation	Description	Group	Granularity	Share of liabilities
Own Funds				
CET1TR	Common Equity Tier 1 capital (net of deductions and after transitional adj.)	CAP	Bank	6.0
AT1CAP	Additional Tier 1 capital (net of deductions and after transitional adj.)	CAP	Bank	0.5
T2CAP	Tier 2 capital instruments	CAP	Bank	1.0
Retail deposits				
NFCS	Deposits (excl. repo): Non-financial corporations - sight	$SIGHT$	Sector-Country-Bank	10.2
HHS	Deposits (excl. repo): Households - sight	$SIGHT$	Sector-Country-Bank	21.7
TERM	Deposits (excl. repo): Non-financial corporations, households, term	$TERM$	Sector-Country-Bank	8.4
RoW	Deposits (excl. repo): Rest of the world - sight and term	RoW	Sector-Bank	10.8
Institutional				
NCB	Deposits (excl. repo): Central banks	$INST$	Sector-Bank	7.8
SOV	Deposits (excl. repo): General governments	$INST$	Sector-Bank	1.2
Wholesale				
SECST	Deposits: Repo	SEC	Sector-Bank	4.2
SECLT	Debt securities issued: ABS and covered bonds	$WHSL$	Sector-Bank	4.9
FINS	Deposits (excl. repo): Credit Institutions and other fin. corps. - sight	$NSEC$	Sector-Bank	6.1
FIN	Deposits (excl. repo): Credit Institutions and other fin. corps. - term	$NSEC$	Sector-Bank	5.2
OTHUNSEC	Debt securities issued: Other securities and hybrid contracts	$NSEC$	Sector-Bank	9.6
Other				
DERIV	Derivatives	$OTHER$	Sector-Bank	-
OTHER	Other liabilities	$OTHER$	Sector-Bank	2.3

Notes: The share for individual liability classes is calculated by excluding derivatives $DERIV$. ABS stands for asset-backed securities.

Table 7: Liability sectors

4.2.2 Evolution of bank capital

The model considers the capital of CET1 $CET1TR$ net of deductions and after applying transitional adjustments:

$$\begin{aligned} CET1TR_{i,t} = {} & CiCET_{i,t} + AOCI_{i,t} + DBPFA_{i,t} + DTA_{i,t} + IRBSf_{i,t} \times (IRBSf_{i,t} < 0) \\ & + CET1Oth_{i,t} + RetEarn_{i,t} \end{aligned} \tag{146}$$

where $CiCET$ are capital instruments eligible as CET1, $AOCI$ is accumulated other comprehensive income, $DBPFA$ are defined benefit pension fund assets net of associated liabilities, DTA are deferred tax assets, $RetEarn$ are retained earnings or accumulated losses (discussed in Section 4.4.5), and $CET1Oth$ are other capital instruments.[52] The shortfall between the to-

[52] $CET1Oth$ sums up other reserves, funds for general banking risk, minority interest given recognition in CET1

tal eligible provisions and the expected regulatory losses $IRBSf$ [53] is fully deducted, without considering tax effects from CET1 capital.

Along with the assumption that banks cannot issue new equity, capital instruments eligible as CET1 $CiCET$ remain most of the time constant over the simulation horizon. They change only after additional Tier 1 $AT1CAP$ or Tier 2 $T2CAP$ capital conversions aimed at absorbing capital losses. The conversion takes place at trigger points of 5.125% for $AT1CAP$ and 4.5% for $T2CAP$ relative to the total risk weighted amounts (for the definition of $TotREA$ see equation (145)) adjusted due to the transitional arrangements of IFRS 9 $TAIFRSREA$:

$$\begin{aligned} CiCET_{i,t} = CiCET_{i,t} + (5.125\% - CET1REA_{i,t-1} > 0) \times \\ min(((5.125\% - CET1REA_{i,t-1}) \times (ToTREA_{i,t-1} + TAIFRSREA_{i,t-1})), \\ AT1CAP_{i,t-1}) + (4.5\% - CET1REA_{i,t-1} > 0) \times \\ min(((4.5\% - CET1REA_{i,t-1}) \times (ToTREA_{i,t-1} + TAIFRSREA_{i,t-1})), \\ T2CAP_{i,t-1})) \end{aligned} \tag{147}$$

The accumulated other comprehensive income $AOCI$ evolves along with the revaluation gains or losses $Reval^FVOCI$ and changes in the liquidity reserves $LiqRes^FVOCI$ for trading assets that mandatorily enter other comprehensive income. It also accounts for a share $Share^{OCIFVPL}$ of revaluation losses on assets that voluntarily enter other comprehensive income $Reval^FVOCIPL$ and a share $Share^{OCIPLCF}$ of revaluation gains or losses for the hedging instruments $Reval^Hedges$ (see Section 4.1.6 for their definitions).

$$\begin{aligned} AOCI_{i,t} = AOCI_{i,t-1} + AOCIOther_{i,t} + \\ (Reval^{FVOCI}_{i,t} + Share^{OCIFVPL}_{i} \times Reval^{FVOCIPL}_{i,t} + Share^{OCIPLCF}_{i} \times Reval^{Hedges}_{i,t} \\ - \Delta LiqRes^{FVOCI}_{i,t}) \times 0.7 \end{aligned} \tag{148}$$

where $AOCIOthere$ tracks other residual items of AOCI and is assumed to remain constant over time (the same as both shares $Share$).

The annual change in defined benefit pension fund assets net of associated liabilities $DBPFA$ and deferred tax assets DTA is conservatively assumed to stay constant so that banks do not accumulate additional deferred tax assets in case of losses:

$$DTA_{i,t} = DTA_{i,t-1} \tag{149}$$

The shortfall between the total eligible provisions and the expected regulatory losses $IRBSf$ is equal to the following:

$$IRBSf_{i,t} = -(ELREG^{IRB}_{i,t} - ProvStock^{IRB}_{i,t} - IRBSF\_AddVal_{i,t}) \tag{150}$$

where banks regulatory expected losses $ELREG^{IRB}$ are defined in equation (140), and $ProvStock^{IRB}$ corresponds to bank IRB-specific stock of provisions:

capital, additional deductions of CET1 capital due to Article 3 CRR, intangible assets (including goodwill), reciprocal cross holdings, excess deduction from AT1 items over AT1 Capital, deductions related to assets which can alternatively be subject to a 1.25% risk weight, holdings of CET1 capital instruments of financial sector entities (non-significant investment), additional deductions of CET1 capital due to Article 3 CRR, CET1 capital elements or deductions - other, transitional adjustments and CET1 instruments of financial sector entities (significant investment).

[53] As defined in Basel III paragraph 73

$$
\begin{aligned}
ProvStock_{i,t}^{IRB} = & \sum_S \sum_C sMethod_i^{IRB,S,C} \times \Big(ProvStockNonDefS1_{i,t}^{S,C} \\
& + ProvStockNonDefS2_{i,t}^{S,C} + ProvStockDef_{i,t}^{S,C} \Big) \\
& + sMethod_i^{IRB,OTHER} \times ProvStock_i^{OTHER} \\
& + sMethod_i^{IRB,EQ} \times ProvStock_i^{EQ}
\end{aligned}
\tag{151}
$$

where $S = \{NFC, HHCC, HHHP, RoW, SOV, FIN, CB\}$, and $IRBSF\_AddVal$ accounts for an exogenous and constant adjustment factor for defaulted and non-defaulted IRB exposures.

Additional Tier 1 capital $AT1CAP$ summarises other instruments eligible for inclusion in Tier 1 but not for common equity, such as contingent convertibles or hybrid securities. The formula accounts for the conversion of AT1 instruments into equity following a trigger event:

$$
\begin{aligned}
AT1CAP_{i,t} = & AT1CAP_{i,t-1} - I(5.125\% - CET1REA_{i,t-1} > 0) \times \\
& min((5.125\% - CET1REA_{i,t-1}) \times (ToTREA_{i,t-1} + TAIFRSREA_{i,t-1}), \\
& AT1CAP_{i,t-1})
\end{aligned}
\tag{152}
$$

Tier 2 capital instruments such as revaluation reserves, hybrid instruments, and subordinated term debt. Additionally, the CRR further prescribes that excess credit risk provisions for IRB banks $IRBSf_{i,t} < 0$ be added to Tier 2 instruments:[54]

$$
\begin{aligned}
T2CAP_{i,t} = & T2CAP_{i,t-1} + min(IRBSF_{i,t}, 0.6\% \times ToTREA_{i,t}) \times (IRBSF_{i,t} > 0) \\
& - min(IRBSF_{i,t-1}, 0.6\% \times ToTREA_{i,t-1}) \times ((IRBSf_{i,t-1} > 0) \\
& - (4.5\% - CET1REA_{i,t-1} > 0) \times min(((4.5\% - CET1REA_{i,t-1}) \\
& \times (ToTREA_{i,t-1} + TAIFRSREA_{i,t-1})), T2CAP_{i,t-1}))
\end{aligned}
\tag{153}
$$

4.2.3 Evolution of bank liabilities

The evolution of bank liabilities depends on the size of bank assets, the supply and costs of different funding instruments, and liquidity considerations. The bulk of assets will typically be funded by non-maturing debt carried over from last quarter and own funds. The remaining funding gap is covered by debt issuance. Banks tap different debt funding sources sequentially, according to a pecking order principle. First, they turn to slower-moving debt instruments, and last, they issue debt in wholesale markets. The order of reaching for different funding sources is informed by the relative costs of funding (starting from cheaper instruments, and progressing to more expensive funding), its stability (starting from most stable and moving toward less stable funding) and last by legal considerations.[55] Banks adjust the duration and collateralization of wholesale funding in response to relative prices for different types of wholesale funding, the supply of unencumbered assets, and regulatory compliance with the liquidity coverage ratio LCR and the net stable funding ratio $NSFR$.

[54] See Article 62(d) of the CRR.

[55] Although the pecking order describing funding choices of non-financial firms has also been used by Myers and Majluf [1984], the two terms are not equivalent. Myers and Majluf [1984] considers funding choices in the presence of information asymmetries between internal funds (retained earnings), debt, and equity issuance. Here, the same term describes banks' choices between different types of debt.

4.2.3.1 The funding gap and pecking order

The funding gap $FundingGap$ is defined as the amount of new debt a bank needs to raise to finance its operations. It amounts to the difference between the funding needs and the funding available to a bank at the beginning of the period, including the own funds $CET1TR$ and $AT1CAP$ and the non-matured or withdrawn debt instruments:

$$\begin{aligned} FundingGap_{i,t} = &\, VolAssetTotal_{i,t} + VolNPE_{i,t} - AssetOverhang_i \\ & - CET1TR_{i,t-1} - AT1CAP_{i,t-1} \\ & - \sum_S \sum_C (1 - ShareMaturing_{i,t}^{S,C})\, VolLiabTotal_{i,t-1}^{S,C} \\ & - \sum_S (1 - ShareMaturing_{i,t}^{S})\, VolLiabTotal_{i,t-1}^{S} \end{aligned} \tag{154}$$

where $S \in \{NFCS, HHS, TERM, RoW, NCB, SOV, SECST, SECLT, FINS, FIN, OTHUNSEC, OTHER\}$. $ShareMaturing$ stands for the proportion of maturing or withdrawn liabilities in the reference quarter. $AssetOverhang$ is a constant parameter that takes into account the inconsistency between asset and liability volumes in the data submitted by banks in EBA/SSM stress test exercises.[56]

For retail sight deposits of households HHS and corporates $NFCS$, the gross quarterly withdrawal rate is set at 10%. This rate lies between the stressed outflow rate assumed by the regulator for the calculation of LCR (see Section 4.3.3.1) and the business-as-usual outflow rate assumed for the calculation of NSFR (see Section 4.3.3.2). For term deposits $TERM$, the proportion of maturing debt follows a distribution $Gamma(k, \theta)$ with $k = 1$ and $\theta = AvgDurationLiab$, analogously to the assumptions followed for bank loans (see Section 4.1.5 and equation (57)).

$$ShareMaturing_{i,t}^{S,C} = \begin{cases} 10\%, & \text{if } S \in \{HHS, NFCS\} \\ F(0, 0.25, AvgDurationLiab_i^{S,C}) & \text{if } S = TERM \end{cases} \tag{155}$$

For non-retail sectors, the share of maturing debt is calculated as follows:

$$ShareMaturing_{i,t}^{S} = \begin{cases} 50\% & \text{if } S = SECST \\ \frac{UnsecuredOutflow_{i,t}}{VolLiabTotal_{i,t}^{S}} & \text{if } S = FINS \\ F(0, 0.25, AvgDurationLiab_{i,t}^{S}) & \text{if } S \in \{RoW, NCB, SOV, \\ & \quad SECLT, FIN, OTHUNSEC\} \\ 0 & \text{if } S = OTHER \end{cases} \tag{156}$$

Half of all repos $SECST$ are assumed to be renewed quarter-by-quarter. For financial sight deposits $FINS$, the outflows of unsecured financial sight deposits are calculated in Section 4.3.3.1.[57] All other non-retail debt matures depending on its duration. For $OTHER$ funding, the model takes a simplified assumption of no-outflow.

[56]The item can include assets and liabilities that are not interest-bearing, such as property and equipment, intangibles or cash assets. The excess funding is then carried over into the next period as spare cash. A negative funding gap can rarely arise in the data.

[57]These are calculated for a stressed scenario over a 30-day period, which we assume to be an adequate proxy for average, business-as-usual outflows over a quarter.

A bank closes its funding gap starting with sight deposits from the private sector $SIGHT$ that include the HHS and $NFCS$ segments. Euro area sight deposits are favourably priced and more stable than institutional or wholesale funding due to deposit insurance [Farag et al., 2013]. Furthermore, banks may not be able[58] to refuse the acceptance of sight deposits. Thereafter, if the gap is still open, banks take advantage of euro area retail term deposits $TERM$, and then of retail deposits from non-euro area countries RoW. Unless private sector deposits are sufficient to fully cover the funding gap, banks resort to central bank NCB and government SOV funding jointly summarised in category $INST$. Finally, if the funding gap persists even if all preferred funding sources have been exhausted, the outstanding funding needs are saturated in the wholesale market, which offers an unlimited supply of funding though at costs sensitive to market and bank-specific conditions.[59] In the wholesale market, banks will first exhaust their ability to issue secured funding SEC, and then only draw on unsecured funding $UNSEC$.

Let $FundingGap^G$ be the residual funding gap after a bank tapped all available funding prior to category G in pecking order. $FundingSupply^G$ stands for the inflow of funding from categories in G, that is, the aggregated supply of funding from sectors S and countries C contained in category G. The sequential closing of the funding gap along the pecking order $G \in \{SIGHT, TERM, RoW, INST, SEC, UNSEC\}$ occurs as follows:

$$\begin{aligned}
FundingGap_{i,t}^{SIGHT} &= max(FundingGap_{i,t}, 0) \\
FundingGap_{i,t}^{TERM} &= max(FundingGap_{i,t}^{SIGHT} - FundingSupply_{i,t}^{SIGHT}, 0) \\
FundingGap_{i,t}^{RoW} &= max(FundingGap_{i,t}^{TERM} - FundingSupply_{i,t}^{TERM}, 0) \\
FundingGap_{i,t}^{INST} &= max(FundingGap_{i,t}^{RoW} - FundingSupply_{i,t}^{RoW}, 0) \\
FundingGap_{i,t}^{SEC} &= max(FundingGap_{i,t}^{SEC} - FundingSupply_{i,t}^{SEC}, 0) \\
FundingGap_{i,t}^{UNSEC} &= 0
\end{aligned} \tag{157}$$

4.2.3.2 Sight and term deposits

The funding supply $FundingSupply$ for $G \in \{SIGHT, TERM, RoW, INST\}$ is equal to:

$$FundingSupply_{i,t}^{G} = \sum_{S \in G} \sum C \left(VolLiabTotal_{i,t-1}^{S,C} \times InflowRate_{i,t}^{S,C} \right) \tag{158}$$

and the gross inflow rate $InflowRate$ for different deposits $S \in G$ is calculated as the sum of net inflows $VolLiabTotal\_gr$ and the replacement of maturing debt $ShareMaturing$:

$$InflowRate_{i,t}^{S,C} = max\left(VolLiabTotal\_gr_{i,t}^{S,C} + ShareMaturing_{i,t}^{S,C}, 0 \right) \tag{159}$$

The growth rate $VolLiabTotal\_gr$ of retail funding is estimated separately for household HHS and non-financial corporate $NFCS$ sight deposits, and term deposits $TERM$. The dynamic behaviour in each of these sectors $S \in \{HHS, NFCS, TERM\}$ is governed by local economic conditions and interest rates on new deposits $EIRLiabNew$. Details of the estimation are provided in Appendix C.7.

[58] EU residents have the right to a bank account.

[59] The assumption of unlimited access to unsecured funding is maintained also for stressed periods. However, the price of unsecured funding under such conditions is expected to reflect a sharp increase in credit risk and a shortage of funding supply.

$$
\begin{aligned}
VolLiabTotal\_gr_{i,t}^{S,C} = {} & \beta_1^S \,\Delta log(VolLiabTotal_{i,t-1}) + \sum_p \beta_{2,p}^S \, YERgr_{t-p}^C + \beta_4^S \, HICgr_{t-1}^C \\
& + \beta_5^S \,\Delta URX_{t-1}^C + \sum_p \beta_{6,p}^S \,\Delta EIRLiabNew_{i,t-p}^{S,C} \\
& + \beta_7^S \,(EIRLiabNew_{i,t-1}^{S,C} - STN_{t-1}^{EA})
\end{aligned} \tag{160}
$$

The growth rate of deposits coming from countries outside the euro area is calculated by weighting the sector-specific parameters from equation (160) with the share of sectors $S \in \{HHS, NFCS, DEPT\}$ in the overall bank deposits from RoW, analogously to equation (15). Macrofinancial variables entering the RoW deposit growth equation also take into account the bank-specific exposure shares to the non-financial private sector in individual countries outside the euro area as in equation (16).

The funding from sovereigns or central banks follows the nominal GDP in the domestic economy of a bank C_i. Therefore, for $S \in \{SOV, NCB\}$:

$$
VolLiabTotal\_gr_{i,t}^{S} = YERgr_t^{C_i} + HICgr_t^{C_i} \tag{161}
$$

A bank draws funding from any source G only to the extent necessary to close a residual gap $FundingGap^G$. Actual funding volumes drawn by a bank from source G make up a monotonously decreasing share $\in [0,1]$ of available $FundingSupply^G$, denoted as $FundingDemand^G$ and defined as:

$$
FundingDemand_{i,t}^G = \frac{min(FundingGap_{i,t}^G, FundingSupply_{i,t}^G)}{FundingSupply_{i,t}^G} \tag{162}
$$

Bank liability volumes amount to the non-matured stock of liabilities plus a gross realised funding inflow. Therefore, for all $S \in G$, where $G \in \{SIGHT, TERM, RoW, INST\}$:

$$
\begin{aligned}
VolLiabTotal_{i,t}^{S,C} = VolLiabTotal_{i,t-1}^{S,C} \Big(& 1 - ShareMaturing_{i,t}^{S,C} \\
& + (1 - Insolvent_{i,t-1}) \times FundingDemand_{i,t}^G \times InflowRate_{i,t}^{S,C} \Big)
\end{aligned} \tag{163}
$$

4.2.3.3 Wholesale funding

The use of wholesale funding $FundingSupply$ for $G \in \{SEC, UNSEC\}$ is the simple sum of instruments $VolLiabIssued$ in each market segment:

$$
FundingSupply_{i,t}^G = \sum_{S \in G} VolLiabIssued_{i,t}^S \tag{164}
$$

The composition of wholesale funding is influenced by considerations of maturity mismatch. A bank has access to secured and unsecured funding, and the mix of wholesale funding is governed by three estimated shares: the desired share of secured wholesale funding in all wholesale funding γ^{SEC}_{WHSL}, the share of long-term secured funding in all secured funding, and the share of long-term unsecured funding in all unsecured funding.

A bank can collateralise sovereign bonds to generate repos $SECST$, or pools of loans to generate ABS or covered bonds $SECLT$. The desired share of secured funding in wholesale funding, $\gamma^{SEC}_{WHSL} \in (0,1)$, is estimated logistically (for estimation details, see Appendix C.11):

$$\begin{aligned}\gamma^{SEC}_{WHSL} = invlogit\Big(&\beta_0 + 4\,\beta_1\,(EIRLiabNew^{FINS}_{i,t} - EIRLiabNew^{SECST}_{i,t}) \\ &+4\,\beta_2\,(EIRLiabNew^{UNSEC}_{i,t} - EIRLiabNew^{SECLT}_{i,t}) \\ &+\beta_3\,log(max(LCR_{i,t-1} - TLCR_{i,t-1}, 0)\Big)\end{aligned} \tag{165}$$

The desired share of secured funding depends positively on the current risk premium on short-term $EIRLiabNew^{FINS} - EIRLiabNew^{SECST}$ and long-term $EIRLiabNew^{UNSEC} - EIRLiabNew^{SECLT}$ unsecured funding. The collateralization of wholesale funding reduces the stock of unencumbered high-quality liquid assets and negatively affects the LCR's numerator. Accordingly, the higher the excess liquidity coverage, i.e., the difference between the bank's LCR and the corresponding regulatory requirement $TLCR$, the greater the availability of collateral for repo operations and the likelihood that a bank seeks secured funding.

The share of long-term funding in secured funding γ^{LT}_{SEC} determines the proportion of ABS and covered bonds $SECLT$ in bank funding. It depends on the relative prices of repos and long-term secured bonds $EIRLiabNew^{SECST} - EIRLiabNew^{SECLT}$, the excess net stable funding $NSFR$ beyond the regulatory requirement $TNSFR$ as the duration of debt funding affects the numerator of NSFR, the amount of encumberable government bonds $EncumbL1SecBuffer$ (which can generate repos) and loans $EncumbLoanBuffer$ (which can generate ABS or covered bonds).

$$\begin{aligned}\gamma^{LT}_{SEC,i,t} = invlogit\Big(&\beta_0 + 4\beta_1\,(EIRLiabNew^{SECLT}_{i,t} - EIRLiabNew^{SECST}_{i,t}) \\ &+\beta_2\,log(max(NSFR_{i,t-1} - TNSFR_{i,t-1}, 0) \\ &+\beta_3\,EncumbL1SecBuffer_{i,t} + \beta_4\,EncumbLoanBuffer_{i,t}\Big)\end{aligned} \tag{166}$$

The share of term deposits FIN and securities $UNSEC$ in unsecured funding, γ^{LT}_{UNSEC}, depends on the relative price of short-term and long-term unsecured funding $EIRLiabNew^{FINS} - EIRLiabNew^{UNSEC}$, and the excess stable funding $(NSFR - TNSFR)$ available to a bank.

$$\begin{aligned}\gamma^{LT}_{UNSEC,i,t} = invlogit\Big(&\beta_0 + 4\,\beta_1\,(EIRLiabNew^{UNSEC}_{i,t} - EIRLiabNew^{FINS}_{i,t}) \\ &+\beta_2\,log(max(NSFR_{i,t-1} - TNSFR_{i,t-1}, 0)\Big)\end{aligned} \tag{167}$$

The volumes of new repos $VolLiabIssued^{SECST}$ and covered bonds or ABS $VolLiabIssued^{SECLT}$ are capped by the available collateral stock. For new repos these, the stock of available collateral is provided by the volume of unencumbered sovereign bonds $UnencumbL1SecBRepo$, and for covered bonds or ABS, the volume of encumberable retail loans $UnencumbLoansBABS$ (for their definitions, see Section 4.3.3.3), both less the corresponding haircut $Haircut$:

$$\begin{aligned}
VolLiabIssued_{i,t}^{SECST} &= min\Bigg((1-Haircut^{SGOV}) \times UnencumbL1SecBRepo_{i,t} \\
&\qquad \gamma_{WHSL,i,t}^{SEC} \times (1-\gamma_{SEC,i,t}^{LT}) \times FundingGap_{i,t}^{SEC}\Bigg) \\
VolLiabIssued_{i,t}^{SECLT} &= min\Bigg((1-Haircut^{LOANS}) \times UnencumbLoansBABS_{i,t} \\
&\qquad \gamma_{WHSL,i,t}^{SEC} \times \gamma_{SEC,i,t}^{LT} \times FundingGap_{i,t}^{SEC}\Bigg)
\end{aligned} \tag{168}$$

For repos, $Haircut^{SGOV}$ is set at 10%. For the issuance of covered bonds or ABS, the haircut $Haircut^{LOANS}$ is higher and amounts to 25%.

The residual funding demand $FundingGap^{SEC}$ after the issuance of secured debt is covered by unsecured debt and allocated according to γ_{UNSEC}^{LT}:

$$\begin{aligned}
VolLiabIssued_{i,t}^{FINS} =& FundingGap_{i,t}^{SEC} \times (1-\gamma_{UNSEC,i,t}^{LT}) \\
VolLiabIssued_{i,t}^{FIN} =& FundingGap_{i,t}^{SEC} \times \gamma_{UNSEC,i,t}^{LT} \times Share^{FIN} \\
VolLiabIssued_{i,t}^{OTHUNSEC} =& FundingGap_{i,t}^{SEC} \times \gamma_{UNSEC,i,t}^{LT} \times (1-Share_i^{FIN})
\end{aligned} \tag{169}$$

The split between financial term deposits FIN and other securities and hybrid contracts $OTHUNSEC$ for unsecured funding is constant and is captured by the calibrated parameter $Share^{FIN}$ derived from historical data.

The total volume of wholesale debt for $S \in \{SECST, SECLT, FINS, FIN, UNSEC, OTHUNSEC\}$:

$$\begin{aligned}
VolLiabTotal_{i,t}^{S} =& (1-ShareMaturing_{i,t}^{S}) \times VolLiabTotal_{i,t-1}^{S} \\
&+ (1-Insolvent_{i,t-1}) \times VolLiabIssued_{i,t}^{S}
\end{aligned} \tag{170}$$

where a bank loses its access to wholesale funding in case of its insolvency.

4.2.4 Total funding volumes

The model simplifies the dynamics for other $OTHER$ liabilities linking them directly to the nominal GDP growth in a country where the banks are headquartered:

$$VolLiabTotal_{i,t}^{OTHER} = VolLiabTotal_{i,t-1}^{OTHER} \times \left(YERgr_t^C + HICgr_t^C + 1\right) \tag{171}$$

while derivatives $DERIV$ are assumed to remain constant over time:

$$VolLiabTotal_{i,t}^{DERIV} = VolLiabTotal_{i,t-1}^{DERIV} \tag{172}$$

The total funding volumes $VolLiabTotal$ sum up liabilities for $S \in \{HHS, NFCS, DEPT, RoW, NCB, SOV, SECLT, SECST, FINS, FIN, OTHUNSEC, OTHER\}$:

$$VolLiabTotal_{i,t} = \sum_S \sum_C VolLiabTotal_{i,t}^{S,C} \tag{173}$$

4.2.5 Costs of debt financing

4.2.5.1 Interest rates on new deposits

The interest rates on new retail sight deposits $EIRLiabNew$ for $S \in \{HHS, NFCS\}$ depend on general macrofinancial conditions. Additionally, the pass through of market interest rates STN in bank deposit rates becomes weaker near the zero-lower bound, which is accommodated with the interaction term between STN and a non-linear function $f(.)$ of $EIRLiabNew$. The empirical specification of deposit pricing also accounts for the competitiveness in retail sight deposits, including the convergence term between the individual bank deposit rates and the average deposit rate $\overline{EIRLiabNew}$ in the relevant market. For estimation details, see Appendix C.8).

$$\begin{aligned}
\Delta EIRLiabNew_{i,t}^{S,C} = &\beta_1^S\, \Delta EIRLiabNew_{i,t-1}^{S,C} + \beta_2^S \Delta EIRLiabNew_{i,t-2}^{S,C} \\
&+\beta_3^S\, YERgr_{t-1}^{C} + \beta_4\, YERgr_{t-2}^{C} \\
&+\beta_5^S\, HICgr_{t-1}^{C} + \beta_6\, HICgr_{t-2}^{C} \\
&+\beta_7^S\, \Delta(LTN_{t-1}^{C} - LTN_{t-1}^{DE}) + \beta_8^S\, \Delta(LTN_{t-2}^{C} - LTN_{t-2}^{DE}) \\
&+\beta_9^S\, \Delta STN_{t-1}^{EA} \times f(EIRLiabNew_{i,t-1}^{S,C}) \\
&+\beta_{10}^S\, (EIRLiabNew_{i,t-1}^{S,C} - \overline{EIRLiabNew_{i,t-1}^{S,C}})
\end{aligned} \tag{174}$$

where $f(x) = (\frac{2}{1+e^{-25max(x,0)}} - 1)$.

Term deposits $DEPT$ depend on a similar set of factors, although the 3-month EURIBOR enters the empirical equation as a two-year moving average.

$$\begin{aligned}
\Delta EIRLiabNew_{i,t}^{DEPT,C} = &\beta_1\, \Delta EIRLiabNew_{i,t-1}^{DEPT,C} + \beta_2\, \Delta EIRLiabNew_{i,t-2}^{DEPT,C} \\
&+\beta_3\, YERgr_{t-1}^{C} + \beta_4\, YERgr_{t-2}^{C} \\
&+\beta_5\, HICgr_{t-1}^{C} + \beta_6\, HICgr_{t-2}^{C} \\
&+\beta_7\, \Delta(LTN_{t-1}^{C} - LTN_{t-1}^{DE}) + \beta_8\, \Delta(LTN_{t-2}^{C} - LTN_{t-2}^{DE}) \\
&+\beta_9\, 0.125\, \Delta_8 STN_{t}^{EA}
\end{aligned} \tag{175}$$

Interest rates on new rest of the world deposits RoW are derived by aggregating the specifications for sight and term deposits, weighted by the shares of the corresponding deposits in banks' non-euro area deposits. Additionally, the macrofinancial variables in equations (174) and (175) are substituted with their weighted-average RoW counterparts as in equation (16).

Interest rates on sovereign SOV and central bank deposits NCB are linked to the domestic yield curve. Letting C_i be the home country of a bank:

$$\Delta EIRLiabNew_{i,t}^{S} = 0.25 \times \Delta Yield_t^C(AvgDurationLiab_i^S) \tag{176}$$

4.2.5.2 Costs of newly issued wholesale funding

Interest rates on secured funding $S \in \{SECST, SECLT\}$ track changes in the euro area yield curve $Yield^{EA}$, which approximates a risk-free rate:

$$\Delta EIRLiabNew_{i,t}^{S} = 0.25 \times \Delta Yield_t^{EA}(AvgDurationLiab_i^{S}) \tag{177}$$

Interests in the unsecured wholesale market are linked to bank-specific yield curves $Yield_i$ taking into account bank-specific funding maturity on newly issued debt $NewDurationLiab$. For $S \in \{FINS, FIN, UNSEC\}$:

$$EIRLiabNew_{i,t}^{S} = EIRLiabNew_{i,t-1}^{S} + 0.25 \times \Delta Yield_{i,t}(NewDurationLiab_{i,t}^{S}) \tag{178}$$

A bank-specific funding yield curve follows a similar specification to the annualized yields on bank security holdings introduced in equations (62) and (63). It is broken down into the idiosyncratic risk of default of a bank $CreditSpread$ and a risk-free interest rate supplied by the euro area yield curve:

$$\begin{aligned} Yield_{i,t}(NewDurationLiab_{i,t}^{S}) = {} & e^{Lin\hat{S}pread_{i,t}(NewDurationLiab_{i,t}^{S})} \\ & + Yield_t^{EA}(NewDurationLiab_{i,t}^{S}) \end{aligned} \tag{179}$$

The linear function $LinSpread_{i,t}(.)$ depends on macroeconomic factors and bank-specific factors, including the bank leverage ratio $LevRatTa$, net NPL ratio $netNPLR$, and the size of the bank's balance sheet approximated with bank total assets TA, in addition to dummies for subsidiary banks $SUBS$ and state-owned banks $LABA$, which jointly capture the idiosyncratic determinants of bank default risk. Macroeconomic factors follow developments in the domestic economy of banks C_i.

$$\begin{aligned} LinSpread_{i,t}(\tau) = {} & \beta_0 + \beta_1\, SUBS_i + \beta_2\, LABA_i \\ & + \beta_3\, LevRatTA_{i,t} + \beta_4\, netNPLR_{i,t} + \beta_5\, TA_{i,t} + \beta_6\, YERgr_t^{C_i} \\ & + log(\tau) \times (\beta_7\, LevRatTa_{i,t} + \beta_8\, netNPLR_{i,t} + \beta_9\, TA_{i,t} + \beta_{10}\, LTN_t^{C_i}) \end{aligned} \tag{180}$$

The parameters $\beta_3 - -\beta_6$ capture the effect of the variables on the level of the yield curve. A positive coefficient estimate translates into an upward shift of the overall yield curve following an increase in the relevant variable. The parameters $\beta_7 - -\beta_1 0$ capture the impact of the variables on the slope of the yield curve. A positive coefficient estimate means that a positive change in the corresponding variables shifts the yield curve upward relatively strongly at the long end, causing the yield curve to steepen. See Appendix C.9 for more information on the estimates.

The risk margin at low to medium maturities is more responsive to changes in the leverage and NPL ratio, whereas for long maturities it reacts more strongly to changes in the size of the balance sheet and country-level risks approximated by LTN.

4.2.5.3 Maturity at issuance for unsecured wholesale funding

The maturity at issuance $NewDurationLiab$ of financial sight deposits $FINS$ is set below or at one quarter:

$$NewDurationLiab_{i,t}^{FINS} = 0.25 \tag{181}$$

The maturity at issuance of financial term deposits FIN and securities $OTHUNSEC$ is projected based on an empirical equation linking it to the expected bank-specific yield curve. Along with the specification discussed in more detail in Appendix C.10, a bank adapts the maturity along with the following:

$$NewDurationLiab^{S}_{i,t} = \beta_0 + \beta_1 LinSpread_{i,t-1}(1) + \beta_2 \frac{\partial LinSpread_{i,t-1}(\tau)}{\partial log(\tau)} \tag{182}$$

where both terms $LinSpread(1)$ and $\frac{\partial LinSpread(\tau)}{\partial log(\tau)}$ are derived from the bank-specific yield curve in equation (180). $LinSpread(1)$ stands for the level of the yield curve when $log(\tau) = 0$:

$$\begin{aligned} LinSpread_{i,t}(1) = & \beta_0 + \beta_1\, SUBS_i + \beta_2\, LABA_i \\ & + \beta_3\, LevRatTa_{i,t} + \beta_4\, netNPLR_{i,t} + \beta_5\, TA_{i,t} + \beta_6\, YERgr^{C}_{t} \end{aligned} \tag{183}$$

and:

$$\frac{\partial LinSpread_{i,t}(\tau)}{\partial log(\tau)} = \beta_7\, LevRatTa_{i,t} + \beta_8\, netNPLR_{i,t} + \beta_9\, TA_{i,t} + \beta_{10}\, LTN^{C}_{t} \tag{184}$$

Consequently, for $S \in \{FINS, FIN, OTHUNSEC\}$ the average duration of liabilities $AvgDurationLiab$ becomes time-varying and equals:

$$\begin{aligned} AvgDurationLiab^{S}_{i,t} = & (NewDurationLiab^{S}_{i,t-1} \times VolLiabNew^{S}_{i,t-1} \\ & + AvgDurationLiab^{S,C}_{i,t-1} \times VolLiabExist^{S,C}_{i,t-1})/ \\ & (VolLiabNew^{S,C}_{i,t-1} + VolLiabExist^{S,C}_{i,t-1}) \end{aligned} \tag{185}$$

where $VolLiabNew$ are the average volumes for the period of new and $VolLiabExist$ of existing liabilities.

4.2.5.4 Interests on existing and maturing liabilities

For all sectors of debt funding $S \in \{HHS, NFCS, DEPT, RoW, NCB, SOV, SECLT, SECST, FINS, FIN, OTHUNSEC\}$, the interest rates on existing and maturing liabilities evolve similarly to the interest rates on existing and maturing assets in Section 4.1.5.2. For existing deposits and wholesale funding, the interest rates $EIRLiabExist$ are the same:

$$\begin{aligned} EIRLiabExist^{S,C}_{i,t} = & (EIRLiabNew^{S,C}_{i,t-1} \times VolLiabNew^{S,C}_{i,t-1} \\ & + EIRLiabExist^{S,C}_{i,t-1} \times VolLiabExist^{S,C}_{i,t-1})/ \\ & (VolLiabNew^{S,C}_{i,t-1} + VolLiabExist^{S,C}_{i,t-1}) \\ & + 0.25\, (RefDurationLiab^{S,C}_{i})^{-1}\, ShareFloatLiab^{S,C}_{i}\, \Delta STN^{EA}_{t} \end{aligned} \tag{186}$$

where $ShareFloatLiab$ is the share of floating interest rate liabilities and $RefDurationLiab$ is the average annualized duration of the reference rate.

The interest rates for maturing liabilities $EIRLiabMat$ evolve along with:

$$EIRLiabMat_{i,t}^{S,C} = EIRLiabMat_{i,t-1}^{S,C} + \Delta EIRLiabExist_{i,t}^{S,C} - 0.25\,(AvgDurationLiab_{i,t}^{S,C})^{-1}\,(EIRLiabMat_{i,t-1}^{S,C} - EIRLiabExist_{i,t-1}^{S,C}) \tag{187}$$

and $AvgDurationLiab$ is a constant parameter for all sectors excluding $S \in \{FINS, FIN, OTHUNSEC\}$.

4.2.5.5 The period average volumes of new, existing and maturing liabilities

The average period volumes of the new $VolLiabNew$, existing $VolLiabExist$ and maturing $VolLiabMat$ liabilities are described analogously to the period average asset volumes in Section 4.1.5.3. The new liability volumes are defined by:

$$VolLiabNew_{i,t}^{S,C} = (1 - PomLiab_{i}^{S,C})\,(\Delta VolLiabTotal_{i,t}^{S,C} + VolLiabMat_{i,t}^{S,C}\,(PomLiab_{i}^{S,C})^{-1}) \tag{188}$$

where $PomLiab$ stands for the point of maturity.

The existing volumes are equal:

$$VolLiabExist_{i,t}^{S,C} = (1 - 0.25(AvgDurationLiab_{i,t}^{S,C})^{-1}) \times VolLiabTotal_{i,t-1}^{S,C} \tag{189}$$

Finally, the law of motion for maturing assets is given by:

$$VolLiabMat_{i,t}^{S,C} = PomLiab_{i}^{S,C} \times 0.25 \times (AvgDurationLiab_{i}^{S,C})^{-1} \times VolLiabTotal_{i,t-1}^{S,C} \tag{190}$$

4.2.5.6 Interest expenses

The total interest expenses $TotalIntExp$ sum up the interest expenses of new, existing and maturing liabilities for $S \in \{HHS, NFCS, DEPT, RoW, NCB, SOV, SECLT, SECST, FINS, FIN, OTHUNSEC\}$:

$$TotalIntExp_{i,t} = \sum_{S}\sum_{C}(VolLiabExist_{i,t}^{S,C} \times EIRLiabExist_{i,t}^{S,C} + VolLiabMat_{i,t}^{S,C} \times EIRLiabMat_{i,t}^{S,C} + VolLiabNew_{i,t}^{S,C} \times EIRLiabNew_{i,t}^{S,C}) + IntExp_{i,t}^{OTHER} + IntExp_{i,t}^{DERIV} \tag{191}$$

The modelling of interest expenses for sectors $S = \{DERIV, OTHER\}$ follows simplified formulas:

$$IntExp_{i,t}^{OTHER} = IntExp_{i,t-1}^{OTHER} \times \left(YERgr_{t}^{C} + HICgr_{t}^{C} - 1\right) \tag{192}$$

$$IntExp_{i,t}^{DERIV} = IntExp_{i,t-1}^{DERIV} \tag{193}$$

4.3 Capital and liquidity requirements

4.3.1 Bank solvency and leverage

The core solvency metric in the model is the Common Equity Tier 1 ratio on a transitional basis $CET1REA$. The nominator of the ratio is the capital of the Common Equity Tier 1 defined in the equation (146). The denominator is the total risk weighted amount $TotREA$ defined in equation (145) and a constant term representing the transitional arrangements for the risk exposure amounts $TAIFRSREA$.

$$CET1REA_{i,t} = \frac{CET1TR_{i,t}}{TotREA_{i,t} + TAIFRSREA_{i,t}} \tag{194}$$

Bank solvency is considered on a consolidated basis only. Accordingly, bank decisions that rely on bank solvency, such as lending, do not factor in the individual standing of banks' branches and subsidiaries.

The Additional Tier 1 capital ratio $AT1CAPR$, net of deductions and after transitional adjustments, is given by:

$$AT1CAPR_{i,t} = \frac{AT1CAP_{i,t}}{TotREA_{i,t} + TAIFRSREA_{i,t}} \tag{195}$$

where $AT1CAP$ is defined in equation (152).

Finally, the Tier 2 capital ratio $T2CAPR$ is equal to:

$$T2CAPR_{i,t} = \frac{T2CAP_{i,t}}{TotREA_{i,t} + TAIFRSREA_{i,t}} \tag{196}$$

and its nominator $T2CAP$ is defined in equation (153).

Another metric to assess leverage in bank activity is the transitional Tier 1 leverage ratio $LevRatTa$. It measures banks' Tier 1 capital stock against its total leverage ratio exposures $LevRatExp$:

$$LevRatTa_{i,t} = \frac{CET1TR_{i,t} + AT1CAP_{i,t}}{LevRatExp_{i,t}} \tag{197}$$

where $LevRatExp$ is calculated on a transitional basis and scaled by the growth of the exposure of banks $TotalExposure$:

$$LevRatExp_{i,t} = LevRatExp_{i,t-1} \times \frac{TotalExposure_{i,t}}{TotalExposure_{i,t-1}} \tag{198}$$

4.3.2 Capital and leverage requirements

The CET1 requirements are composed of the uniform Pillar I requirements (4.5%), Pillar I combined buffer requirement $COMB$, bank-specific Pillar II requirements $P2R$ and Pillar II guidance $P2G$:

$$TCET1REA_{i,t} = 4.5\% + P2R_{i,t} + COMB_{i,t} + P2G_{i,t} \tag{199}$$

The combined buffer requirement $COMB$ is defined as the sum of the conservation buffer CCB, the bank-specific countercyclical capital buffer $CCYB$, and the systemic risk buffers. The latter include the systemic risk buffer that applies to domestic exposures only $SYSCAPDOMB$, and the maximum of buffers applicable for global systemically important institutions $GSIIB$, buffers for other systemically important institutions $OSIIB$ and systemic risk buffer $SYSCAPB$ that applies to general exposures of banks $SYSCAPB$, respectively.

$$COMB_{i,t} = sSRB_{i,t} + SYSCAPDOMB_{i,t} + max(max(GSIIB_{i,t}, OSIIB_{i,t}), SYSCAPB_{i,t}) \tag{200}$$

The surplus or shortfall of capital relative to the bank-specific regulatory requirements is given by $CET1SurShortfall$:

$$CET1SurShortfall_{i,t} = CET1REA_{i,t} - TCET1REA_{i,t} - AT1T2SHORT_{i,t} \tag{201}$$

The CET1 capital surplus or shortfall $CET1REA - TCET1REA$ is augmented with potential shortfalls in the capital of Tier 1 and Tier 2, $AT1T2SHORT$, in the event that these are binding.

The Tier 1 capital requirements are higher than the CET1 capital requirements by $0.035 + P2RAT1$, where $P2RAT1$ represents the Pillar II requirements that can be met by the AT1 capital. The requirements for own funds are higher than those for Tier 1 capital by $0.02 + P2RT2$ with $P2RT2$ being the Pillar II requirements for Tier 2 capital instruments. Consequently:

$$\begin{aligned} AT1T2SHORT_{i,t} = max(0, 3.5\% + P2RAT1 - AT1CAPR_{i,t} \\ - min(2.0\% + P2RT2_{i,t}, T2CAPR_{i,t})) \end{aligned} \tag{202}$$

Finally, a bank that does not meet the minimum capital requirement of 4.5% should not grant new loans and lose access to funding. This is governed by the variable $Insolvent$ defined as[60]:

$$Insolvent_{i,t} = (CET1REA_{i,t} < 4.5\%) \tag{203}$$

An additional regulatory requirement is 3% the Basel III leverage ratio requirement for the Tier 1 leverage ratio $LevRatTa$. The corresponding shortfall is defined by:

$$LEVRSurShortfall_{i,t} = LevRatTa_{i,t} - TLevRatTa_{i,t} \tag{204}$$

where $TLevRatTa$ is higher for global systemically important banks $GSIIB$ according to the Basel III finalisation package:

$$TLevRatTa_{i,t} = 3\% + 0.5 \times GSIIB_{i,t} \tag{205}$$

[60] In practise, the specification of this variable differs between simulations performed with different aims in mind. For instance, for simulations where the bail-in regime is to be emphasised, we introduce time dependency in the variable and expand it to include the information on the available AT1 and Tier 2 capital available to a bank. The specification presented in this paper serves as a simple benchmark solution.

4.3.3 Liquidity

The model tracks two liquidity metrics, the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). Jointly, they provide a representation of the firm's liquidity situation in the very short term (< 30 days) and short-to-medium term (< 1 year) respectively, and correspond with regulatory requirements introduced in Basel III. The components of the two regulatory requirements are summarised in Table 8.

Regulatory Ratio	Numerator and Denominator	Component	Model Name	Nominal Amount	Weighted Amount
Liquidity Coverage Ratio (LCR)	High Quality Liquid Assets (HQLA)	Level 1 assets excl. EHQCB	*L1*	92%	92%
		Extremely high quality covered bonds (EHQCB)		3%	3%
		Level 2A assets	*L2A*	2%	2%
		Level 2B assets	*L2B*	2%	2%
	Outflows	Unsecured transactions and deposits	*RetailOutflow*, *UnsecOutflow*	87%	83%
		Secured lending and capital market-driven transactions		11%	6%
		Collateral swaps	*ResOutflow*	-	7%
		Other sources		2%	4%
	Inflows	Unsecured transactions and deposits	*RetailInflow*, *UnsecInflow*	36%	48%
		Secured lending and capital market-driven transactions		44%	15%
		Collateral swaps		-	16%
		Group or institutional protection	*ResInflow*	16%	16%
		Foreign exchange transactions		5%	6%
Net Stable Funding Ratio (NSFR)	Available Stable Funding	Capital items and instruments	ASF^{CAP}	8%	12%
		Retail Deposits	ASF^{DEP}	34%	41%
		Financial customers and central banks	ASF^{ST},	22%	19%
		Non-financial customers	ASF^{LT}	11%	9%
		Operational deposits		6%	5%
		Undetermined counterparty	*ResASF*	12%	12%
		Other		7%	2%
	Required Stable Funding	Loans	RSF^{NFIN}, RSF^{NPL}	50%	74%
		Central bank assets	RSF^{UNENC},	17%	1%
		Liquid assets	RSF^{ENC},	11%	6%
		Securities other than liquid assets	RSF^{FIN}	4%	7%
		Off-balance sheet items	*ResRSF*	10%	1%
		Other		10%	11%

Table 8: Components of LCR and NSFR

4.3.3.1 LCR

The LCR measures available high-quality liquid assets, $HQLA$, against stressed net outflows over the next 30 days, $NetOutflow$.

$$LCR_{i,t} = \frac{HQLA_{i,t}}{NetOutflow_{i,t}} \tag{206}$$

$HQLA$ are defined in Basel III standards as assets that can be converted into cash immediately, with little or no loss of value. HQLA assets are subdivided into unencumbered Level 1, $L1$, and Level 2 Assets, $L2$. Level 1 assets $L1$ enter HQLA without a haircut. Level 2 assets are subject to a haircut, depending on asset class, quality, and market liquidity in a stressed scenario.

$$HQLA_{i,t} = max(0, L1_{i,t} + L2_{i,t} + ResLiquid_{i,t}) \tag{207}$$

A residual item $ResidualLiquid$ captures elements of $HQLA$ that evade the model definition of unencumbered $L1$ and $L2$ assets.[61] For most banks, $HQLA$ is predominantly made up of Level 1 assets $L1$ (see Table 8).

Level 1 assets consist of cash and performing reserves held at central banks $VolPe^{CB}$ (see the definition in equation (84)), extremely high quality covered bonds $EHQCB$,[62] and unencumbered high quality[63] government bonds $UnencumbL1SecARepo$ (see Section 4.3.3.3):

$$L1_{i,t} = VolPe^{CB}_{i,t} + EHQCB_{i,t} + UnencumbL1SecARepo_{i,t} \tag{208}$$

Since $EHQCB$ are issued only by credit institutions, it is assumed that their volumes move in a par with the volumes of all non-defaulted securities issued by financial institutions $VolPe^{SFIN}$:

$$EHQCB_{i,t} = EHQCB_{i,t-1} \times \frac{VolPe^{SFIN}_{i,t}}{VolPe^{SFIN}_{i,t}} \tag{209}$$

Level 2 assets aggregate assets with a haircut of 15%, $L2A$,[64] and assets with a haircut of either 25 or 50%, $L2B$.[65] Both enter the definition of HQLA after the application of a prescribed haircut and only insofar as they are not encumbered. Since both $L2A$ and $L2B$ contain assets which can be issued by financial or non-financial corporates, they are linked to the volumes of performing financial and non-financial corporate securities held on banks' balance sheet.[66]

$$L2_{i,t} = L2A_{i,t} + L2B_{i,t} \tag{210}$$

$$L2A_{i,t} = L2A_{i,t-1} \times \frac{VolPe^{SFIN}_{i,t} + VolPe^{SNFC}_{i,t}}{VolPe^{SFIN}_{i,t-1} + VolPe^{SNFC}_{i,t-1}} \tag{211}$$

$$L2B_{i,t} = L2B_{i,t-1} \times \frac{VolPe^{SFIN}_{i,t} + VolPe^{SNFC}_{i,t}}{VolPe^{SFIN}_{i,t-1} + VolPe^{SNFC}_{i,t-1}} \tag{212}$$

The residual item $ResidualLiquid$ is assumed to grow with the volume of performing government bonds:

$$ResLiquid_{i,t} = ResLiquid_{i,t-1} \times \frac{VolPe^{SGOV}_{i,t}}{VolPe^{SGOV}_{i,t-1}} \tag{213}$$

The LCR denominator, $NetOutflow$, corresponds to the level of gross liquidity outflows $UnexGrossOutflow$ netted against the level of gross cash inflows $GrossInflow$:

[61] More precisely, the residual item includes $L1$ assets which are not accounted for by equation (208).

[62] $EHQCB$ are exceptionally liquid covered bonds issued by EU credit institutions. For more detail, see Commission Delegated Regulation 2015/61 Article 10(f)

[63] ECAI: > AA-

[64] Mostly liquid sovereign bonds not qualifying for L1 (ECAI between A+ and AA-) and liquid non-financial corporate bonds (with ECAI ≥ AA-)

[65] Liquid, high-quality (ECAI: > AA-) RMBS consisting of full-recourse mortgages with an LTV < 80% qualify for the 25% haircut. Liquid non-financial corporate debt securities that do not qualify for the 25% haircut, but with ECAI ≥ BBB-, and non-financial common equity shares receive the 50% haircut.

[66] Technically, $L2A$ may also include government bonds with a risk weight larger than 20%. However, these tend to have marginal positions on the bank balance sheets.

$$NetOutflow_{i,t} = max(0, UnexGrossOutflow_{i,t} - min(0.75 \times UnexGrossOutflow_{i,t}, GrossInflow_{i,t}) \tag{214}$$

Up to 75% of $UnexGrossOutflow$ may be netted away by $GrossInflow$ due to loans maturing within the 30-day period. Then:

$$UnexGrossOutflow_{i,t} = (1 - ShareExempt_i) \times GrossOutflow_{i,t} \tag{215}$$

with a constant parameter $ShareExempt$[67] representing a bank-specific share of funding exempted from the outflow calculation.

$GrossOutflow$ represents total funding outflows from retail deposits, $RetailOutflow$, and unsecured wholesale funding, $UnsecOutflow$:

$$GrossOutflow_{i,t} = RetailOutflow_{i,t} + UnsecOutflow_{i,t} + ResOutflow_{i,t} \tag{216}$$

A catch-all residual item $ResOutflow$ captures all outflows from other funding sources. Most of the time, these are outflows from standing facilities (e.g. credit lines), secured funding, and outflows resulting from derivatives.[68]

The stressed outflows from the retail deposits $RetailOutflow$ depend on the composition of sight deposits captured by the bank-specific parameter that measures the outflow rate of the retail deposit $RetailOutR$:

$$RetailOutflow_{i,t} = RetailOutflowR_i \times \sum_C \left(VolLiabTotal_{i,t}^{HHS,C} + VolLiabTotal_{i,t}^{NFCS,C} \right) \tag{217}$$

The outflow rate of the retail deposit $RetailOutR$ assumes that a share of retail deposits $ShareRetail$ that are publicly insured or guaranteed INS runs at 5%. Regular retail deposits not covered by deposit insurance $UNINS$ receive a runoff rate of 10%. Additionally, national supervisors have the discretion to ask for higher run-off rates for high-value or easily withdrawable deposits (e.g., Internet deposits). The resulting jurisdiction-dependent shares of these deposits are sourced from COREP reporting and are subdivided into two categories $H15$ with a runoff rate of 15% and $H20$ with a runoff rate of 20%.[69]

$$\begin{aligned} ShareOutflow_i = & 0.05 \times ShareRetail_i^{INS} + 0.1 \times ShareRetail_i^{UNINS} \\ & + 0.15 \times ShareRetail_i^{H15} + 0.2 \times ShareRetail_i^{H20} \end{aligned} \tag{218}$$

Unsecured outflows $UnsecOutflow$ recognise that empirically the majority of unsecured outflows relate to deposits of financial institutions and are tied to the outflow rate $UnsecOutflowR$:

$$UnsecOutflow_{i,t} = UnsecOutflowR_i \times VolLiabTotal_{i,t}^{FINS} \tag{219}$$

[67] Sourced from COREP reporting.

[68] These outflow categories are less important, making up around 10%, 5% and 1% of weighted outflows respectively, justifying grouping those under a residual category.

[69] See LCR 40.7-18 for more information on the composition of liquidity outflow buckets.

The outflow rate $UnsecOutflowR$ assumes that the share of unsecured funding $ShareOper$ that facilitates an activity carried out by the depositing bank by providing access to payment systems, clearing services or performing other operational purposes is eligible for a runoff rate stressed 25%. The remaining undsecured funding is assumed to be withdrawn within a 30 day stressed scenario.

$$UnsecOutflowR_i = 0.25 \times ShareOper_i + 1 - ShareOper_i \tag{220}$$

Finally, the residual element $ResidualOutflow$ captures the remaining, generally less empirically relevant, elements of stressed outflows and is projected using total liability volumes $VolLiabTotal$ defined in equation (173).

$$ResOutflow_{i,t} = ResidualOutflow_{i,t-1} \times \frac{VolLiabTotal_{i,t}}{VolLiabTotal_{i,t-1}} \tag{221}$$

$GrossInflow$ is composed of inflows due to retail loans $RetailInflow$, inflows from unsecured loans to financial corporations $UnsecInflow$, and a residual item $ResInflow$:

$$GrossInflow_{i,t} = RetailInflow_{i,t} + UnsecInflow_{i,t} + ResInflow_{i,t} \tag{222}$$

Retail inflows are calculated taking into account that half of all loans to the non-financial private sector are assumed by the regulator to be extended and the other half to be paid back at the latest contractually agreed time of maturity. $RetailInflow$ is calculated applying the $Gamma(k, x, \theta)$ function introduced in equation (57) to performing loans to sectors $S \in \{NFC, HHCC, HHHP, RoW\}$:

$$RetailInflow_{i,t} = 0.5 \times \sum_S \sum_C VolPe_{i,t}^{S,C} \times F(0, 0.083, AvgDuration_i^{S,C}) \tag{223}$$

where fraction 0.083 is for the annualized maturity below 1 month. And, for the inflows from loans to financial corporations $UnsecInflow$:

$$UnsecInflow_{i,t} = VolPe_{i,t}^{FIN} \times F(0, 0.083, AvgDuration_i^{FIN}) \tag{224}$$

And finally, the residual item $ResInflow$ if projected along with the simplified formula:

$$ResInflow_{i,t} = ResInflow_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{225}$$

4.3.3.2 NSFR

The net stable funding ratio $NSFR$ measures the ability to make debt repayments up to the medium term. To this end, the volume of assets that are illiquid over a one-year horizon, that is, the amount of required stable funding RSF, is expected to be matched by available stable funding, that is, funding that does not mature or is withdrawn within a year ASF:

$$NSFR_{i,t} = \frac{ASF_{i,t}}{RSF_{i,t}} \tag{226}$$

Assets entering the definition of ASF are reversely weighted according to their liquidity within the year. A factor of 0 indicates that an asset can be fully liquidated within one year, and therefore requires no stable funding. A factor of 1 indicates a fully illiquid asset that requires a matching amount of stable funding. ASF consists of five components:

$$ASF_{i,t} = ASF^{CAP}_{i,t} + ASF^{DEP}_{i,t} + ASF^{ST}_{i,t} + ASF^{LT}_{i,t} + ResASF_{i,t} \tag{227}$$

Capital ASF^{CAP} contributes fully to stable funding:

$$ASF^{CAP}_{i,t} = T1Cap_{i,t} + T2Cap_{i,t} \tag{228}$$

The ASF arising from retail deposits ASF^{DEP} is a weighted aggregate of sight deposits and term deposits maturing in less than one year. The latter are assumed to be renewed at a rate of 90%:

$$\begin{aligned} ASF^{DEP}_{i,t} =& (0.95 \times ShareASF5_i + 0.9 \times ShareASF10_i) \\ & \times \sum_C \left(VolLiabTotal^{HHS,C}_{i,t} + VolLiabTotal^{NFCS,C}_{i,t} \right) \\ & + 0.9 \times \sum_C VolLiabTotal^{DEPT,C}_{i,t} \times F(0,1,AvgDurationLiab^{DEPT,C}_i) \\ & + 0.9 \times VolLiabTotal^{RoW}_{i,t}) \times F(0,1,AvgDurationLiab^{RoW}_i) \end{aligned} \tag{229}$$

$ShareASF5$ and $ShareASF10$ are the percentage of sight deposits assumed by the regulator to run off at 5 and 10% respectively. Sight deposits assumed to run off at 5% include insured deposits INS and deposits exempted from outflow calculations $ShareExempt$.

$$ShareASF5_i = ShareRetail^{INS}_i + ShareExempt_i \tag{230}$$

The deposits assumed to run off at 10% consist of uninsured deposits $UNINS$, and deposits that receive a 15% runoff $H15$ or a 20% runoff $H20$ in the LCR outflow calculation:

$$ShareASF10_i = ShareRetail^{UNINS}_i + ShareRetail^{H15}_i + ShareRetail^{H20}_i \tag{231}$$

Non-retail debt for sectors $S \in \{NCB, SECST, SECLT, FIN, OTHUNSEC\}$ maturing within one year but not earlier than six months contributes to total ASF at a rate 50%. Operational financial sight deposits also receive a rate 50%. Exempted from this rule is the sovereign debt SOV, which contributes to ASF at a rate of 50%, even if it matures earlier than six months.

$$\begin{aligned} ASF^{ST}_{i,t} = 0.5 \times \Bigg(& VolLiabTotal^{FINS}_{i,t} \times ShareOper_i \\ & + VolLiabTotal^{SOV}_{i,t} \times F(0,1,AvgDurationLiab^{SOV}_i) \\ & + \sum_S VolLiabTotal^{S}_{i,t} \times F(0.5,1,AvgDurationLiab^{S}_{i,t}) \Bigg) \end{aligned} \tag{232}$$

All other long-term debt maturing in more than one year, including the share of retail term deposits and funding volumes from $S \in \{NCB, SOV, RoW, FIN, FINS, OTHUNSEC, SECST, SECLT\}$, contribute to ASF without reduction:

$$\begin{aligned} ASF^{LT}_{i,t} =& \sum_C VolLiabTotal^{DEPT,C}_{i,t} \times F(1,\infty,AvgDurationLiab^{DEPT}_i) \\ & + \sum_S VolLiabTotal^{S}_{i,t} \times F(1,\infty,AvgDurationLiab^{S}_{i,t}) \end{aligned} \tag{233}$$

The residual component grows proportionally to the bank's balance sheet:

$$ResASF_{i,t} = ResASF_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{234}$$

The amount of required stable funding RSF sums up the weighted volumes of unencumbered $UNENC$ and encumbered ENC securities, performing financial FIN and non-financial $NFIN$ assets, and non-performing assets NPL:

$$RSF_{i,t} = RSF_{i,t}^{UNENC} + RSF_{i,t}^{ENC} + RSF_{i,t}^{FIN} + RSF_{i,t}^{NFIN} + RSF_{i,t}^{NPL} + ResRSF_{i,t} \tag{235}$$

Assets enter the RSF with weights proportional to their illiquidity. The weight of 0 is assigned to assets that can be transformed into cash in one year and 1 to assets that cannot be liquidated in one year.

The required stable funding from unencumbered securities RSF^{UNENC} is defined by the regulator as:

$$RSF_{i,t}^{UNENC} = 0.05 \times UnencumbL1SecARepo_{i,t} + 0.15 \times L2A_{i,t} + 0.5 \times L2B_{i,t} \tag{236}$$

The contribution of encumbered securities RSF^{ENC} to the required stable funding is based on the estimate of the volume of encumbered assets. The latter is calculated indirectly, using the volumes of secured funding generated by encumbered assets, whereby government bonds are used as collateral in the creation of short-term secured debt $VolLiabTotal^{SECST}$ and loans in the creation of long-term secured funding $VolLiabTotal^{SECLT}$ (see Section 4.2.3.3).Both volumes are divided by one minus the haircut applied.

$$\begin{aligned}
RSF_{i,t}^{ENC} = \frac{VolLiabTotal_{i,t}^{SECST}}{1 - Haircut^{SGOV}} \times \Big(& 0.05 \times F(0, 0.5, AvgDurationLiab_{i,t}^{SECST}) \\
& + 0.5 \times F(0.5, 1, AvgDurationLiab_{i,t}^{SECST}) \\
& + F(1, \infty, AvgDurationLiab_{i,t}^{SECST}) \Big) \\
+ \frac{VolLiabTotal_{i,t}^{SECLT}}{1 - Haircut^{LOANS}} \times \Big(& 0.5 \times F(0, 1, AvgDurationLiab_{i,t}^{SECLT}) \\
& + F(1, \infty, AvgDurationLiab_{i,t}^{SECLT}) \Big)
\end{aligned} \tag{237}$$

For the required stable funding for financial assets RSF^{FIN}, the regulator distinguishes between money deposited at another financial institution for operational purposes, with its share of $ShareOper_i$, versus non-operational assets. For operational deposits, the regulator assumes that half of all outstanding performing positions can be retrieved within the next year. For non-operational financial assets, a gradation is made based on remaining maturity.

$$\begin{aligned}
RSF_{i,t}^{FIN} = & VolPe_{i,t}^{FIN} \times \Big(ShareOper_i \times 0.5 \\
& + (1 - ShareOper_i) \times \Big(0.15 \times F(0, 0.5, AvgDuration_i^{FIN}) \\
& + 0.5 \times F(0.5, 1, AvgDuration_i^{FIN}) + F(1, \infty, AvgDuration_i^{FIN}) \Big) \Big)
\end{aligned} \tag{238}$$

The required stable funding for performing non-financial assets RSF^{NFIN} depends on the residual maturity of the asset and the credit risk weight assigned to it by the regulator. The distribution of individual risk weights in a portfolio is assumed to follow a Gamma distribution. Consequently, the share of assets assigned a risk weight above x but below y is approximately equal to $F(x,y,NonDefCRRW)$ where $NonDefCRRW$ is the average risk weight for performing exposures as defined in Section 4.1.7.2. For assets that mature later than in one year, the share of assets below 35% risk weights receives a 65% factor, whereas the share of assets above the 35% threshold receives a 85% factor.

$$RSF_{i,t}^{NFPS} = RSF_{i,t}^{HHHP} + RSF_{i,t}^{HHCC} + RSF_{i,t}^{NFC} + RSF_{i,t}^{SOV} + RSF_{i,t}^{RoW} \tag{239}$$

where:

$$\begin{aligned} RSF_{i,t}^{S} = \sum_{C} VolPe_{i,t}^{S,C} \times \Big(& 0.5 \times F(0,1,AvgDuration_{i}^{S,C}) \\ & + F(1,\infty,AvgDuration_{i}^{S,C}) \times \Big(0.65 \times F(0\%,35\%,NonDefCRRW_{i,t}^{S,C}) \\ & + 0.85 \times F(35\%,\infty,NonDefCRRW_{i,t}^{S,C}) \Big) \Big) \end{aligned} \tag{240}$$

Non-performing exposures to the non-financial private sector $S \in \{HHHP, HHCC, NFC, SOV, FIN, RoW\}$ must be fully funded by stable sources of debt:

$$RSF_{i,t}^{NPL} = \sum_{S} \sum_{C} VolNpe_{i,t}^{S,C} \tag{241}$$

Finally, a residual item $ResidualRSF$ changes along with the size of total assets:

$$ResidualRSF_{i,t} = ResidualRSF_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{242}$$

4.3.3.3 Encumbrance

The encumbrance of sovereign bonds and retail loans affects the composition of wholesale funding decisions and the regulatory ratios of LCR and NFSR. The quantity $EncumbL1Sec$ represents all encumberable Level 1 securities, the majority of which are non-defaulted sovereign bonds, be they encumbered or unencumbered:

$$EncumbL1Sec_{i,t} = VolPe_{i,t}^{SGOV} + Excess_{i,t}^{SGOV} \tag{243}$$

where $Excess^{SGOV}$ captures inconsistencies in reporting of sovereign bond holdings between the supervisory reporting and the EBA / SSM stress test templates. It is projected with a simplified formula:

$$Excess_{i,t}^{SGOV} = Excess_{i,t-1}^{SGOV} \times \frac{VolPe_{i,t}^{SGOV}}{VolPe_{i,t-1}^{SGOV}} \tag{244}$$

The volume of unencumbered sovereign bonds before the issuance of repos $UnencumbL1SecBRepo$ is equal to the level of unencumbered sovereign bonds after the issuance of repos $UnencumbL1SecARepo$ at the end of the previous period, plus the volume of newly acquired government bonds and the collateral released with maturing repos which are not renewed. The share of the latter is given by $ShareMaturing^{SECST}$ as defined in equation (156).

Following the issuance of repos, the net issued volume of repos is then deducted from $UnencumbL1SecBRepo$ to produce $UnencumbL1SecARepo$, a period-end measure for unencumbered sovereign bonds.

$$\begin{aligned} UnencumbL1SecARepo_{i,t} = max\Bigg(& 0, UnencumbL1SecBRepo_{i,t} \\ & - \frac{VolLiabTotal^{SECST}_{i,t} - (1 - ShareMaturing^{SECST}) \times VolLiabTotal^{SECST}_{i,t-1}}{1 - Haircut^{SGOV}}\Bigg) \end{aligned} \tag{246}$$

Similarly, for encumberable retail loans $UnencumbLoansBefore$, the volume of unencumbered loans before the issuance of asset-backed securities and covered bonds $UnencumbLoansBABS$ is equal to:

$$\begin{aligned} UnencumbLoansBABS_{i,t} = max\Bigg(& 0, UnencumbLoansAABS_{i,t-1} \\ & + \frac{ShareMaturing^{SECLT}_{i,t}}{1 - Haircut^{LOANS}} \times VolLiabTotal^{SECLT}_{i,t-1}\Bigg) \end{aligned} \tag{247}$$

where the unencumbered loans after the issuance of asset-backed securities and $UnencumbLoansAABS$:

$$\begin{aligned} UnencumbLoansAABS_{i,t} = max\Bigg(& 0, UnencumbLoansBABS_{i,t} \\ & - \frac{VolLiabTotal^{SECLT}_{i,t} - (1 - ShareMaturing^{SECLT}_{i,t}) \times VolLiabTotal^{SECLT}_{i,t-1}}{1 - Haircut_{LOANS}}\Bigg) \end{aligned} \tag{248}$$

Lastly, buffers that express the number of quarters a bank could fund its excess funding needs only by encumbering securities $EncumbL1SecBuffer$ and retail loans $EncumbLoanBuffer$ are calculated as:

$$EncumbL1SecBuffer_{i,t} = \frac{1 - Haircut_{SGOV} \times UnencumbL1SecBRepo_{i,t}}{WholesaleGap_{i,t}} \tag{249}$$

$$EncumbLoanBuffer_{i,t} = \frac{1 - Haircut_{LOANS} \times UnencumbLoansBABS_{i,t}}{WholesaleGap_{i,t}} \tag{250}$$

where $WholesaleGap$ is a trailing average of volumes funded on the wholesale markets:

$$WholesaleGap_{i,t} = 0.25 \times \sum_{k=0}^{3} FundingDemand^{WHSL}_{i,t-k} \tag{251}$$

4.3.3.4 Liquidity requirements

Both the liquidity coverage ratio LCR and the net stable funding ratio $NSFR$ are subject to regulatory thresholds. The LCR requirement was phased in between October 2015 and January 2019, with the threshold value gradually increasing from 60% to 100%.

$$TLCR = 100\% \tag{252}$$

The $NSFR$ requirement of 100% became mandatory in June 2021.

$$TNSFR = 100\% \tag{253}$$

4.3.4 Bank resolvability

In order to ensure the effectiveness of resolution tools, banks are required to maintain a minimum amount of their own funds and liabilities considered to be eligible for bail-in. This target amount constitutes the minimum requirement for own funds and eligible liabilities $MREL$. It is calculated as:

$$MREL_{i,t} = \begin{cases} TLAC_{i,t} & \text{for G-SIIs} \\ maxMRELCapExp_{i,t}, MRELLevExp_{i,t}, MRELTAExp_{i,t} & \text{otherwise.} \end{cases} \tag{254}$$

where:

$$TLAC_{i,t} = (0.18 + COMB_{i,t}) \times (TotREA_{i,t} + TAIFRSREA_{i,t}) \tag{255}$$

$$\begin{aligned} MRELCapExp_{i,t} = \Big(& (1 + AdjF_{i,t}) \times (0.08 + P2R_{i,t}) + AdjF_{i,t} \times (CCyB_{i,t} - COMB_{i,t}) \\ & + COMB_{i,t} \Big) \times (TotREA_{i,t} + TAIFRSREA_{i,t}) \end{aligned} \tag{256}$$

$$MRELLevExp_{i,t} = (1 + AdjF_{i,t}) \times TLevRaTa_{i,t} \times LevRatExp_{i,t} \tag{257}$$

$$MRELTAExp_{i,t} = 0.08 \times TA_{i,t} \tag{258}$$

Hence, for global systemically important institutions (G-SIIs) a floor for the MREL target is set in line with TLAC requirements. $AdjF$ represents an adjustment factor introduced by the Single Resolution Board guidelines on MREL with the objective of lowering the target for banks to pursue a transfer resolution strategy[70]. In the model $AdjF$ is set according to the size of the banks' assets:

$$AdjF_{i,t} = \begin{cases} 0.75 \text{ if less than 15 billions of assets} \\ 0.8 \text{ if assets between 15 and 35 billions} \\ 0.85 \text{ if assets between 35 and 50 billions} \\ 1 \text{ if more than 50 billions of assets} \end{cases} \tag{259}$$

[70] Single Resolution Board (2021), Minimum Requirement for Own Funds and Eligible Liabilities: SRB Policy Under the Banking Package, May 2021, `https://www.srb.europa.eu/system/files/media/document/mrel_policy_may_2021_final_web_0.pdf`

The amount of liabilities considered eligible for resolution purposes is composed of CET1 capital[71], AT1 capital $AT1CAP$, Tier 2 capital $T2CAP$, senior non-preferred debt $SeniorNPD$, and senior unsecured debt $SeniorUD$:

$$\begin{aligned} MRELLiab_{i,t} = (CET1REA_{i,t} - P2G_{i,t} - P2RAT1_{i,t}) \\ \times (TotREA_{i,t} + TAIFRSREA_{i,t}) \\ + AT1CAP_{i,t} + T2CAP_{i,t} + SeniorNPD_{i,t} + SeniorUD_{i,t} \end{aligned} \tag{260}$$

where:

$$SeniorNPD_{i,t} = ShareNPD_i \times TotREA_{i,t} \tag{261}$$

$SeniorNPD$ represents the bank-specific issued amount of non-preferred senior debt, with $ShareNPD$ being a constant parameter sourced from FINREP.

Also, the bank-specific issued amount of senior unsecured debt that covers MREL requirements:

$$\begin{aligned} SeniorUD_{i,t} = 0.333 \times \Big(VolLiabTotal_{i,t}^{UNSEC} - (4 \times VolLiabMat_{i,t}^{UNSEC} \\ - ShareSubUD_i \times TotREA_{i,t}) \Big) \end{aligned} \tag{262}$$

It is assumed that one third of the total volume of unsecured liabilities is eligible for MREL purposes, after having subtracted from this amount maturing liabilities and subordinated unsecured debt. $ShareSubUD$ is a constant parameter sourced from FINREP.

The extent to which each bank complies with MREL requirements can be expressed as:

$$MRELShortfall_{i,t} = MRELLiab_{i,t} - MREL_{i,t} \tag{263}$$

4.4 Profit and loss

The profit and loss (P&L) model equations summarise income and expense flows of a bank. Table 9 provides an overview of the main sources of bank income and expenses, while Figure 28 reports the breakdown of total operating income and expenses for the banks in the euro area between 2017 and 2021.

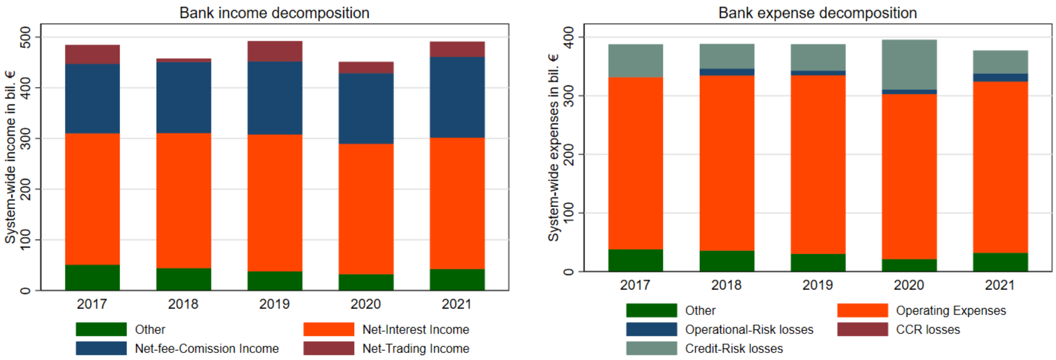
Net interest income NII has made up approximately 55% of the total income of banks on average between 2018 and 2022. Net trading income NTI, with an average share of 6% of the total income of the banks, is another important income source, especially for large banks in the euro area. The third largest income source for banks in the euro area is net fee and commission income $NFCI$. Although it is a relatively stable source of income, it has also been negatively correlated with NII in recent years (Kok et al. [2019]). The remaining income items, grouped under other operating income $OthOpInc$, play a lesser role in the bank's profit and loss accounts.

The lion's share of bank expenditures is bank operating expenses $OpExpense$ that have covered on average almost 76% of total operating expenses between 2017 and 2021. These include administrative expenses and depreciation. Credit risk losses $ImpFA$ come second and have

[71] Excluding the capital used to cover P2G buffers.

Income		Expenditure	
Abbreviation	Description	Abbreviation	Description
NII	Net interest income	$ImpFa$	Credit risk losses
NTI	Net-trading income	$OpExpense$	Operating expenses
$NFCI$	Net-fee-comission income	$GainsOpr$	Operational risk losses
$OthOpInc$	Other operating income	CCR	Counterparty credit risk losses
		$OthOpExp$	Other operating expenses

Table 9: Structure of income and expense flows



(a) Income **(b)** Expenses

Notes: The plot illustrates the annual income and expense flows of 89 systemically important banks included in the BEAST based on supervisory reporting information.

Figure 10: Break-down of bank income and expense flows

made up 14% of bank operating expenses on average over the five years. The third most material category of expenses is operational risk losses $GainsOpr$. The remaining costs categories, therein the counterparty credit risk CCR and items grouped under other operating expenses $OthOpExp$, play, on average and in aggregate, an even more marginal role.

This section discusses P&L accounts and next moves to how retained earnings at the end of each period are derived taking into account banks' profit distribution function, management buffers, and regulatory requirements.

4.4.1 Income sources

The total operating income $TotOpInc$ sums up the net interest income NII, the net trading income NTI, the net fee and commission income $NFCI$ and other operating income $OthOpInc$.

$$TotOpInc_{i,t} = NII_{i,t} + NTI_{i,t} + NFCI_{i,t} + OthOpInc_{i,t} \tag{264}$$

The residual term $OthOpInc$ aggregates the following subitems: non-trading income $NonTI$, gains and losses from hedge accounting HAI,dividend income $DivInc$, gains or losses on (de-)recognition of financial $GainsNFV$ and non-financial $GainsDerfNFV$ assets not measured at fair value, expenses on share capital repayable on demand $ExpShare$, and gains and losses from exchange differences Exc.[72]

[72] $OthOpInC = NonTI + HAI + DivInc + GainsNFV + GainsDerfNFV + ExpShare + Exc$

The net interest income of the bank NII is equal to the total interest income $TotalIntInc$ (Section 4.1.5) minus the total interest expenses $TotalIntExp$ (Section 4.2.5):

$$NII_{i,t} = TotalIntInc_{i,t} - TotalIntExp_{i,t} \tag{265}$$

Net trading income NTI consists of client revenues $ClientRev$, changes in liquidity $\Delta LiqRes^{HFT}$ and credit valuation adjustments $\Delta CVARes$ reserves, gains, or losses from revaluation of net assets held with trading intent $Reval^{TI}$ and economic hedges $Reval^{EH}$ (all of which are defined in Section 4.1.6 with the exception of client revenues).

$$\begin{aligned} NTI_{i,t} = {} & ClientRev_{i,t} - \Delta LiqRes^{HFT}_{i,t} - \Delta CVARes_{i,t} \\ & + Reval^{TI}_{i,t} + Reval^{EH}_{i,t} \end{aligned} \tag{266}$$

Client revenues are derived from the empirical equation of the ratio of client revenues to total assets TA. This ratio evolves along with changes in stock market growth $ESXgr$ and the spread between bank lending rates BLR and the 3-month EURIBOR STN in the domestic country of a bank C_i (see Appendix D.4 for more information).

$$\begin{aligned} ClientRev_{i,t} = {} & (\beta_1 \frac{ClientRev_{i,t-1}}{TA_{i,t-1}} + \beta_2 \, \Delta ESXgr^{C_i}_{t-1} \\ & + \beta_3 \, \Delta(BLR^{C_i}_{t-1} - STN^{EA}_{t-1})) \times TA_{i,t} \end{aligned} \tag{267}$$

The net fee and commission income $NFCI$ to total assets TA is empirically linked to the growth rate of the GDP of the domestic country $YERgr$, the dynamics of the stock market $ESXgr$, and the change in long-term LTN and short-term STN interest rates. Additionally, the specification allows for potential substitution effects between NII and $NFCI$ that can be observed in a low interest rate environment (more information on the estimates can be found in Appendix D.3).

$$\begin{aligned} NFCI_{i,t} = {} & NFCI_{i,t-1} + \Delta(\beta_1 \frac{NFCI_{i,t-1}}{TA_{i,t-1}} + \beta_2 \, YERgr^{C}_{i,t} \\ & + \beta_3 \, \Delta LTN^{C}_{i,t} + \beta_4 \, \Delta STN^{EA}_{i,t} + \beta_5 \, ESXgr^{C}_{i,t} + \beta_6 \frac{NII_{i,t-1}}{TA_{i,t-1}}) \times TA_{i,t}) \end{aligned} \tag{268}$$

Furthermore, it is assumed that the fee and commission expenses FCE change proportionally to the size of the balance sheet.

$$FCE_{i,t} = FCE_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{269}$$

From the above it follows that fee and commission income FCI:

$$FCI_{i,t} = NFCI_{i,t-1} - FCE_{i,t} \tag{270}$$

Other operating income $OthOpInC$ is assumed to remain in a constant proportion to the total asset of the banks TA:

$$OthOpInc_{i,t} = OthOpInc_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{271}$$

4.4.2 Expenditures

Bank expenses consist of changes in loan loss provisions for the banking book $ImpFA$, operating expenses $OpExpense$, operational risk gains or losses $GainsOpr$, counterparty credit risk losses CCR, and other operating expenses $OthOpExp$:

$$\begin{aligned} TotOpExp_{i,t} = & ImpFA_{i,t} - OpExpense_{i,t} + GainsOpr_{i,t} + CCR_{i,t} \\ & + OthOpExp_{i,t} \end{aligned} \tag{272}$$

The residual cost item $OthOpExp$ is summing up provisions or reversal of provisions $Prov$, other income and expenses from continuing operations $OthIncCon$, impairment on non-financial assets $ImpNonFinAssets$, negative goodwill $NeggD$ and P&L from investments in subsidiaries $SharePrf$.[73]

Credit risk losses $ImpFA$ result from changes in loan loss provisioning $\Delta ProvStock$ (see equation (48)) combined with impairments from securitised portfolios $TotalImpLosses^{SEC}$:

$$ImpFA_{i,t} = -(\Delta ProvStock_{i,t} + TotalImpLosses^{SEC}_{i,t}) \tag{273}$$

where impairments from securitised portfolios remain constant over time:

$$TotalImpLosses^{SEC}_{i,t} = TotalImpLosses^{SEC}_{i,t-1} \tag{274}$$

For banks operating expenses $OpExpense$, the model allows for a degree of economies of scale with estimates consistent with a slightly increasing cost efficiency per asset unit. The operating expenses equation takes account of the general economic conditions approximated by annual nominal GDP growth YER in the domestic economy and includes an error correction term relative to the average market cost efficiency (see Appendix D.5 for more information).

$$\begin{aligned} OpExpense_{i,t} = exp\Big(& log(OpExpense_{i,t-4}) + \beta_1\, \Delta_4 log(OpExpense_{i,t-1}) \\ & + \beta_2\, \Delta_4 TA_{i,t-1} + \beta_3\, \Delta_4 log(YER^{C_i}_{t-1} \times HIC_{c,t-1}) \\ & + \beta_4\, (\frac{OpExpense_{i,t-1}}{TA_{i,t-1}} - \frac{\sum_i OpExpense_{i,t-1}}{\sum_i TA_{i,t-1}})\Big) \end{aligned} \tag{275}$$

The final item on the banks cost side is operational risk losses and provisioning. Here, the model treats the operational risk due to conduct $GainsOpr\_Conduct$ and other operational risks $GainsOpr\_OOR$ separately:

$$GainsOpr_{i,t} = GainsOprConduct_{i,t} + GainsOprOOR_{i,t} \tag{276}$$

where the dynamics of both operational risk due to conduct $GainsOprConduct$ and other operational risks $GainsOprOOR$ reflects the assumption of constant operational risk efficiency per unit of assets:

$$GainsOprConduct_{i,t} = GainsOprConduct_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{277}$$

[73] $OthOpExp = Prov + OthIncCon + ImpNonFinAssets + NeggD + SharePrf$

$$GainsOprOOR_{i,t} = GainsOprOOR_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{278}$$

The counterparty credit losses CCR remain constant over time:

$$CCR_{i,t} = CCR_{i,t-1} \tag{279}$$

Finally, other operating expenses $OthOpExp$ are constant as a share of total assets TA:

$$OthOpExp_{i,t} = OthOpExp_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{280}$$

4.4.3 Profit

Bank profit before tax $ProfBTCO^{UNADJ}$ is calculated by subtracting total operating expenses $TotOpExp$ and write-offs $TotWrOff$ (see equation (37)) from total operating income $TotOpInc$:

$$ProfBTCO_{i,t}^{UNADJ} = TotOpInc_{i,t} + TotOpExp_{i,t} - TotWrOff_{i,t} \tag{281}$$

where this excludes adjustments coming from the impact of binding maximum distributable amounts (MDA). In effect, some expenditures[74] are already booked in $TotOpExp$ without regard for breaches in MDA.

In case of breaches of the maximum distributable amounts (MDA) thresholds some expenditures[75] can be deferred and profits are adjusted up with the adjustment factor $PreAdjPreTax$ (see Section 4.4.4). The realised profit is after tax $ProfATCO$ is then calculated applying the 30% tax rate:

$$ProfATCO_{i,t} = 0.7 \times (ProfBTCO_{i,t}^{UNADJ} + PrjAdjPreTax_{i,t}) \tag{282}$$

4.4.4 Maximum Distributable Amount

The Maximum Distributable Amount (MDA) limit is calculated by contrasting the bank's capital position with regulatory buffers. The bindingness of the limit for a bank is encoded in the variable $MDAFactor$.

$$MDAFactor_{i,t} = \begin{cases} 100\%, & \text{if } CET1RNUSE_{i,t} \geq COMB_{i,t} \\ 60\%, & \text{if } CET1RNUSE_{i,t} \in [0.75COMB_{i,t}, COMB_{i,t}] \\ 40\%, & \text{if } CET1RNUSE_{i,t} \in [0.5COMB_{i,t}, 0.75COMB_{i,t}] \\ 20\%, & \text{if } CET1RNUSE_{i,t} \in [0.25COMB_{i,t}, 0.5COMB_{i,t}] \\ 0\%, & \text{if } CET1RNUSE_{i,t} < 0.25COMB_{i,t} \end{cases} \tag{283}$$

As long as the bank's capital ratio above own funds requirements $CET1RNUSE$ meets or exceeds the combined buffer requirements $COMB$, i.e. $MDAFactor = 100\%$, the bank can distribute all profits. Otherwise, the MDA factor decreases proportionally to the gap between $CET1RNUSE$ and $COMB$ and the bank can distribute only a fraction of the profits.

[74] For instance, variable remuneration and pension benefits $REMPENBEN$ or dividends paid out to AT1 Capital, which usually occur on a fixed schedule but can be deferred in case of business or regulatory need.

[75] For instance, variable remuneration and pension benefits $REMPENBEN$ or dividends paid out to AT1 capital.

The bank's capital ratio above the own funds requirements $CET1RNUSE$ equals:

$$CET1RNUSE_{i,t} = CET1RBDistDiv_{i,t} - 4.5\% - P2R_{i,t} - AT1T2SHORT_{i,t} \tag{284}$$

where the capital shortfall $AT1T2SHORT$ has been introduced in equation (202) and $CET1RBDistDiv$ amounts to the hypothetical ratio of CET1 capital in which no profit is distributed:

$$CET1RBDistDiv_{i,t} = \frac{CET1BDistDiv_{i,t}}{TotREA_{i,t} + TAIFRSREA_{i,t}} \tag{285}$$

and:

$$\begin{aligned} CET1BDistDiv_{i,t} = &\ CiCET_{i,t} + AOCI_{i,t} + DBPFA_{i,t} + DTA_{i,t} + min(0, IRBSf_{i,t}) \\ &+ CET1Oth_{i,t} + RetEarn_{i,t-1} + 0.7 \times ProfBTCO^{UNADJ}_{i,t} \end{aligned} \tag{286}$$

The minimum capital conservation ratio $MCCR$ contrasts the leverage ratio with the target leverage ratio. This quantity also has an associated factor, $MCCRFactor$, which restricts payouts.

$$MCCRFactor = \begin{cases} 1, & \text{if } LevRatTa_{i,t-1} \geq TLevRatTa_{i,t} \\ 0.6, & \text{if } LevRatTa_{i,t-1} \in [0.75\,TLevRatTa_{i,t},\ TLevRatTa_{i,t}] \\ 0.4, & \text{if } LevRatTa_{i,t-1} \in [0.5\,TLevRatTa_{i,t},\ 0.75\,TLevRatTa_{i,t}] \\ 0.2, & \text{if } LevRatTa_{i,t-1} \in [0.25\,TLevRatTa_{i,t},\ 0.5\,TLevRatTa_{i,t}] \\ 0, & \text{if } LevRatTa_{i,t-1} < 0.25TLevRatTa_{i,t} \end{cases} \tag{287}$$

The resulting maximum distributable amount calculated before tax $MDAPreTax$ is equal to:

$$MDAPreTax_{i,t} = max(0, ProfBTCO^{UNADJ}_{i,t}) \times min(MDAFactor_{i,t}, MCCRFactor_{i,t}) \tag{288}$$

4.4.5 Dividends & retained earnings

The maximum distributable amount $MDAPreTax$ can be paid in the form of dividends on CET1 shares, payments on fixed-schedule AT1 capital, and variable remuneration or pension benefits. Variable remuneration and pension benefits$RemPenBen$, because they are tax-deductible, are assumed to be paid preferentially. The target amount of remuneration and pension benefits grows proportionally to the bank's balance sheet:

$$RemPenBen_{i,t} = RemPenBen_{i,t-1} \times \frac{TA_{i,t}}{TA_{i,t-1}} \tag{289}$$

Variable remuneration or pension benefits are paid up to the maximum distributable amount $MDAPreTax$, and amounts exceeding $MDAPreTax$ are added back to the profit before tax, as $PrjAdjPreTax$ (see equation (4.4.3)):

$$PrjAdjPreTax_{i,t} = max(0, RemPenBen_{i,t} - MDAPreTax_{i,t}) \tag{290}$$

And, the remaining MDA space $MDAPostTax$ amounts to:

$$MDAPostTax_{i,t} = 0.7 \times (MDAPreTax_{i,t} - RemPenBen_{i,t} + PrjAdjPreTax_{i,t}) \tag{291}$$

Items that are not deductible include, in preference order, profits attributable to minority interests $Attr2MinInt$, dividends on AT1 shares $DivAT1$ and dividends on CET1 shares $DivCET1$. Minority interests are assumed to constitute a constant share $ShareMinorityInterest$ or bank profits (with bank-level parameters calibrated from FINREP data):

$$Attr2MinInt_{i,t} = max(0, ShareMinorityInterest_i \times ProfATCO_{i,t}) \tag{292}$$

Payments on AT1 capital (such as preferred stock or hybrid instruments) $DivAT1$ are modelled to grow with the size of AT1 capital:

$$DivAT1_{i,t} = DivAT1_{i,t-1} \times \frac{AT1CAP_{i,t}}{AT1CAP_{i,t-1}} \tag{293}$$

Profits before dividends on CET1 capital $ProfBDiv$ amount to:

$$ProfBDiv_{i,t} = ProfATCO_{i,t} - Attr2MinInt_{i,t} - DivAT1^{Desired}_{i,t} \tag{294}$$

The desired level of CET1 payments depends on the actual versus the target bank capital. A management buffer $ManBuf$ expresses an internal capital target above regulatory requirements and buffers (see Appendix C.12 for estimation details).

$$\begin{aligned} ManBuf_{i,t} = exp\Big(&\beta_0 + \beta_1\, log(TA_{i,t}) + \beta_2 \frac{FCI_{i,t}}{TA_i} + \beta_3\, netNPLR_{i,t} \\ &+ \beta_4\, CovbonRatio_i \times \frac{VolLiabTotal^{SECLT}_{i,t}}{VolLiabTotal_{i,t}} + \beta_5\,(1 - CovbonRatio_i) \times \frac{VolLiabTotal^{SECLT}_{i,t}}{VolLiabTotal_{i,t}} \\ &+ \beta_6 \frac{VolLiabTotal^{NFPS}_{i,t}}{VolLiabTotal_{i,t}} + \beta_7 \frac{VolLiabTotal^{SOV}_{i,t}}{VolLiabTotal_{i,t}} + \beta_8 \frac{VolLiabTotal^{WHSL}_{i,t}}{VolLiabTotal_{i,t}}\Big) \end{aligned} \tag{295}$$

where $CovbonRatio$ is the share of covered bonds within secured long-term funding instruments. The specification of the management buffer links banks' internal capital targets to the characteristics of their balance sheet. For example, a bank that relies more heavily on wholesale funding will prefer a higher level of capitalisation, which can help mitigate the risk of triggering the funding-solvency feedback outlined in Section 2.1.3.

The log-linear specification hypothesises that absolute changes in the level of the management buffer depend on the existing level of the management buffer. For example, changing the internal capital target from 1% to 2% is likely a more drastic change in the banks' policy than going from 11% to 12%.

The management buffer is added to the regulatory capital requirements and buffers to yield the desired level of CET1 capital $TCET1TR$.

$$TCET1TR_{i,t} = (TCET1REA_{i,t} + ManBuf_{i,t}) \times (TotREA_{i,t} + TAIFRSREA_{i,t}) \tag{296}$$

Whenever possible, a bank will retain profits before the CET1 dividends $ProfBDiv$ to match the desired level of capital, and all profits exceeding the necessary amount will be paid to CET1 shareholders as $DivCET1$.

$$DivCET1_{i,t} = max(0, min(ProfBDiv^{Ann}_{i,t} + CET1TR_{i,t-1} - TCET1TR_{i,t}, ProfBDiv^{Ann}_{i,t})) \quad (297)$$

where $ProfBDiv^{Ann}$ denotes the quarterly annualized profit of a bank. This quantity maps the stylised fact that dividends are commonly paid out annually.

$$ProfBDiv^{Ann}_{i,t} = 1/4 \sum_{k=0}^{3} ProfBDiv_{i,t-k} \quad (298)$$

The payouts including dividends on CET1 shares must comply with the remaining MDA space $MDAPostTax$. Non-tax-deductible payouts to shareholders cancelled due to MDA restrictions are included in an adjustment item $PrjAdjPostTax$:

$$PrjAdjPostTax_{i,t} = max(0, Attr2MinInt_{i,t} + DivCET1_{i,t} + DivAT1_{i,t} - MDAPostTax_{i,t}) \quad (299)$$

Profit retained $ProfOwnDiv$ is then equal to:

$$ProfOwnDiv_{i,t} = ProfBDiv_{i,t} - DivCET1_{i,t} + PrjAdjPostTax_{i,t} \quad (300)$$

and adds to the stock of retained earnings $RetEarn$:

$$RetEarn_{i,t} = RetEarn_{i,t-1} + ProfOwnDiv_{i,t} \quad (301)$$

5 Closing the model

The model ties the dynamics of euro area economies with the aggregated banking sector lending activity. The model entails two optional real-financial sector feedback loop mechanisms. The first mechanism, referred to as feedback loop 1 hereafter, focuses on excessive bank deleveraging equated with the non-linear response of bank lending likely to emerge in adverse economic conditions. This excessive deleveraging is translated into additional credit supply shocks and feeds back to the real economy. The second mechanism, called feedback loop 2, introduces aggregated bank-level lending volumes and interest rates directly into the economic module.[76]

5.1 Aggregating bank-level lending information

The outstanding bank loans to the non-financial private sector $S \in \{NFC, HHHP, HHCC\}$ in a country in the euro area C can be derived by summing up the information about individual bank loan exposures to the country C defined in equation (22):

$$TotalLoans^{C}_{t} = \sum_{i}\sum_{S} TotalLoans^{S,C}_{i,t} \quad (302)$$

[76] Both approaches preserve the role and interplay between loan demand and supply factors. However, feedback loop 1 puts more emphasis on the propagation mechanisms ingrained in the estimated VAR-type macrofinancial equations, while feedback loop 2, gives relatively more prominence to the propagation mechanisms resulting from the estimated bank-level equations.

Analogously, one can define a country-level measure of interest rates on new lending to the non-financial private sector by aggregating bank-specific lending rates to country C defined in equation (56):

$$EIRAssetNew_t^C = \frac{\sum_i \sum_S \left(VolAssetNew_{i,t}^{S,C} \times EIRAssetNew_{i,t}^{S,C} \right)}{\sum_i \sum_S VolAssetNew_{i,t}^{S,C}} \tag{303}$$

Additionally, in order to introduce the feedback loop 1, we define a country-level measure of excessive deleveraging. It is derived by aggregating the non-linear loan supply responses as in equation (14) under an additional assumption that banks can deleverage only by limiting the issuance of new loans. The latter is ensured by imposing the limit that negative non-linear loan supply adjustments are not larger than the amount of maturing and written off loans in $Outflows$:

$$LoanSupplyNonLin_t^C = \sum_i \sum_S max\left(TotalLoans_{i,t-1}^{S,C} \times LoanSupplyNonLin_{i,t}^{S,C}, -Outflows_{i,t}^{S,C} \right) \tag{304}$$

5.2 Feedback loop involving the interpretation of loan supply shocks - feedback loop 1

The workings of the first real economy - financial sector feedback loop relies on the transformation of banks' non-linear credit supply response into an additional structural credit supply shock in the macroeconomic block. The aggregated non-linear response of banks $LoanSupplyNonLin^C$ is first translated into percentage of outstanding loans:

$$LoanSupplyInnov_t^C = \frac{LoanSupplyNonLin_t^C}{TotalLoans_{t-1}^C} \tag{305}$$

$LoanSupplyInnov^C$ equal to 1% would speak about 1% reduction in country-level bank lending due to the non-linear loan supply response of banks. The reduction in credit supply is then translated into a credit supply shock that is appropriate for such a magnitude of the aggregate credit response $LoanSupplyInnov^C$ immediately after shock realisation. Let $\varepsilon_{1,t}^C$ be the first element of the vector of structural residuals in equation (3) that (along with Table 3) corresponds to a structural credit supply shock. Let d_1^C be the first diagonal element of the matrix D^C. A credit supply shock triggering a response of lending volumes of exactly $LoanSupplyInnov^C$ magnitude would then equal:[77]

$$\tilde{\varepsilon}_{1,t}^C = \frac{1}{d_1^C} \times LoansupplyInnov_t^C \tag{306}$$

[77] In actual applications, we replace $LoansupplyInnov_t^C$ in equation (306) with the deviation of innovations from their 4-quarter moving average i.e. $LoansupplyInnov_t^C - \overline{LoansupplyInnov_t^C}^{4q}$ which additionally the some state-dependency present in lending equation formulas.

This additional credit supply component can be added to other credit supply shocks present in the model solution.[78]

The additional shock is implemented in the macroeconomic block of the model by modifying v_t^C in equation (3) into:

$$v_t^C \rightarrow v_t^C + D^C \tilde{\varepsilon}_t^C \tag{307}$$

where $\tilde{\varepsilon}_t^C$ is a vector with only one non-zero element ordered first $\tilde{\varepsilon}_{1,t}^C$.

The feedback loop based on a measure of excessive deleveraging builds on a specific interpretation of the model equations. Euro area economies are represented by linear vector autoregression equations, including the description of country-level aggregate of bank lending. Such representation should well map the evolution of lending supply and demand factors in normal times, though may fail to capture non-linearities such as excessive deleveraging in crisis times. These non-linearities, if present in the sample, would be reflected in historical credit supply shocks. Furthermore, one can postulate the correspondence between the linear structure of the lending equations in the macroeconomic block and the linear elements of the bank-level loan volume equations. The latter includes loan demand factors and the linear part of the loan supply equation. Consequently, the non-linear part of the bank-level lending equations can be mapped into exogenous credit supply adjustments.

The main mechanism of the real economy-financial sector feedback loop is illustrated in Figure 11. At first, selected macroeconomic shocks affect the real economy. These shocks can occasionally lead to a deterioration in economic conditions reflected in lower output, increase in inflation, or deterioration in asset valuations. The resulting economic conditions influence the riskiness and quality of bank assets, as well as the costs of funding, and finally banks' overall profitability. In response, banks will endeavour to restore their profitability and solvency by adjusting the supply of loans, increasing lending margins, and adjusting the distribution of profits. Thereby, the degree of the credit supply responses depends mainly on banks' individual capitalisation level. If minimum capital requirements are violated or banks are exposed to a surge in credit defaults, the supply response may exceed the one expected in normal times when banks' solvency targets are not strained. This excessive credit shortage translates into a further adverse credit supply shock that adds to the set of structural shocks in the next quarter.

5.3 Feedback loop integrating bank lending behaviour into the macroeconomic block - feedback loop 2

The alternative real economy - banking sector feedback loop mechanism substitutes the bank volumes and lending rates in the macroeconomic block with their aggregated individual bank-level counterparts. Vector Y_t^C in equations (1) and (2) includes a measure of loan volumes CPN^C and interest rates on new lending to the non-financial private sector BLR^C. These are replaced on the right-hand side of equations with:

$$\begin{aligned} CPN_t^C &\rightarrow TotalLoans_t^C \\ BLR_t^C &\rightarrow EIRAssetNew_t^C \end{aligned} \tag{308}$$

[78] Most of the applications involving the feedback loop 1 are preceded with the decomposition of an existing macro-financial scenario into structural shocks, assuming absence of credit supply shocks. In such cases, the only credit supply shocks present in model simulations are provided by equation (306). See Section 6.1 for the discussion of the scenario decomposition and Section 8.1 for an example of the application and interpretation of the feedback loop.

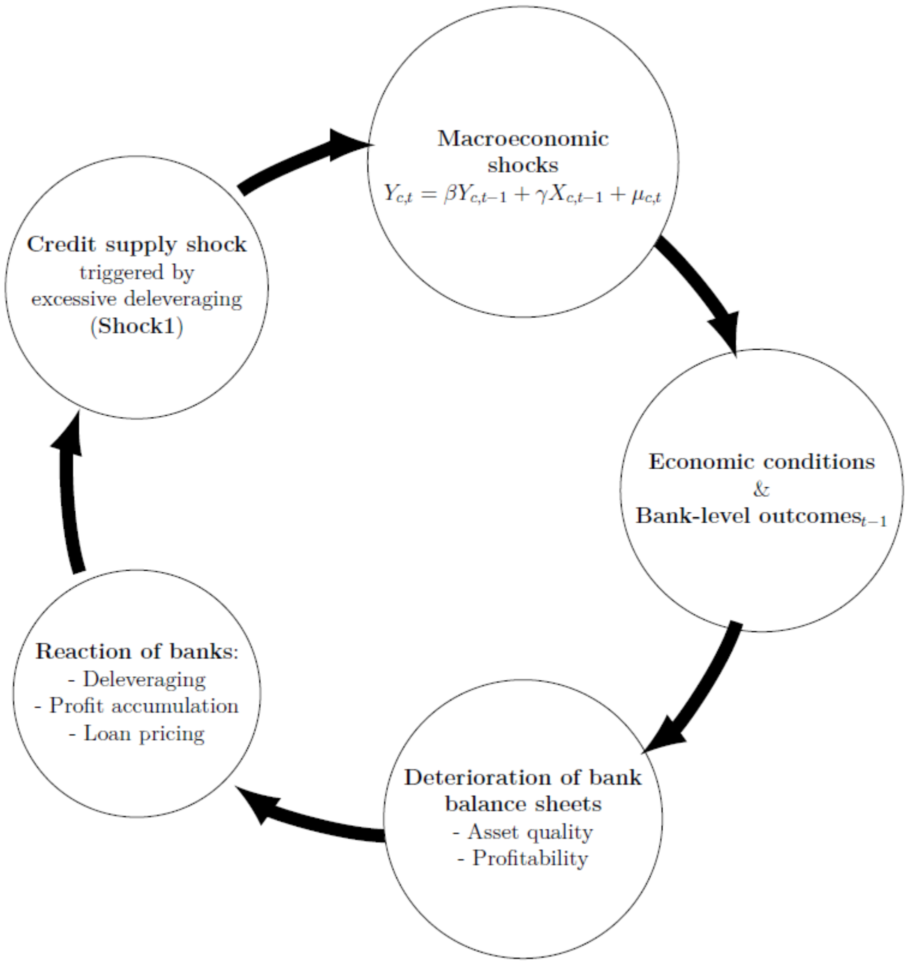


Figure 11: Schematic illustration of the real economy-financial sector feedback loop

and the equations that have CPN^C or BLR^C on their right-hand side are removed from the system.

This allows both positive and negative reactions of banks to be captured and translated into the financial conditions in each country. For example, if banks increase loan supply in response to favourable changes in the regulatory environment, this has a positive impact on country-level lending conditions and indirectly on all other macro-financial variables in the macroeconomic block.

6 Solving the model and scenario analysis

The model equations are all stacked together in one system and solved simultaneously and sequentially for each period of the forecast horizon. In order to obtain the solution efficiently, the model is split into recursive and non-recursive blocks of equations. To this end, we use the graph representation of the model with variables as vertices (nodes) and equations that form edges.[79] The full graph representing the model is condensed into sets of strongly connected components (SCCs) and topologically sorted. Since the condensed graph becomes an acyclic graph, the

[79] Since each equation has only one endogenous left-hand side variable, each graph node corresponds both to a variable and to an equation. Accordingly, the tail ends of the incoming edges point to the dependent variables on the right-hand side of that equation.

model can be simulated by solving the SCCs one after another in topologically sorted order. Consecutive SCCs form simple recursive blocks. The remaining components, each of which consists of more than one node and represents a system with simultaneous equations, form non-recursive blocks. The non-recursive blocks are solved numerically with a quasi-Newton trust region algorithm.[80]

It is convenient to adopt a simplifying notation, where all model equations are denoted by $\mathscr{M}$, all model parameters by $\mathscr{P}$, and all predetermined variables at simulation time by $\mathscr{X}$. Predetermined variables can include the values of endogenous and exogenous variables up to the current period t. Furthermore, let us denote the values of some fixed variables, endogenous or exogenous, incl. shocks, for $t+1$ and the following periods, by $\mathscr{C}$. A single model solution $\mathscr{M}(\mathscr{P}^{\star}, \mathscr{X}^{\star})$ assumes particular values of parameters $\mathscr{P}^{\star}$ and exogenous variables $\mathscr{X}^{\star}$. Some applications of the model involve the assessment of model outcomes that are conditional on pre-specified paths of selected variables, including their values in future periods. Therefore, for such "conditional simulations", we seek $\mathscr{X}$ which provides the endogenous variable outcomes consistent with conditions $\mathscr{C}$, that is, $\mathscr{X}|\mathscr{C}$. Furthermore, we often refer to the sequences of structural or reduced-form shocks from the macro-financial and banking block entering $\mathscr{X}^{\star}$ as single scenarios.

The BEAST model can be solved in a deterministic or stochastic way. Stochastic simulations can be described as repetitively taking a random,[81] Monte Carlo (MC) sampled, set of parameters $\mathscr{P}$ and/or set of exogenous variables $\mathscr{X}$, drawn from estimated (or calibrated) distributions, and then solving the model $\mathscr{M}$ for all endogenous variables. Stochastic sampling is repeated independently[82] for each simulation. By increasing the number of stochastic simulations, our results asymptotically approach the underlying probability distributions of endogenous variables.

Stochastic simulations are applied to assess forecast uncertainty, derive at-risk measures, and design relevant macrofinancial scenarios. Parameter uncertainty can be evaluated by repetitive simulations of $\mathscr{M}(\mathscr{P}, \mathscr{X}^{\star})$ using different combinations of $\mathscr{P}$. The uncertainty related to structural or reduced-form shocks in empirical equations, called scenario uncertainty, can be evaluated by repetitive simulations of $\mathscr{M}(\mathscr{P}^{\star}, \mathscr{X})$ using different combinations of $\mathscr{X}$.[83] Both parameter and scenario uncertainty can be broken down into uncertainty originating from the macroeconomic block and uncertainty stemming from the banking sector block (see Table 10).

[80]For a description of trust region methods, see Chapter 4 in Nocedal and Wright [2006]. Each non-recursive block (system of simultaneous equations) may comprise many non-linear, non-differentiable (or other not well-behaved) functions, so we use numerical methods that do not depend on the analytical form of the Jacobian or Hessian matrix. The solver minimises the differences (residuals) between the left-hand side (LHS) and right-hand side (RHS) of every equation, until these residuals are approximately zero. The previous period's solution is used as an initial guess. The number of iterations is directly proportional to the number of residuals. Therefore, to reduce iterations, we use manually selected pivotal variables. Pivotal variables form the (desirably smallest) set of feedback variables that can be used to break all closed cycles within the non-recursive block. In the literature, this is called a minimal essential set or a minimum feedback vertex set and can be defined as the subset $V(G) \subseteq V$ belonging to the digraph $G = (V, E)$, whose removal induces an acyclic graph. See, e.g. Guardassi (1971) and Cheung and Kuh (1974). Then, only the equations for the pivotal variables need to be expressed as LHS-RHS differences, reducing the number of residuals that need to be minimised. Theoretically, there may be more than one solution. We are able to evaluate the validity of a solution by inserting it into the original equations and then calculating the norm of the residuals vector, which should be approximately zero for a valid solution.

[81]Applying Matlab's SIMD-oriented fast Mersenne twister pseudorandom number generator dsfmt19937.

[82]As stochastic simulations are independent of each other, we make can use of CPU parallel processes (e.g. a pool of parallel workers) or a GPU to speed up the computation process.

[83]The assessment of parameter and scenario uncertainty applies mostly to model equations which have been identified empirically. Assessing this source of uncertainty has been perceived as a priority, while with time it can be expanded to calibrated parts of the model.

	Macroeconomic block	Banking block
Parameter uncertainty	Parameter draws from the posterior parameter distribution of an estimated Bayesian structural panel VAR model	Parameter draws from the multivariate normal parameter distributions of estimated bank-level panel regressions
Scenario uncertainty	Sequences of VAR shocks: • structural or reduced-form • drawn jointly for the euro area and independently the rest of the world countries • sampled from estimated distributions (parametric) or via bootstrapping	Sequences of bank-level shocks: • drawn jointly for all banks but independently for each bank-level equation • sampled from estimated distributions (parametric), via bootstrapping or from calibrated distributions

Table 10: Parameter versus scenario Uncertainty: an overview

This chapter proceeds as follows. First, it discusses the conditioning of model outcomes on a particular scenario, which, for simplicity, is discussed for the case of single parameter and exogenous variable values, i.e. $\mathscr{M}(\mathscr{P}^{\star}, \mathscr{X}^{\star}|\mathscr{C}^{\star})$. Then, it moves to the discussion of the parameter uncertainty, i.e. $\mathscr{M}(\mathscr{P}, \mathscr{X}^{\star})$ or $\mathscr{M}(\mathscr{P}, \mathscr{X}^{\star}|\mathscr{C}^{\star})$, which can be used to measure confidence bands around projected values of endogenous variables. Later, it discusses scenario uncertainty, $\mathscr{M}(\mathscr{P}^{\star}, \mathscr{X})$ or $\mathscr{M}(\mathscr{P}^{\star}, \mathscr{X}|\mathscr{C}^{\star})$. Lastly, it discusses two applications of stochastic simulations employing both parameter and scenario uncertainty, $\mathscr{M}(\mathscr{P}, \mathscr{X})$ or $\mathscr{M}(\mathscr{P}, \mathscr{X}|\mathscr{C}^{\star})$, namely deriving at-risk type measures and performing scenario selection.

6.1 A single macrofinancial scenario

The model is often applied to analyse the impact of a pre-specified economic scenario, or the impact of policies conditional on such a scenario. In such cases, we are provided with future paths of at least some of the macrofinancial variables. This calls for an out-of-sample forecast where we impose conditional paths $\mathscr{C}^{\star}$ for one or more endogenous macroeconomic variables entering the macroeconomic block (see Section 3).

Our approach to simulations conditional on pre-specified scenarios consists of two steps. First, considering only the macroeconomic block VAR equations, we derive a set of structural shocks which can replicate the postulated behaviour of macrofinancial variables. This step is often referred to as scenario decomposition. Second, the derived series of shocks enter $\mathscr{X}^{\star}$ together with other predetermined variables and the complete model is simulated. This two-step method allows the derived values of selected endogenous variables to very closely replicate the postulated conditions, and at the same time the model preserves its endogenous mechanisms. The relevant simplification is the use of only VAR equations from the macroeconomic block while performing the scenario decomposition in the first step. This simplification is justified by its numerical viability[84] but has the implication that the conditions $\mathscr{C}^{\star}$ might be replicated only approximately by $\mathscr{M}(\mathscr{P}^{\star}, \mathscr{X}^{\star}|\mathscr{C}^{\star})$. The difference in macro-financial variables from

[84]The inversion of all model equations, involving many non-linearities, would impose very high computational demands.

$\mathscr{M}(\mathscr{P}^\star, \mathscr{X}^\star | \mathscr{C}^\star)$ and $\mathscr{C}^\star$ can be later interpreted as the result of second-round effects between the real economy and the banking sector.

The scenario decomposition closely follows the approach for computing the exact finite sample distribution of conditional forecasts by Waggoner and Zha [1999]. The starting point is the reduced-form specification of each country-level VAR introduced in Section 3.1:

$$\overline{Y}_t^C = a^C + \sum_{l=1}^{L} A_l^C \overline{Y}_{t-l}^C + \sum_{l=1}^{L} E_l^C \overline{X}_{t-l}^C + D^C \varepsilon_t^C \tag{309}$$

where $\overline{Y}_t^C = [Y_t^C, M_t^C]'$ is a vector of endogenous variables, $\overline{X}_t^C = [X_t^C, Z_t^C]'$ is a vector of exogenous variables, a is a vector of constants and A, E and D are coefficient matrices. L denotes lag number and C is the country superscript. The exact mapping between the exposition in equation (309) here and that in equation (1) from Section 3.1 can be found in Appendix B.

The n-step forecast of the endogenous variables in the system of equations (309) at time t is:

$$\underbrace{\overline{Y}_{t+n}^C}_{\text{conditional forecast}} = \underbrace{G_{n-1}^C a^C + \sum_{l=1}^{L} H_{n,l}^C \overline{Y}_{t+1-l}^C + \sum_{l=1}^{L} K_{n,l}^C \overline{X}_{t+1-l}^C}_{\text{unconditional forecast}} + \underbrace{\sum_{i=1}^{n} N_{n-i}^C \varepsilon_{t+i}^C}_{\text{effect of shocks}} \tag{310}$$

The resulting matrices G_n^C, $H_{n,l}^C$, and $K_{n,l}^C$ are fully specified for each time point $t+n$ and can be expressed in terms of the original matrices A_l^C and E_l^C (Waggoner and Zha [1999]).[85] Similarly, the matrix N_n^C also depends only on the original parameter matrices A_l^C and D^C.

The first three terms on the right-hand side in equation (310) make up the dynamic forecast in the absence of shocks, i.e. the unconditional deterministic forecast of the VAR, further denoted as Z_{t+n}:

$$Z_{t+n}^C = G_{n-1}^C a^C + \sum_{l=1}^{L} H_{n,l}^C \overline{Y}_{t+1-l}^C + \sum_{l=1}^{L} K_{n,l}^C \overline{X}_{t+1-l}^C \tag{311}$$

The last term refers to the effect of the structural shocks via their respective impulse response function (IRF) matrices. Rearranging the equation, the impact of the structural shocks can be expressed as a difference of the conditional and unconditional forecasts:

$$\sum_{i=1}^{n} N_{n-i}^C \varepsilon_{t+i}^C = \overline{Y}_{t+n}^C - Z_{t+n}^C \tag{312}$$

For convenience, z should denote all parameters such as coefficient matrices, constant terms, and exogenous variables that affect the unconditional forecast and remove the country superscript. Accordingly, the unconditional forecast Z at time $t+n$ becomes a deterministic function $Z_{t+n}(z)$.

$$\sum_{i=1}^{n} \underbrace{N_{n-i}}_{\text{orthogonalized IRFs}} \varepsilon_{t+i} = \underbrace{\overline{Y}_{t+n}}_{\text{conditional forecast}} - \underbrace{Z_{t+n}(z)}_{\text{unconditional forecast}} \tag{313}$$

[85] This notwithstanding, they will differ with each parameter draw of A_l^C, E_l^C and D_l^C post estimation.

Let $R(z)$ be the stack matrix of the shock impulse responses, considering all n time points from $t+1$ to $t+n$, conditional on the information contained in $\overline{Y}$ and z. Then the system of equations (313) for all n time points, and including intertemporal correlations, can be expressed as:

$$R(z)\varepsilon = r(z), \text{ where:} \tag{314}$$

$$R(z) = \begin{pmatrix} N_0 & 0 & \dots & 0 \\ N_1 & N_0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ N_{n-1} & N_{n-2} & \dots & N_0 \end{pmatrix}, \varepsilon = \begin{pmatrix} \varepsilon_{t+1} \\ \varepsilon_{t+2} \\ \vdots \\ \varepsilon_{t+n} \end{pmatrix}, r(z) = \begin{pmatrix} \overline{Y}_{t+1} - Z_{t+1} \\ \overline{Y}_{t+2} - Z_{t+2} \\ \vdots \\ \overline{Y}_{t+n} - Z_{t+n} \end{pmatrix}$$

Here $r(z)$ are the differences to the conditional forecasts needed for the scenario to match, n is the total number of time points in the forecast horizon, $N_n = \sum_{i=1}^{n} N_{t-i}A_i$, with the convention that $N_0 = D$ and $A_i = 0$ for $i > L$. We search for relevant vectors of structural shocks ε that can match the desired scenario. The elements of $R(z)$ are themselves square matrices, each with the same size and structure as D, in other words, their rows denote the equation in the original VAR specification and their columns correspond to each structural shock. The elements in the upper right are zero since the final values of $r(z)$ at time t are not affected by future shocks at time $t+i$, whereas shocks since time point 1 can affect future values of $r(z)$.

This compact form allows us to represent multiple constraints across time points, endogenous variables, and shocks. The rows of $R(z)$ correspond to each time point with non-zero shocks, and the columns correspond to the time points that will be affected by these shocks. If conditions are imposed for all variables and time points, then $R(z)$ is a square with side n, which is the number of time points in the forecast horizon. Excluding one or more endogenous variables at one or more time points, and thus making them unconditional with respect to any scenario, amounts to dropping the corresponding rows in the system, i.e., from $R(z)$ and $r(z)$. We can also limit the number of structural shocks used to obtain the scenario – effectively limiting the values of the remaining structural shocks to zero – by dropping the corresponding columns within the matrix elements comprising $R(z)$ as well as from all vectors ε.

In the most general case, when q is the total number (sum for all time points) of imposed conditions such that the scenario variables must match given values at some future time point, and k is the total number (sum for all time points) of future structural shocks used in the scenario decomposition, the size of $R(z)$ is $[q \times k]$, the size of ε is $[k \times 1]$, and the size of $r(z)$ is $[q \times 1]$. For example, in a simulation with 24 time points in the simulation forecast horizon, where we impose conditions on 10 of 12 endogenous variables for periods 1-4 and 9-20, and we use 11 of 12 possible shocks for shock decomposition, then $q = 10 \times 16 = 160$, $k = 11 \times 16 = 171$.[86]

The system has a viable solution, as long as the number of nonzero shocks is equal to or greater than the number of scenario restrictions[87]. In other words, the number of columns must be equal to or greater than the number of rows $q \leq k \leq mn$, because we need to have nonzero singular values for each scenario variable restriction (m is the number of endogenous variables

[86]This applies for each country, as consider each of them in the panel VAR separately. Spillovers in this step are assumed to be a predetermined exogenous variable.

[87]If the number of free shocks is equal to the number of restrictions (conditional variable points in the scenario). This would be a non-stochastic outcome. Otherwise, there are infinitely many solutions, and the solution we choose is the mean shock path, which is the solution that has the smallest Euclidean length among the set of all infinitely possible vector linear combinations.

i.e. length of vector $\overline{Y}$, i.e. also maximum possible number of structural or reduced-form shocks). Additionally, $R(z)$ should be full rank and all singular values should not be too close to zero.

From proposition (2) in Waggoner and Zha [1999], it follows that shocks from equation (314)[88] are distributed as follows:

$$p(\varepsilon|_{R(z)\varepsilon=r(z)}) = \mathcal{N}(R^T(RR^T)^{-1}r, I - R^T(RR^T)^{-1}R) \tag{315}$$

We use a simplification of this formula, taken from Jarocinski [2010], which makes use of the singular value decomposition (svd) of $R(z)$ into three matrices U, S and V:

$$\begin{aligned} USV &= svd(R) \\ \varepsilon|z &= \mu_t + V_2\xi_t \text{ , where} \\ \mu_t &= V_1 S_1^{-1} U^T r \text{ , and} \\ \xi_t &\sim \mathcal{N}(0, I_{(k-1)\times(k-1)}) \end{aligned} \tag{316}$$

A vector of structural shocks $\varepsilon|z$ is decomposed into the scenario decomposition μ_t and a term $V_2\xi_t$. Matrix V_1 denotes the first q columns of V. V_2 is composed of the last $k-q$ orthogonal vectors of V, i.e. the last $k-q$ right singular vectors of $R(z)$.[89] Matrix S_1 denotes the first q columns of S. Any random sampling of $V_2\xi_t$ equals zero after it is multiplied by $R(z)$ (impulse responses) and does not affect the scenario.

The scenario decomposition for the rest of the world employs a simpler approach. We fix the values of conditional forecasts directly via reduced-form shocks, which are equal to the difference from the unconditional projection. Following equation (4), where $\tilde{\mu}$ is the difference from the scenario and $\tilde{\Sigma}^C$ is the covariance matrix of reduced-form shocks, this becomes:

$$\begin{aligned} \tilde{Y}_t^C &= \tilde{a}_{\tilde{Y}}^C + \sum_{l=1}^{L} \tilde{A}_l^C \tilde{Y}_{t-l}^C + \tilde{v}_t^C \\ \tilde{v}_t^C &= \tilde{\mu}_t^C + \tilde{\xi}_t^C chol(\Sigma^C) \\ \tilde{\xi}_t^C &\sim \mathcal{N}(0, 1) \end{aligned} \tag{317}$$

6.2 Parameter uncertainty

Parameter uncertainty refers to the uncertainty regarding the values of coefficients in the model equations. This type of uncertainty can arise due to measurement errors, sampling errors, variability, and limited availability of historical data. In the BEAST model, it is treated separately for the parameters entering the macro-financial block on the one hand and the banking block on the other.

The uncertainty of parameters in macrofinancial equations is captured by repetitively drawing parameters of the vector autoregression (see Section 3.1) from their joint posterior distribution derived in a Bayesian framework (see Appendix **??**).[90] A different parameter set will lead

[88] Assuming i.i.d. Gaussian shocks

[89] If the number of shocks is equal to the number of restrictions (conditional variable points in the scenario), there is only one solution, and V_2 is an empty matrix.

[90] The parameter uncertainty of the macro-financial block allows to evaluate the uncertainty related to propagation of different structural and reduced-form shocks, therein of credit supply shocks and the functioning of the real economy - banking sector feedback loop.

to a different variance-covariance matrix for the structural shocks in the macrofinancial block and to a different set of shocks for scenario decomposition.

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

$$y_{i,t} = X_{i,t}\beta + \alpha_i + \varepsilon_{i,t} \tag{318}$$

where $y_{i,t}$ is the dependent bank variable observed at time t for bank i, $X_{i,t}$ is the vector $1 \times k$ of the regressors (where k is the number of independent variables), β is the vector $k \times 1$ of the model parameters, $\beta_{0,i}$ is the unobserved time-invariant individual effect, and $\varepsilon_{i,t}$ is the error term.

We assume that the Gauss-Markov theorem holds and that the residuals are normally distributed, that is, $\varepsilon \sim \mathcal{N}(0, \sigma^2\mathbb{I})$. Resultantly, the estimated parameter vector $\hat{\beta}$ is normally distributed, and we draw parameter coefficients in individual equations from:

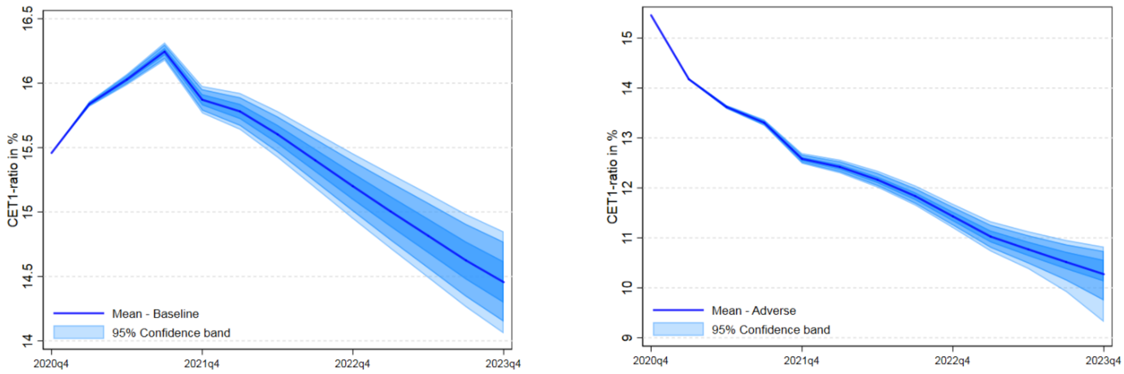
$$\hat{\beta} \sim \mathcal{N}(\beta, \sigma^2(X^\top X)^{-1}) \tag{319}$$

The uncertainty of the model parameters is considered independently for equations that were estimated separately. Table 11 summarises the equations in the banking sector block for which we evaluate the model uncertainty. In particular, these include equations most relevant for the mapping of the real economy - banking sector feedback loop (lending volume and pricing equations), solvency - funding costs feedback loop (unsecured funding costs) and profit retention strategies of banks. Currently, the evaluation of parameter uncertainty does not involve calibrated coefficients and model equations that map macrofinancial scenarios into bank balance sheet parameters.[91]

Equation	Reference	Equations	Estimates
Bank lending volumes	(4.1.2)	(11), (13) and 14	Table 29 and 32
Write-offs of defaulted exposures	(4.1.3)	(35)	Table 34
Bank lending interest rates	(4.1.5)	(56)	Table 36
Bank security holding volumes	(4.1.5)	(73) and (74)	Table 29 and 38
Banks deposit volumes	(4.2.3)	(160)	Table 42
Bank deposit interest rates	(4.2.5)	(174) and (175)	Table 44
Unsecured wholesale funding cost	(4.2.5)	(180)	Table 46
Management buffer	(4.4.5)	(295)	Table 52

Table 11: List of bank-level equations with parameter uncertainty

The impact of parameter uncertainty on model results has been illustrated in the 2021 macroprudential stress test exercise (Budnik et al. [2021a]). Figure 12 cites these results by depicting the evolution of the euro area CET1 ratio in the baseline and adverse scenarios. The shades of blue represent different percentiles of the CET1 ratio distribution spanned by different parameter values. The uncertainty of estimates tends to increase with the length of the projection horizon. The solvency rate distribution in the adverse scenario is more asymmetric, i.e. skewed



(a) Baseline **(b)** Adverse

Notes: The shade of blue represent different quantiles of CET1 ratio in each reference quarter: the darkest shades of blue represent the 25th to the 75th percentiles, the lighter shades of blue represent the 10th to the 90th percentiles, and the lightest shades of blue represent the 5th to the 95th percentiles. Source: Budnik et al. [2021a].

Figure 12: Euro area CET1 ratio projection in the macroprudential stress test 2021

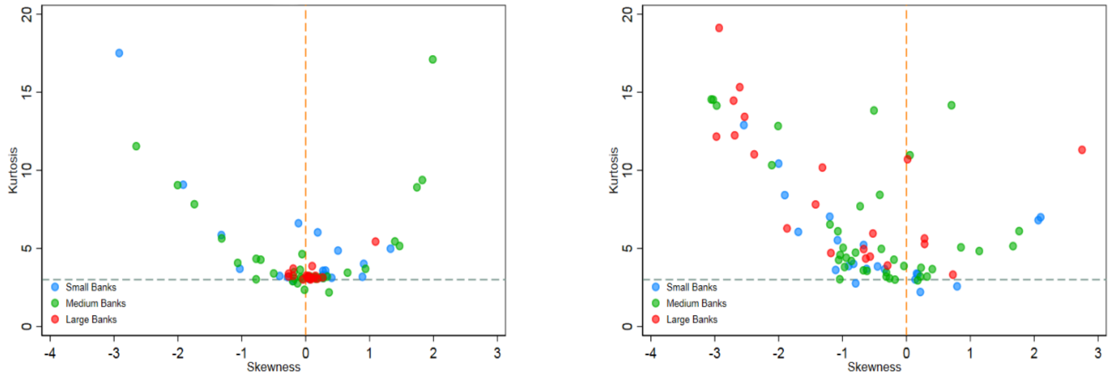
toward lower CET1 ratios than in the baseline scenario.[92]

Figure 13 further illustrates the effect of the uncertainty of the parameters on the results at the bank level. The distribution of each bank's CET1 ratio in 2023 is represented by a dot in a 2-dimensional space, with the skewness of the distribution on the x-axis and its kurtosis on the y-axis. The skewness is measured by the Fisher's moment coefficient and speaks about the asymmetry of the distribution. It is zero when the distribution is symmetric (vertical orange dashed line) and positive when the mean of a distribution is greater than its median, and the probability of bank's CET1 ratios being below the mean is higher than the probability of its realisation below the median. The kurtosis measures the flatness of tails, i.e. the relative probability of extreme events. It is considered as the excess kurtosis compared to the kurtosis of the normal distribution, which is equal to three and is marked by the horizontal grey dashed line. Kurtosis higher than three means that the distribution has a fatter tail than a normal distribution, implying a relatively higher probability of very positive or very negative realisations of CET1 ratios.

A significant share of bank-level CET1 ratio distributions are close to normal in the baseline scenario, but they become predominantly negatively skewed and with fatter tails in the adverse scenario. Under benign economic conditions, large banks have symmetric CET1 ratio distributions in most cases. Only some small and medium-sized banks have CET1 ratio distributions that have a higher degree of skewness or fat tails. The adverse scenario is more likely to trigger model non-linearities, such as the non-linear reaction to the distance from target capital ratios in lending equations, the real economy – banking sector, or solvency – funding costs amplification mechanisms, or activate regulatory limits (e.g. MDA restrictions, AT1 triggers). For large and smaller banks alike, the left tails of the CET1 ratio distributions are more stretched compared to their right tails, implying a higher mass of probability of less favorable CET1 outcomes. The

[91]This notwithstanding, we aim at acknowledging parameter uncertainty in all equations and gradually expanding the areas where it is incorporated.

[92]Assessing model uncertainty in stress test exercises is most relevant when the distributions of main results are flat (high variance) or exhibit strong asymmetry (significantly higher probability of favourable versus non-favourable outcomes, or vice versa). For example, if the mean estimate of the system-wide CET1 ratio is soundly above supervisory targets, but the probability mass below these targets is 40%, the assessment of the risks for the whole system will be different from using the same mean estimate, while the probability mass below the targets is 10%.



(a) Baseline **(b)** Adverse

Notes: CET1 ratio distributions have fat tails in both scenarios, and are negatively skewed with even heavier tails in the adverse scenario. The orange and grey lines represent the skewness ($=0$) and kurtosis ($=3$) of the normal distribution. Banks in the lowest quartile as measured by balance sheet size are classified as "small banks", banks within the interquartile range are classified as "medium banks", and banks in the highest quartile are classified as "large banks". Source: Budnik et al. [2021a].

Figure 13: Differences in the third and fourth moments of euro area banks CET1 ratio distributions in 2023 in the macroprudential stress test 2021

distributions are also relatively flat, indicating that the probability of realisation is likely to be very different from the mean estimate.

Figure 14 represents the distribution of the CET1 ratios for three different banks in the adverse scenario and at the end of the time horizon. These are selected to differ in business model and location and include (a) a large retail bank, (b) a large universal bank and (c) a small local bank. The uncertainty of the parameters for the CET1 ratio is marked by a dashed line and later broken down by model equations as in Table 11. The figure illustrates the heterogeneity of the impact of parameter uncertainty on individual banks. Bank (b) is mostly affected by the uncertainty in the funding cost equation, whereas bank (a) and (c) are mostly affected by the uncertainty in the loan supply equation.

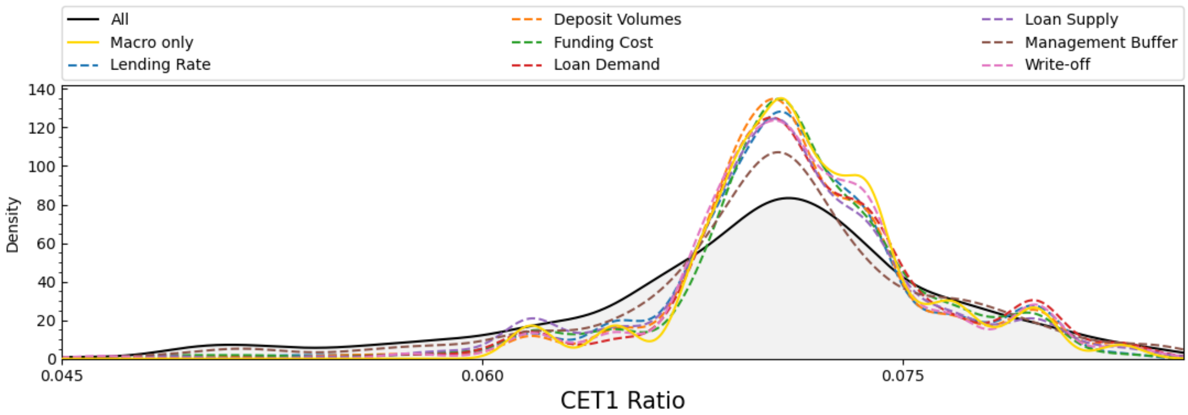
6.3 Scenario uncertainty

The model can be used to construct multiple stochastic scenarios. Each scenario consists of a series of structural ε_t^C or reduced-form ν_t^C shocks entering the representations of the euro area countries (see Section 3.1), and reduced-form shocks $\tilde{\nu}_t^C$ entering the representations of the rest of the world countries (see Section 3.2). Additionally, stochastic scenarios can integrate stochastic generation of exogenous variables X_t[93] and bank-level reduced-form shocks e_t (see Section 6.2).[94] The overview of the main options for scenario generation, focusing mainly on macrofinancial variables, is included in Table 12.

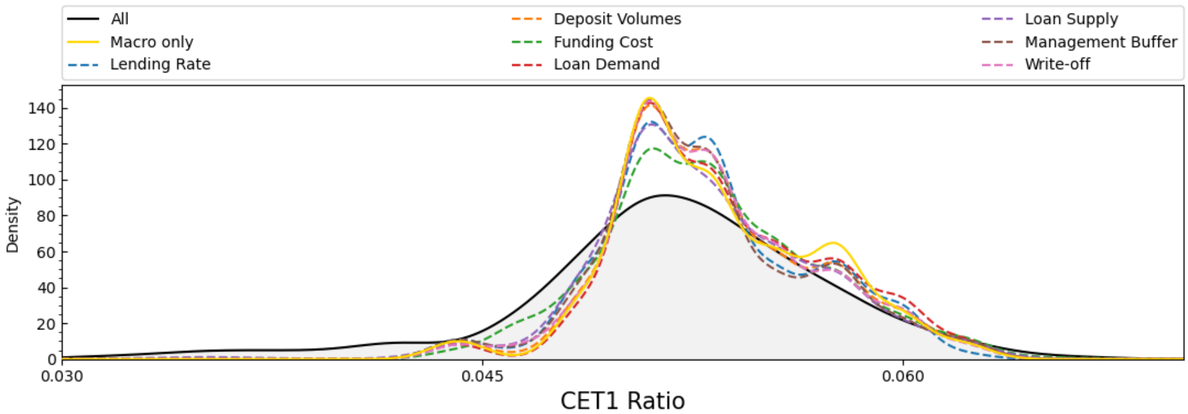
The first columns of Table 12 distinguish between stochastic scenarios generated around the unconditional model forecasts, and stochastic scenarios taking into account a mean shift related to the pre-specified scenario (see Section 6.1). In the latter case, stochastic scenarios are used to build scenario uncertainty ranges around the known behaviour of macrofinancial variables. For

[93] For example, oil, gas and solid fossil fuel prices are generated from a multivariate constant conditional correlation generalised autoregressive conditional heteroskedasticity (CCC-GARCH) model, following Bollerslev [1990].

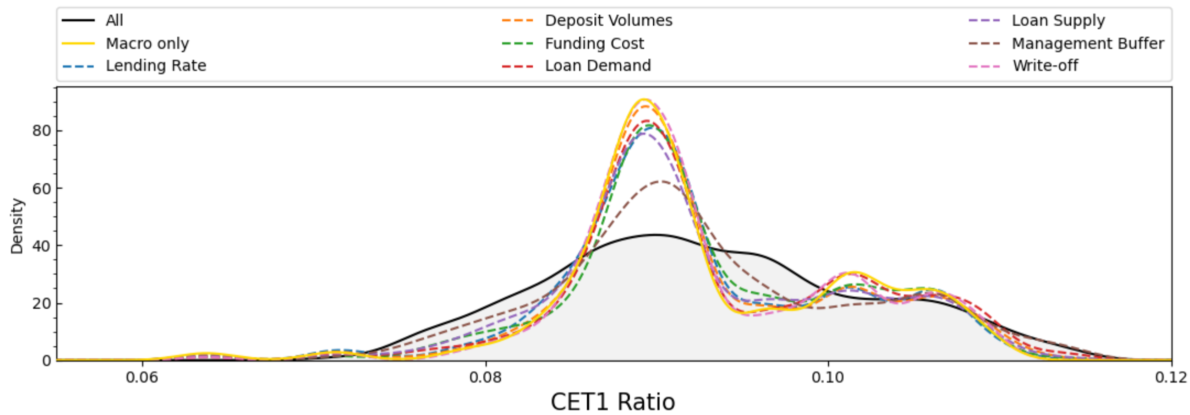
[94] Bank-level shocks can be sampled from different empirical bank-level equations. Currently, bank-level shocks are regularly sampled only for operational risk shocks based on the empirically fitted gamma distribution.



(a) Bank one



(b) Bank two



(c) Bank three

Notes: Each distribution is the result of a simulation with parameter uncertainty in only one type of equations, plus macro uncertainty. The golden line correspond to macro uncertainty only. The black line and shaded area correspond to parameter uncertainty in all types of equations (see Table 11).

Figure 14: Distribution of CET1 ratio at the end of the time horizon for the adverse scenario of the macroprudential stress test 2021 and for three representative banks

conditional simulations, the reduced-form residuals are decomposed into two elements μ_t^C and ε_t^C. The μ_t^C is a deterministic component, which is shared between all stochastic simulations.

Sampling type	Mean component		Random component
	Unconditional	Conditional	
Deterministic	0	μ	0
Parametric	0	μ	Estimated distributions
Bootstrapping	0	μ	Historical residuals

Table 12: Summary of sampling approaches for the macroeconomic block

$$v_t = D^C \varepsilon_t^C \rightarrow D^C(\mu_t^C + \varepsilon_t^C) \tag{320}$$

The last rows of Table 12 point out that scenario uncertainty can be explored by drawing sequences of shocks in either of two ways:

- Involving the estimated (joint) posterior probability distributions of structural or reduced-form shocks in the macrofinancial block, thereby relying on the parametric assumptions present in the estimation process
- Bootstrapping from historical residuals for equations in the macrofinancial block

Different simulation options can be combined, offering additional flexibility in the use of the model. For instance, the model can be solved in a deterministic setup and conditional on the pre-specified scenario for the first simulation quarters and using stochastic parametric sampling to construct an unconditional forecast thereafter.

6.3.1 Stochastic simulations with parametric assumptions

Estimation of SVAR equations representing single euro area economies from equation (1) is performed under the assumption of i.i.d. normally distributed residuals (see Appendix **??**). Accordingly:

$$\begin{aligned} v_t^C &\sim \mathcal{N}(0, \Sigma^C) \text{ with } E\left(v_t v_s'\right) = 0 \text{ if } t \neq s \\ \varepsilon_t^C &\sim \mathcal{N}(0, 1) \text{ with } E\left(\varepsilon_t \varepsilon_s'\right) = 0 \text{ if } t \neq s \end{aligned} \tag{321}$$

where the estimates of Σ^C (or D^C) are available. Stochastic simulations employing the same parametric assumptions boil down to the construction of the series of innovations $(v_t)_{t>t_0}$ or $(\varepsilon_t)_{t>t_0}$ from a well-described multivariate normal distribution.

6.3.2 Bootstrapping

An alternative sampling scheme for reduced-form residuals relies on bootstrapping. The main advantages of bootstrapping are the absence of parametric assumptions on sampled residuals, the possibility of generating heteroskedastic paths, and the relatively low computational cost. To address the dependence structure of the observed data related to its time-series dimension, we rely on the combination of the geometric block bootstrap (Lahiri [1999]) and the wild bootstrap (Mammen [1993]).

The block bootstrap is used when the errors in a model are correlated. The block bootstrap tries to replicate the correlation by resampling sequences (or blocks) of data. The geometric block bootstrap is an extension of the moving blocks where the block length l follows a geometric distribution and can therefore vary among blocks.[95] The wild bootstrap allows producing shocks which are larger than those in the historical data, thereby affecting the tails of the shock distributions which may not be properly specified in shorter data samples (as a reminder, our macro data begin in 2003 Q1). Adjusted shocks will have the same variance as original bootstrapped errors, but their distribution will have fatter tails.

Let T be the size of the historical data sample. The vector v_t, with $t =\in [1,T]$, is the residuals of all the equations representing the countries of the euro area considered together. As such, the vector v_t replicates the correlations between countries. The generation of a single bootstrapped series for the horizon t_h can be described by the following algorithm:

1. Define the infinite series indexed by integer $s = 0, 1, ...,,$ $\tilde{v}_s := v_{s \mod (T)}$ for modulo T. In this new series $\tilde{v}_s$ the last historical observation v_T is followed by the first historical observation v_0.

2. Let $i_0, i_1, ...i_j, ..., i_m$ be drawn i.i.d. from a uniform distribution on the set $\{1,2,...,T\}$. They are indices of the starting points of blocks indexed by j. The number of blocks m must be large enough so that the sum of all block lengths is greater than the horizon t_h.

3. Let $l_0, l_1, ..., l_j, ..., l_m$ be drawn i.i.d. from a geometric distribution with the parameter p. They represent the lengths of individual blocks j while the mean length of a block is $1/p$.

4. Construct m blocks of innovation series $\hat{v}^1, \hat{v}^2, ..., \hat{v}^m$ such that:

$$\hat{v}_t^j = \tilde{v}_{i_j+t-1}, \text{ with } t = 1, ..., l_j \text{ and } j = 1, ..., m$$

5. Concatenate all the blocks to obtain the bootstrapped series $\hat{v}_t$.

6. Multiply the innovation elementwise by a vector of a standard joint normal distribution.

$$v_t^{\star} = z_t \odot \hat{v}_t \text{ with } z_t \sim \mathcal{N}(0, \mathbb{I}).$$

The series $\hat{v}_t$ and $v_t^{\star}$ have the same variance, the bootstrap errors mimic the second-moment structure of the original innovations but with fatter tails in the distribution.

The residuals for the VARs of the rest of the world (see equation (4)) are bootstrapped in the same way, with a vector of residuals for third countries independent of the vector of residuals for countries in the euro area.

The selection of the average block size l is based on the notion of spectral estimation through flat top lag windows of Politis and White [2004]. They proposed estimators of the optimal block size for the block bootstrap methods that are characterised by the fastest possible rate of convergence, which is adaptive on the strength of the correlation of the time series as measured by a correlogram. In our case, the optimal block size is 5.

6.3.3 Pruning

Simulations in a model with non-linear elements can lead to occasional instabilities and result in explosive paths (Lan and Meyer-Gohde [2013], Kim et al. [2008], Fernández-Villaverde et al. [2016]). Pruning removes these paths and ensures that the final distribution of the outcomes is

[95] Lahiri [1999] has shown that geometric block bootstrap has the property of higher-order accurate estimation of the distribution of the sample mean.

economically viable. However, by intention, pruning should not discard valuable information from the tail of the distributions.

Pruning removes simulated paths that include variables with large jumps or spikes. The rejected path corresponds to highly unrealistic values or jumps that are several orders of magnitude away from the steady state and historical variations and emerge as a numerical outcome resulting from the accumulation of non-linearities and specific shock values.

To identify numerically problematic paths, we first select a subset of variables projected by nonlinear equations $\{X\}$, which are most likely to be a source of explosive behaviour. These are mainly bank-level variables and each selected variable X is given a characteristic scale X_s based on its historical value.

At each time step τ of a simulation we approximate the first derivative of each scaled variable $x = X/X_s$ at time τ and $\tau - 1$ by the backward difference quotient:[96]

$$\left.\frac{dx}{dt}\right|_{t=\tau} \approx x(\tau) - x(\tau - 1)$$
$$\left.\frac{dx}{dt}\right|_{t=\tau-1} \approx x(\tau - 1) - x(\tau - 2)$$

The pruning algorithm independently monitors jumps and spikes in each time step τ. Jumps are removed if the absolute value of the first derivative is greater than a threshold J:

$$\left|\left.\frac{dx}{dt}\right|_{t=\tau}\right| > J$$

The spikes are removed if the two consecutive absolute values of the first derivative are higher than a threshold S ($S << J$):

$$\left|\left.\frac{dx}{dt}\right|_{t=\tau}\right| > S \quad \& \quad \left|\left.\frac{dx}{dt}\right|_{t=\tau-1}\right| > S$$

If one of the two previous conditions is satisfied, the simulation is pruned (discarded), and the model is run again with a new random shock sample. We only reject explosive behaviours that correspond to highly unrealistic values, i.e., the values of the threshold parameters are high, $S \sim 100$ and $J \sim 1000$.

According to our definition, explosive paths occur in only 0.3% of the simulations and regardless of the particular parameter draws. It is important to note that these discarded paths do not represent potential extreme crises. Instead, they depict doomsday scenarios in which multiple vicious or virtuous feedback loops within the model are activated simultaneously.

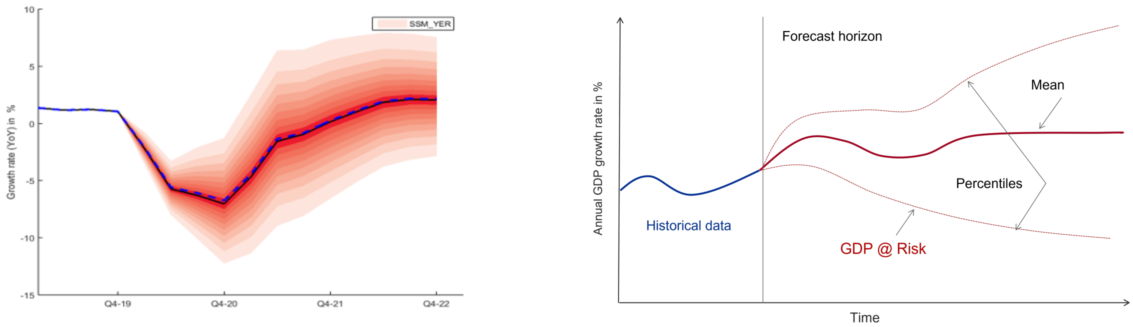
6.4 Stochastic simulations and at-risk measures

Random draws from the distributions of model parameters and shocks can build a full distribution of plausible outcomes. Such a distribution may be created either as a fully unconditional projection, or around a mean scenario path as in Section 6.1. Each simulation in $\mathscr{M}(\mathscr{P}, \mathscr{X})$ describes the unique evolution of country-level GDP, unemployment, domestic and bank-level lending, bank-level CET1 ratios, which are consistent with past data and the structure of the model. The results contain a large set of both "strong" and "weak" scenarios, for example, some with highly positive and others highly negative GDP growth rates.

[96] The time step between τ and $\tau - 1$ is assumed to have a length of 1.

An important way to utilise the full distribution of model outcomes is to analyse its tails. The tails of GDP, CET1 ratio, or lending distributions can mark events that can pose a systemic risk, e.g. economic recessions, while their shifts can speak about changes in resilience, e.g. due to regulatory changes. Tails can be observed by looking at lower percentiles or expected shortfall measures.

Figure 15 shows the mapping between the results of the stochastic simulations of the model and the at-risk measures. On the left-hand side, there is a forward-looking assessment of the evolution of the euro area GDP growth (derived with an illustrative cut-off date of 2Q 2022). The distribution is right-skewed with the mean above the median with moderately fatter tails than the normal distribution. On the right-hand side, there is a stylised exposition of the outcome with the emphasis on the central tendency (mean) and two percentiles, the 10th and the 90th. The lower percentile of the distribution can be interpreted as a measure of growth at risk. Similar at-risk measures can be derived for any endogenous variable in the model.



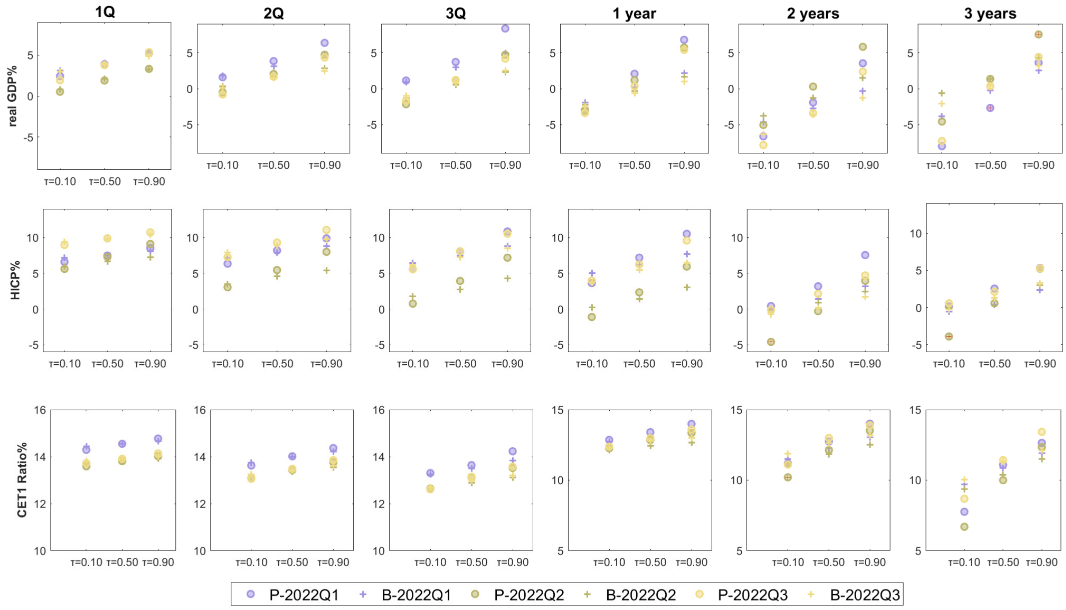
(a) Actual fanchart **(b)** Stylised fanchart

Figure 15: Euro area GDP year-on-year

Figure 16 gives an example of the use of at-risk measures to track the evolution of risk factors for financial stability over time. Forward-looking assessment of GDP growth, inflation rate, and CET1 ratio in the euro area that is included in the regular assessment of financial stability aspects of monetary policy along with the revised ECB strategy from 2021. The assessment is based on information available in 1Q, 2Q, and 3Q 2022 and relies on (unconditional) forecasts taking into account scenario and parameter uncertainty. For each reference date, we look at the moments of the distributions one quarter, two quarters, one year, two years, and three years ahead. In addition, the results differentiate between two sampling methods: P characterises the draws obtained by parametric sampling and B those that are sampled by bootstrapping. Figure 17 displays the corresponding kernel densities on the one-year and three-year horizons.

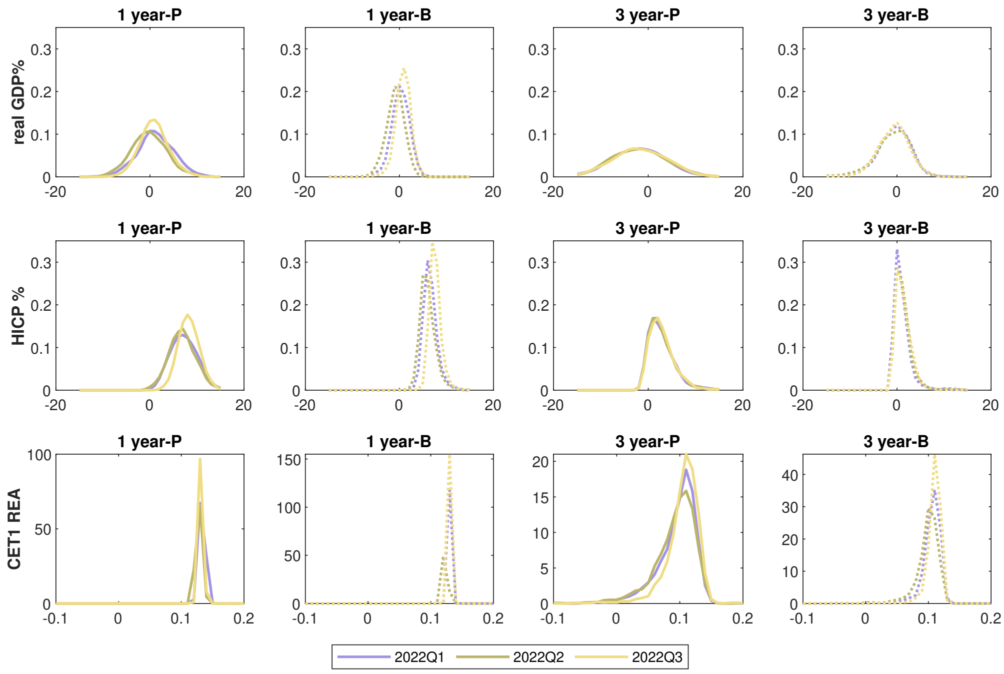
The distributions of the bootstrapped draws are more heterogeneous than the distributions of the draws from simulations employing parametric assumptions. For both sampling methods, the stability of the distributions increases with the projection horizon.

Medium term real GDP growth (first row in Figures 16-17 , 50^{th} percentile) declined over 2022, as well as its at-risk measure (10^{th} percentile). Consecutive projections accommodating later data foresaw a sustained bleak outlook for real GDP growth on account of the economic ramifications of the unfolding Russian - Ukrainian war and its impact on energy prices, as combined with supply chain bottlenecks perpetuated by global transport disruptions and rigid COVID-19 containment measures in China. Increasing scepticism about the future growth outlook can also be seen in the shape of the distribution of the 1-year ahead real GDP projections, which became more pronounced centred around zero in 2022 Q3 as compared to the two earlier quarters.



Notes: Data as of 2022Q1, 2022Q2, 2022Q3 (purple, green and yellow), simulations based on the parametric sampling method characterised by P and dots while simulations from bootstrapping are indicated by B and the cross symbol. The selected quantiles are 10^{th}, 50^{th} and 90^{th}.*y-axis* adjusted across projection horizons for better visibility for the CET1 ratio.

Figure 16: Unconditional projections of at-risk real euro ara GDP, inflation (HICP) and CET1 ratio at different horizons



Notes: Data as of 2022Q1, 2022Q2, 2022Q3 (purple, green and yellow), simulations based on parametric sampling method characterised by P while simulations from bootstrapping are denoted by B. Note that the y-axis of CET1 REA is adjusted differently across horizons for better readability.

Figure 17: Kernel densities of unconditional projections for real euro area GDP, inflation (HICP) and CET1 ratio at different horizons

The central and at-risk short-term forecast of inflation has been revised upwards (second row) over 2022, the medium-term forecasts of inflation relatively stable. Revisions of the short-term projections reflect gradual accommodation of the prolonged effect of pandemic shock on inflation and of rising energy and food prices. Also, the distribution of 1-year ahead inflation projections with data as of 2022 Q3 is more left-skewed than in the earlier quarters. This implies that a larger share of the distribution is concentrated above 0% in 2022 Q3.

Up to 1 year ahead, projections of the euro area CET1 ratio were revised downward throughout 2022. The gradual deterioration of the short-term solvency outlook over 2022 is related to an increase in latent credit risk resulting from the uncertain economic outlook and increased funding costs. Over 2022, the distributions of 1- to 3-year-ahead forecasts have become stronger concentrated around the mode, signalling increasing certainty of the deteriorating CET1 outlook.

6.5 Narrative criteria and stochastic scenario selection

On occasion, we are interested in a macrofinancial scenario that exemplifies a particular economic narrative. For stress test applications, this macrofinancial scenario should also represent a tail event or a "severe but plausible scenario" BCBS [2009]). To these ends, we have developed a novel approach in which a scenario is sourced from the full distribution of stochastic outcomes along with the desired narrative, a process we refer to as narrative scenario generation.

The method exploits the results of Monte Carlo simulations, which preserve internal model mechanisms and endogenous feedbacks. It combs through projected outcomes to identify scenarios that emphasise risks and vulnerabilities in the narrative.[97] The selected macro-financial scenarios follow the desired economic storyline and at the same time remain statistically valid by preserving the correlations present in historical time series, that is, the scenario remains plausible. In this way, the method combines the advantages of statistical (economic plausibility) and hypothetical (flexibility of designing scenarios different from historical episodes) scenario generation methods.[98]

The methodology places emphasis on a narrative, including risks identified by the scenario designers, while at the same time staying consistent with the distributional properties of the model being used (letting the model "speak"). Because the selected scenario is taken from the actual simulated distribution of the model itself, rather than from an external source, it is dynamically consistent. It is also intra-temporally consistent, i.e. within each time point all variables are derived jointly. The designer can pinpoint the storyline and the desired severity (adversity) by sorting all scenarios and without imposing exact values.

The approach follows four steps:

- Generating the full distribution of plausible scenarios

[97] The algorithm laid down in this chapter is universal and can be transferred to any model providing stochastic scenarios.

[98] There are several alternative ways in which stress test scenarios are constructed. The historical approach sets the level of stressed variables based on their past realisations (for example, during a specific past recession). The hypothetical approach uses custom-made scenarios that reflect a "hypothetical adverse situation triggered by the materialisation of risks to which the EU banking system is exposed" (ESRB [2021]). The probabilistic approach relies on statistical inference from an estimated distribution of past values for variables or external shocks. Another approach to selecting a relevant scenario is described by Pritsker [2017], who proposes dimension reduction techniques to intelligently specify shocks corresponding to an increase in systemic risk. Finally, a reverse-engineered scenario uses a series of shocks that will result in the desired values for the relevant variables. In this case, the scenario designer would need to know the response function (e.g., loss function) of the agent being stress tested (e.g., the bank), as in Glasserman et al. [2013] and Flood and Korenko [2015].

- Mapping of the narrative into a set of criteria applied to endogenous or exogenous variables
- Sorting of simulations along with the criteria
- Selecting "best performing" scenarios

This algorithm, along with examples, is described in more detail in Appendix E.

The relevant step of the procedure is to map the desired economic narrative into a set of criteria. These criteria take the form of simple functions applied to endogenous, exogenous variables, both on macro- and bank-level, or their combinations, and at different time horizons. By calibrating the appropriate set of criteria, it should be possible to replicate conditions that correspond to a wide range of the state of affairs of the general economy.

In the next step, a multidimensional non-parametric sorting algorithm ranks all simulations according to chosen criteria. The algorithm is based on ordinal sorting for scenario generation as described by Sarychev [2014]. In practise, all simulations are sorted separately along with each criterion. The final rank of each simulation is a weighted sum of its sorting position for each individual criterion; thereby we can tailor features of the scenario by adjusting the weight assigned to each criterion to signify its importance relative to the others.

Simulations right next to each other in the final sorting order (by weighted sums of ranks) are expected to represent relatively similar outcomes and be consistent with the same narrative. However, they can differ with regard to the exact evolution of the variables included in the criteria, and especially other variables. To take into account the uncertainty of the scenario and the model, we take a narrow strip of simulations in each such scenario equivalence class,[99] and collapse them via a mean[100] in a stylised representative scenario — a scenario path.[101] In this way, we ensure that the results do not depend on a single timing and magnitude of shocks to macroeconomic (or other shocked) variables. Scenario paths inherit the mean ranking of simulations used for their creation.

The simulations with the lowest ranks best satisfy the desired narrative and hence they are usually the most preferred. In some situations, especially with simpler criteria, it may be useful to look at other parts of the sorting order (see Section 8.2 for an example of such an application). For example, these can be the strips of simulations around those corresponding to the 1^{st}, 5^{th}, or 10^{th} quantiles in the final sorting order of simulations.

Figure 18 illustrates the selection of a scenario with a short-lasting stagflation. The criteria applied to select this scenario pertain to the cumulative growth in GDP and inflation from 2022 Q3 until 2023 Q4. The example entails sorting the simulations along with the two criteria, i.e. by the magnitude of drop in GDP and in prices. The three scenarios marked green on the surface of the fan charts of four variables correspond to the means of simulation strips in 1^{st}, 5^{th}, or 10^{th} quantiles in the sorting order.

[99] If desired, individual simulations may belong to several distinct strips (scenario paths).

[100] We use the mean for most applications because of its property that the mean of a sum is the sum of the means — which preserves relationships between variables. Otherwise, it is possible to use the median or another aggregating function instead.

[101] Moreover, even though they ranked close to each other, a few of the simulations within a strip can differ sharply from the majority. Simulations that are too dissimilar may skew the results of a mean and thus the scenario path. Since the purpose is to obtain similar simulations within each strip, we use a local outlier factors algorithm based on the concept of a local density to check for and select outliers within the strip.

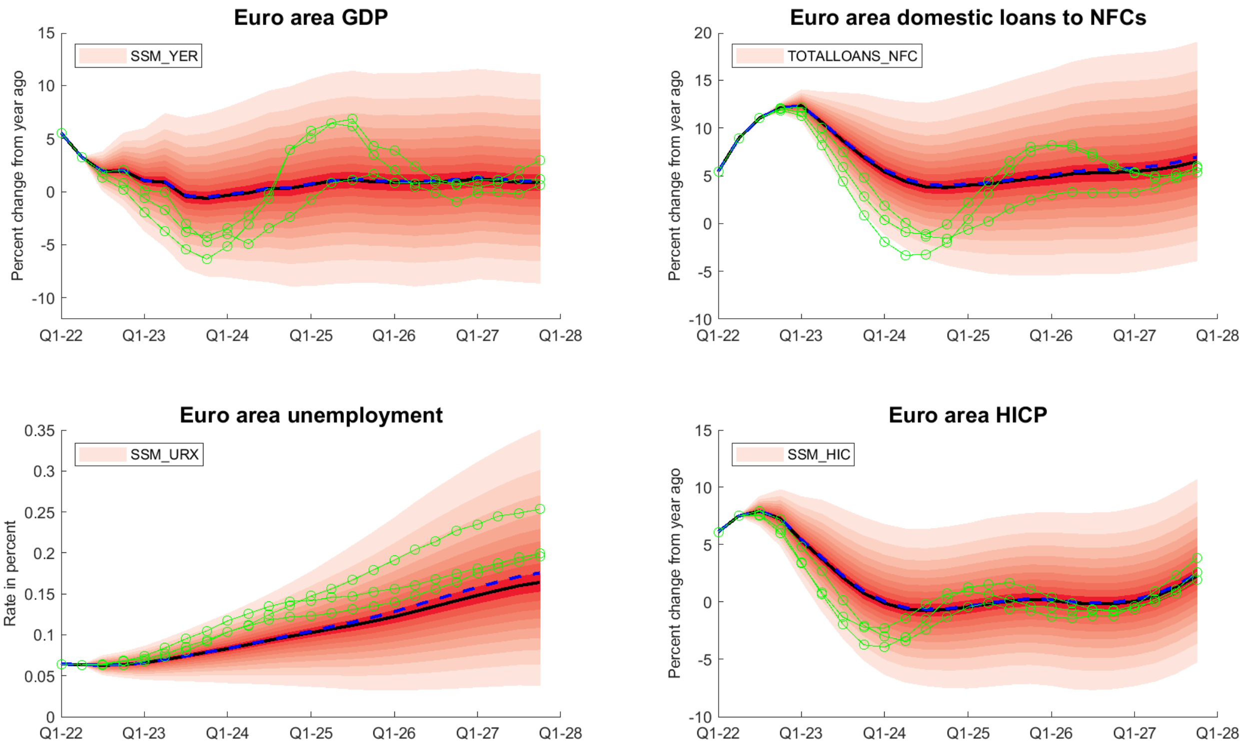


Figure 18: Selection of a short-lived stagflation scenario represented by GDP, loans to NFCs, unemployment rate and inflation (sorting by GDP and HICP)

7 Model properties

This chapter looks at model properties, which are reflected in its applications, and zooms into the process of developing a large model. The phase-in of the BEAST model in a policy process involved an ongoing monitoring of various qualitative and quantitative criteria, which can be grouped into criteria regarding the quality of policy advice derived from the model (policy impact criteria), as well as operational, technical, and quantitative economic criteria. These groups are presented in Figure 19.

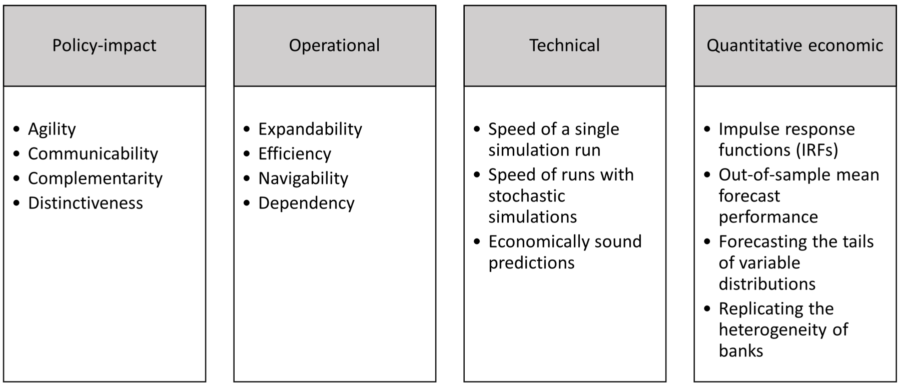


Figure 19: Expectations and monitoring criteria for the BEAST model

The continuous monitoring of policy impact and operational criteria has led to the development of an exceptionally versatile model, which is now witnessing a surge in demand for its analytical capabilities. Among those, the emphasis has been put on: (i) agility, the model's ability to analyse a wide range of topics with minimal intervention or modifications to its structure; (ii) communicability, the model's capacity to deliver analyses that can be intuitively understood and effectively utilised by policy-makers; (iii) complementarity, the model's ability to assimilate and utilise information from internal and external databases and analyses; and (iv) distinctiveness, the model's capacity to provide insights that are not captured by other models or analyses.

Section 8 provides a summary of various analyses that indirectly demonstrate the agility and communicability of the model. The complementarity of the model has been enhanced through a consciously adapted model structure and related infrastructure. The distinctiveness of the model has been evidenced by instances in which its outcomes sharply contrasted with other available analyses and proved accurate when validated by realisations of data or additional information. For example, it accurately predicted high lending growth and robust bank profitability in 2021-2022, fending off more pessimistic expectations. Additionally, the model correctly identified the positive impact of early interest rate increases on the banking system as a whole and observed a substantial reduction in non-performing loans (NPLs) over the past few years. The distinctiveness of the model is also evident in policy exercises, such as when the BEAST model more accurately revealed the impact of sectoral capital buffers in national banking systems characterised by a high degree of cross-border interdependencies.

The formulation and regular examination of operational criteria ensured that over time the model has become more efficient in providing responses to policy questions and also more user-friendly. These operational criteria include: (v) expandability, the ease with which the model and the surrounding infrastructure can be extended to incorporate new features or enhancements; (vi) efficiency, the ability to produce results in a timely and resource-efficient manner, including considerations of human resources; (vii) navigability, the ease with which a new user can be trained to operate the model effectively and accurately interpret its results; and (viii) dependency, measures taken to minimise the risk of disruptions that would hinder or restrict the use of the model.

Currently, most analyses that do not require a new model extension or reestimation can now be completed within a working week by one or two modelers. This represents significant progress compared to the early stages, when new analyses often required tedious and resource-intensive weeks of preparation, simulations, and post-simulation processing. The reestimation of selected model equations or model extensions, both involving also multiple testing within the overall framework and readjustments (see Section 7.5), have also become significantly more efficient and take from one day up to two weeks and often require only one modeller, causing no disruption to other workflows. The time needed to train a person to perform an independent model analysis has been reduced to as little as one month in certain cases.

Qualitative criteria have been progressively complemented by quantitative criteria. These include technical criteria such as (i) the speed of a single simulation run, (ii) the option to produce runs with stochastic simulations, and (iii) the ability to provide economically sound predictions for all variables, e.g. ensuring that probability metrics are between zero and one, avoiding unexplained jumps or explosive trends in the forecasts. These add to quantitative economic criteria, including (iv) impulse response functions, (v) out-of-sample forecasting performance for mean forecasts, (vi) forecasting performance for the tails of variable distributions, whereby we looked at the results under different assumptions used in stochastic simulations, and finally (vii) the ability to replicate the heterogeneity of bank performances observed in reality.

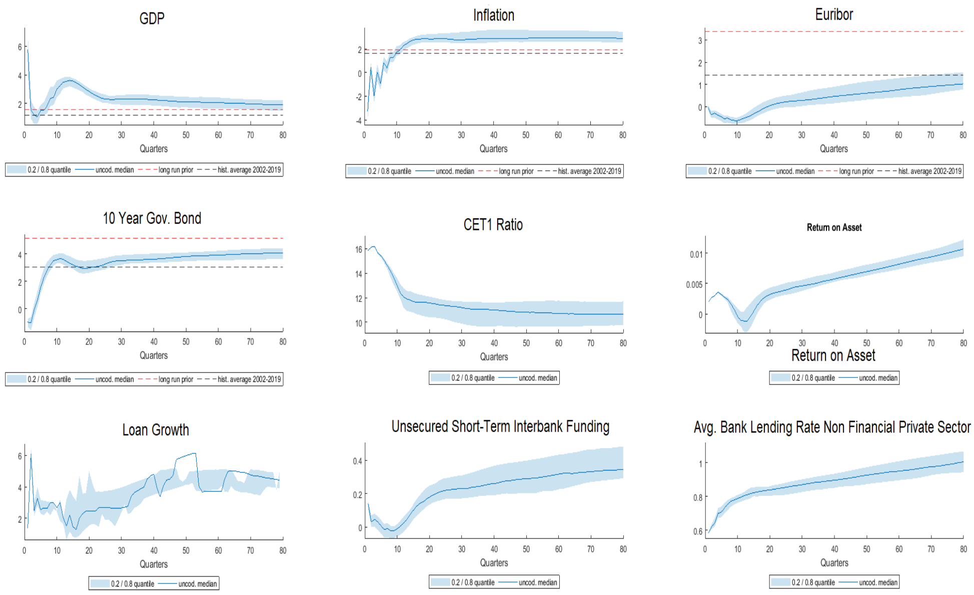
This chapter focuses mainly on the quantitative economic criteria. First, the chapter discusses the long-term properties of the model and its selected impulse response functions. Then, it moves to illustrating the model ability to replicate the heterogeneity of the euro area banking system. Finally, it looks at the forecast performance of the model. The closing section discusses how the process of developing the model with thousands of equations and parameters has been disciplined, and what was the role of regular assessment of model properties in this process.

7.1 Long-term properties

Long-run stability and convergence to a sensible steady state are crucial for the applications of the model in any longer-run simulations, and therefore the analysis of its medium-run responses to shocks. Both the macro- and banking blocks of the model are carefully specified to preserve convergence to a stable long-term solution. In the macroeconomic block, it is achieved by ensuring the stationary of transformed macro variables and estimating country dynamics with the use of long-term priors. In the banking block, the main empirical equations are estimated taking into account dynamic homogeneity. However, the ultimate check for long-term stability of the model is its long-term solution in the absence of shocks.

Figure 20 shows the convergence of key macroeconomic and banking variables in the absence of shocks. GDP, inflation, and the short- and long-term rates are the weighted average of the individual country values. The red dashed line is the weighted average of the individual country long run prior while the black dashed line is the weighted average of the individual country historical values from 2002-2019. CET1 ratio, return on assets, unsecured short-term interbank funding are the aggregate values of the euro area banking sector.

GDP growth rate and the inflation rate converge to a level slightly higher than 2%, consistent with expectations and stylised facts about the economy of the euro area. Short- and long-term



Notes: Unconditional long-run simulation with GDP, HICP inflation, and loan growth to the non-financial private sector are presented in annualised quarter-on-quarter percentage growth rate, and 3-month EURIBOR, 10-year government bond yields, CET1 ratio, return on assets, unsecured short-term interbank funding rates are presented in percentage points.

Figure 20: Unconditional long run simulation

interest rates gradually return to levels close to the weighted average historical data.[102] The nominal lending growth to the non-financial private sector in the long run converges to around 4% annually. The aggregate CET1 ratio converges to a level of around 11%, that is, above the overall capital requirements and buffers (including Pillar II guidance) for CET1 of 10.6% as in 2022. This reflects the presence of voluntary management buffers in the steady-state. Bank interest rates, funding costs, and long-term profitability are above the levels observed in 2020, in line with the gradual convergence of market interest rates to their higher equilibrium levels.[103]

7.2 Impulse response function analysis

The impulse response function (IRF) analysis illustrates how a single structural shock is transmitted through the model. Thus, IRFs are a suitable and important tool for identifying the model propagation mechanisms. We focus on the propagation of three structural shocks: an aggregate demand shock affecting all economies at the same time, a standard monetary policy shock, which is reflected in an unexpected increase of 3-month EURIBOR, and an unconventional monetary policy shock commensurate with an unexpected increase in the ECB balance sheet. Structural shocks follow the identification discussed in Section 3.1.

For each type of shock, we compare IRFs derived under different assumptions to elicit model non-linearities. We show the structural shocks for the two specifications of the feedback

[102]The starting point of the simulation is 2020 Q4 which has been strongly impacted by the developments related to COVID-19 pandemic and is thus far away steady state to which the model converges.

[103]The model does not capture mergers or acquisitions of banks, which can be the source of higher profitability of the banking sector over longer time horizons.

loop described in Section 5. Second, we look at the transmission of both positive and negative shocks and, last, we specify "small" and "large" shocks correspondingly as 1 and 3 standard deviations. For 1 standard deviation shocks, we present the IRFs with parameter uncertainty, while for the 3 standard deviations, we only present the mean to ensure readability of the figures. In addition, the IRFs that capture the impact of negative shocks are multiplied by -1 so that the response dynamics of positive and negative shocks is displayed in the same quadrant of the Cartesian coordinate system and it becomes easier to interpret the difference in magnitude of the responses. IRFs are derived from the starting point 1Q 2021.[104]

7.2.1 Aggregate demand shock

A positive one-standard deviation aggregate demand shock affecting all euro area countries at a time leads to a persistent expansion of GDP and an increase in inflation. The GDP of the euro area initially increases by close to 2.7 pp and consumer prices by 2.2 pp on an annualised basis (two upper rows of Figure 21). It takes around 2.5 years for GDP and HICP growth rates to converge to their baseline levels. There are no marked differences in model responses for the two alternative specifications of the real economy - banking sector feedback loop.

A positive demand shock leads to an increase in the short- and long-term interest rates, by around 0.5 and 0.6 pp correspondingly, likely reflecting the monetary policy reaction. The 10-year government bond yields take about one and a half years to converge back to their baseline levels.

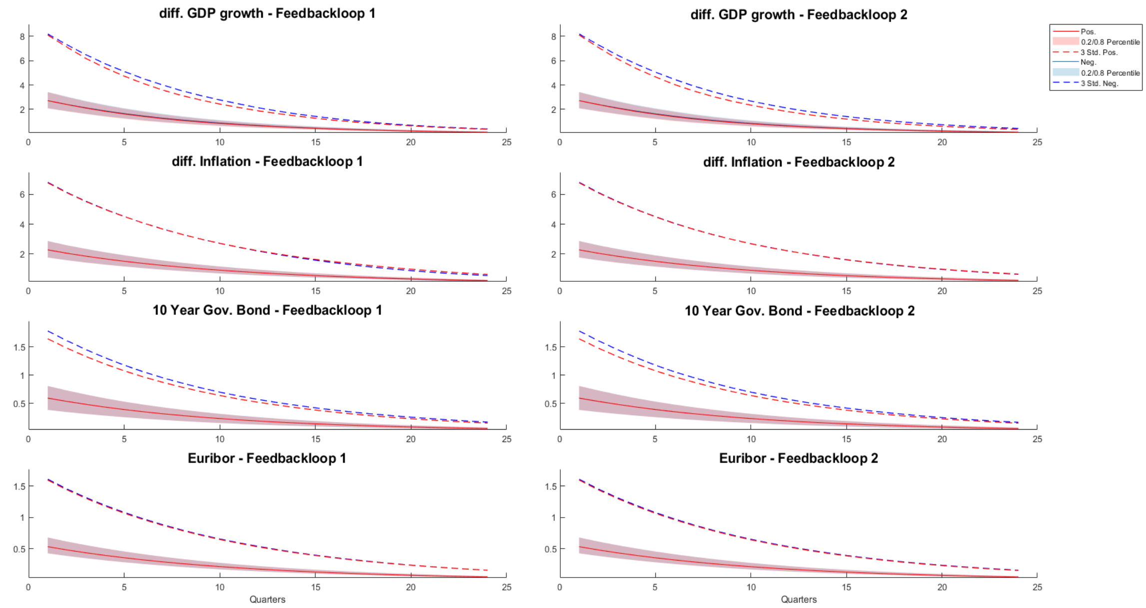
The asymmetry between positive and negative shocks can be seen only for large (3 standard deviation) shocks with a marginally stronger response of GDP and the 10-year bond yields a positive as compared to negative aggregate demand shock.

A positive aggregate demand shock boosts loan demand and is reflected in a persistent increase in bank lending volumes to the non-financial private sector. The volume of loans is around 7.3% higher 4.5 years after the shock. An expansion in assets results in a moderate and permanent decrease in the CET1 ratio by around -0.5 pp. For a negative one-standard deviation aggregate demand shock, the changes in the CET1 ratio are of opposite sign (an increase) but of the same magnitude. However, for a three standard deviation aggregate demand shock, the CET1 response reflects model non-linearities. The CET1 impact of a three-standard deviation positive shock is 3.5 times larger than the impact of a same-signed one-standard deviation shock. Furthermore, the response of CET1 ratio to a positive three standard deviation shock is by 1 pp greater than its reversed response to a large negative shock.

Higher market interest rates partially pass through the elevated costs of unsecured short-term interbank funding. The price of unsecured short-term interbank funding increases by more than 0.1 pp following a positive one standard deviation aggregate demand shock. Lending rates adjust both to higher funding costs and stronger credit demand and go up by around 0.02 pp.

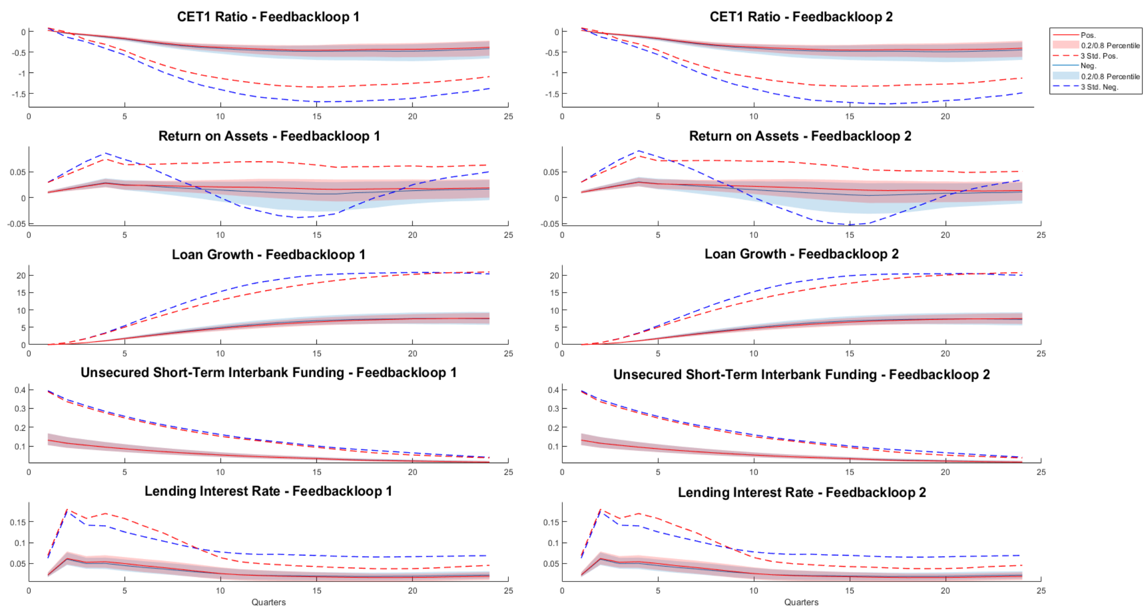
Profitability measured by return on assets is subtly but positively impacted by small positive shocks, though it converges back to its baseline level in around a year following the shock. Moreover, there are asymmetries in the impact of large positive and negative shocks. Large negative shocks have a more persistent negative impact on bank profitability compared to large positive shocks and their positive impact on bank profits.

[104] In a non-linear model, banks responses depend on the their initial situation e.g. initial capitalisation impacts whether a shock is partially absorbed or even amplified.



Notes: GDP and HICP inflation are presented in annualised quarter-on-quarter percentage growth rate, 3-month EURIBOR and 10-year government bond yields in percent.

Figure 21: Impulse response functions of macroeconomic variables to a one-std. and a three-std. aggregate demand shock



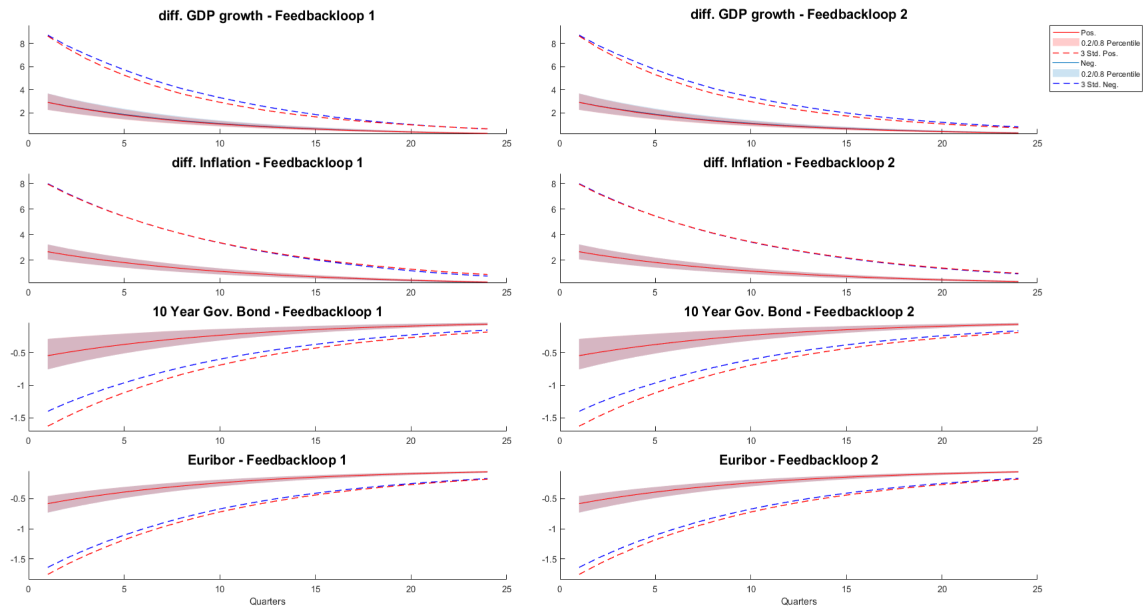
Notes: CET1 ratio, Return-on-Assets, interest rate on lending to the non-financial private sector and unsecured short-term interbank funding rate are displayed in percent points, loan volumes to the non-financial private sector as percentage increase in the volume.

Figure 22: Impulse response functions of aggregated banking variables to a one-std. and a three-std. aggregate demand shock

7.2.2 Standard monetary policy shock

A one-standard deviation accommodating (standard) monetary policy shock is initially reflected in a reduction of EURIBOR by close to -0.6 pp. It is followed by a slightly lower reduction in 10 year bond yields of around -0.5 pp. GDP and inflation move up on impact and smoothly converge back to the original level.

For large shocks, which are more likely to push the monetary policy into a zero lower bound territory, the effect of monetary policy tightening is proportionally stronger than that of policy loosening. EURIBOR goes up by 1.9 for the policy tightening commensurate with three standard deviation monetary policy shock, whereas it goes down by 1.8 pp in case of same scale policy loosening. The same is the case for the 10-year government bond yields, with a 1.6 pp increase and a -1.4 pp reduction, respectively.



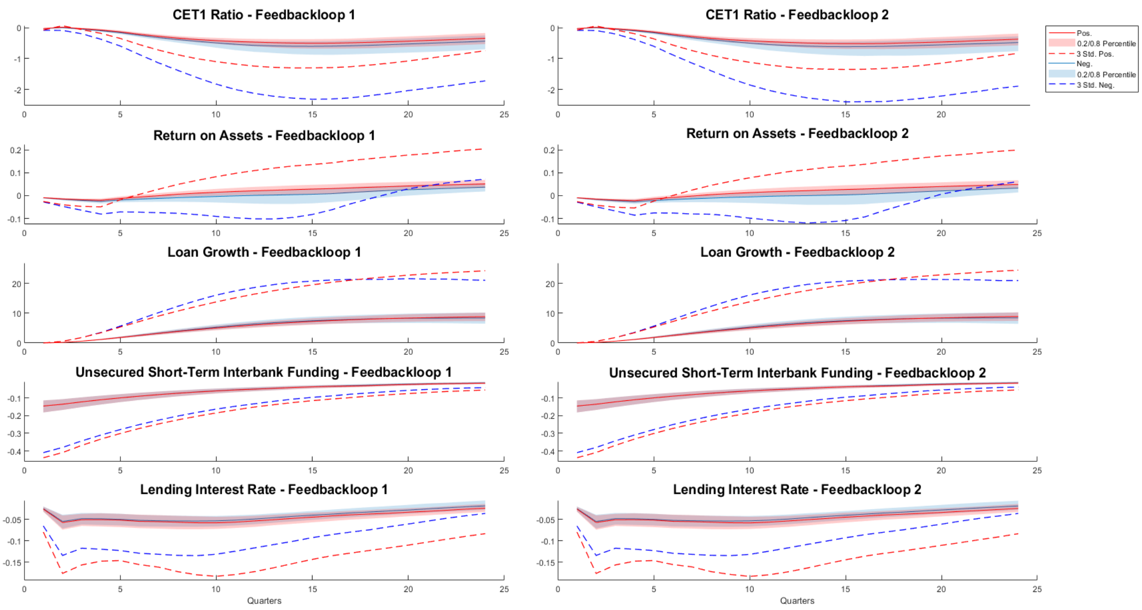
Notes: GDP and HICP inflation are presented in annualised quarter-on-quarter percentage growth rate, 3-month EURIBOR and 10-year government bond yields in percent. The red lines and areas illustrate a loosening of monetary policy, and the blue a tightening of monetary policy.

Figure 23: Impulse response functions of macroeconomic variables to a one-std. and a three-std. conventional monetary policy shock

Lower market interest rates lead to a reduction in unsecured short-term interbank funding costs and facilitate the reduction in bank lending rates. The price of unsecured short-term interbank funding goes down by over -0.15 pp following a positive standard monetary policy shock, while lending rates by around -0.02 pp.

The response of loan volumes is slower, but positive. Loan volumes to the non-financial private sector 5 years following a policy shock are 8.3% higher than in the absence of the shock.

Finally, the response of bank profitability and the CET1 ratio was slightly positive and lasting, reflecting the improved economic conditions.



Notes: CET1 ratio, Return-on-Assets, interest rate on lending to the non-financial private sector and unsecured short-term interbank funding rate are displayed in percent points, loan volumes to the non-financial private sector as percentage increase in the volume. The red lines and areas illustrate a loosening of monetary policy, and the blue a tightening of monetary policy.

Figure 24: Impulse response functions of aggregated banking variables to a one-std. and a three-std. conventional monetary policy shock

7.2.3 Unconventional monetary policy shock

Along with our identification scheme, an expansive unconventional monetary policy shock is equivalent to an exogenous increase in the euro system balance sheet that leads to an immediate flattening of the yield curve. The expansive unconventional monetary policy shock leads to a contemporaneous increase in the balance sheet of the euro system by 7.7% and a higher growth rate of the balance sheet for up to 7 years. The contemporaneous impact on the 10-year government bond yields is -0.5 pp, with close to none impact of the shock on EURIBOR.

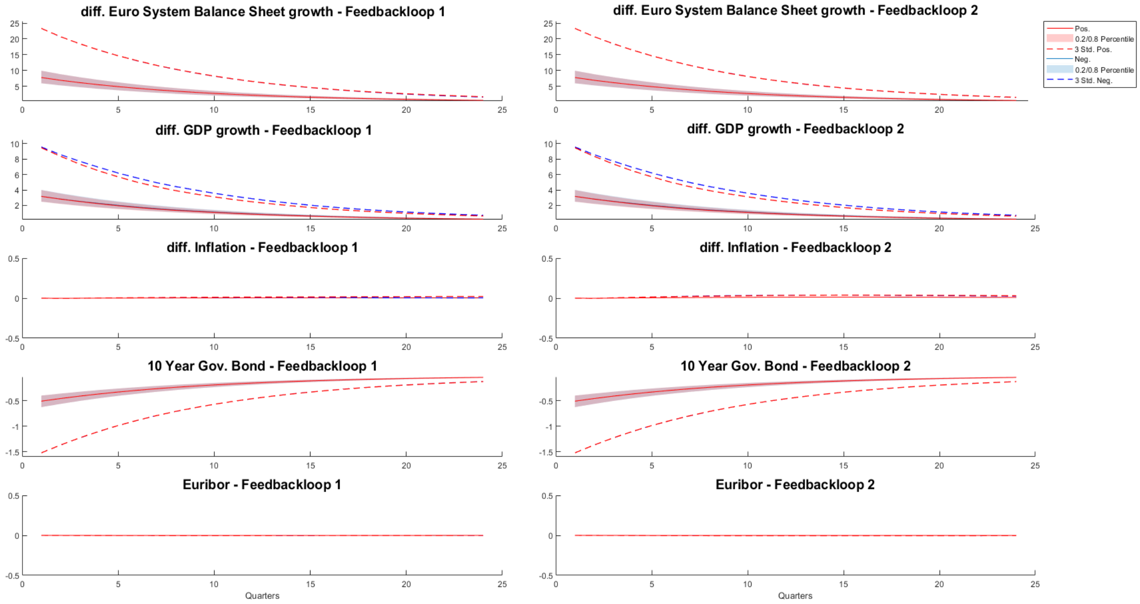
An unconventional accomodative monetary policy shock leads to an expansion of GDP and has a negligible impact on inflation. As is the case for a standard monetary policy shock, the response of GDP appears marginally stronger to a contractionary shock compared to an accomodative large magnitude shock.

The unsecured short-term interbank funding and lending interest rate respond gradually and relatively weakly. Unsecured funding costs go down by less than 1bp, while interest rates on lending double the magnitude.

Bank profitability and loan volumes also increase marginally with time. CET1 ratio remains relatively stable with the counterbalancing effects of asset expansion and improved profitability.

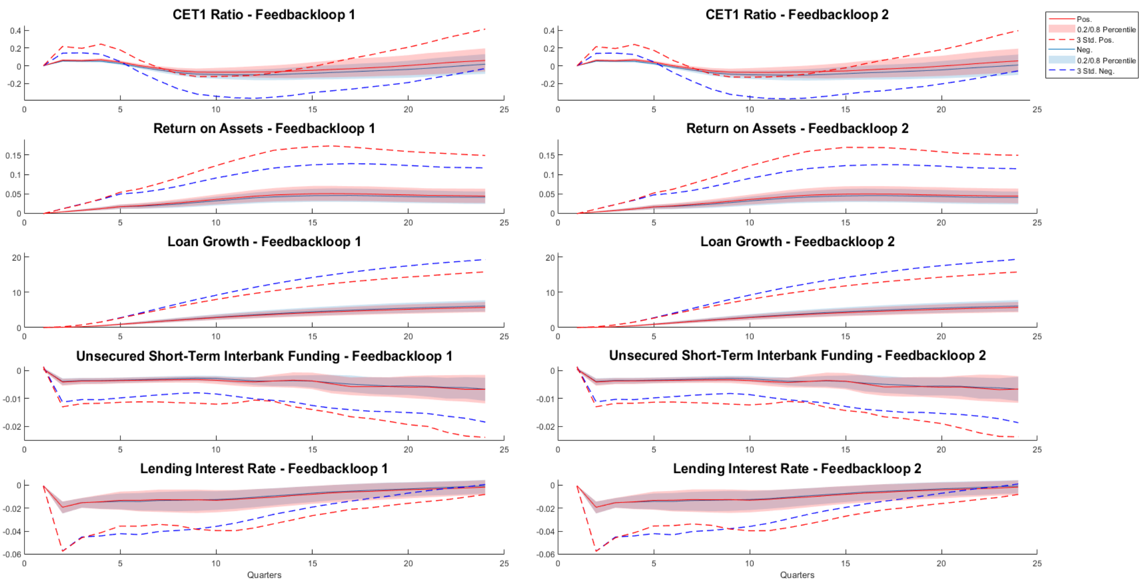
7.3 Heterogeneity of bank responses

One of the unique features of the BEAST is the combination of macroeconomic and bank-level dynamics. The model preserves substantial bank heterogeneity, and this heterogeneity matters for macrofinancial outcomes. Bank heterogeneity emerges in most of the model simulations, including those underlying IRFs in the previous section. This section constructs yet another example which emphasises the heterogeneity of the initial shock, along with the heterogeneity



Notes: Euro system balance sheet, GDP and HICP inflation are presented in annualised quarter-on-quarter percentage growth rate, 3-month EURIBOR, and 10-year government bond yields in percent. The red lines and areas illustrate a loosening of monetary policy, and the blue a tightening of monetary policy.

Figure 25: Impulse response functions of macroeconomic variables to a one-std. and a three-std. unconventional monetary policy shock



Notes: CET1 ratio, Return-on-Assets, interest rate on lending to the non-financial private sector, and unsecured short-term interbank funding rate are displayed in percent points, loan volumes to the non-financial private sector as percentage increase in the volume. The red lines and areas illustrate a loosening of monetary policy, and the blue a tightening of monetary policy.

Figure 26: Impulse response functions of aggregated banking variables to a one-std. and a three-std. unconventional monetary policy shock

of bank responses.

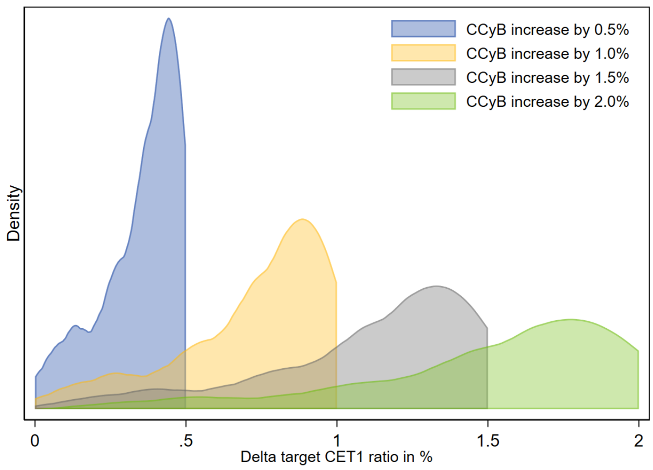
We consider a euro-area wide increase in CCyB buffers, by the same margin of 0.5, 1, 1.5 and 2 pp across jurisdictions. The impact on the bank-level CCyBs and the average bank-level CCyB is lower than the change in the country-level CCyBs rate due to the fact that a share of bank exposures is to non-euro-area jurisdictions. However, the change is proportional with a factor of proportionality of around 0.7; for an increase of 1 pp in euro area CCyBs the actual euro area regulatory target ratios increase by 0.7 pp (see Table 13).

An increase in CCyB leads to an increase in actual CET1 ratios and a moderate reduction in lending to the non-financial private sector. For an increase of 0.5 pp, the average increase in capital ratios over a 5-year horizon is 0.2 pp, while the reduction in lending to the non-financial private sector amounts to a moderate 0.6% in cumulative terms over a 5-year horizon (or 0.1% in annual terms). For an increase in CCyB of 2 pp, the average increase in capital ratios is 0.8 pp, and the reduction in lending 3.7% (0.7% annually). Importantly, the reduction in lending is proportionally stronger in response to more aggressive CCyB policies. For an increase of 0.5 pp in CCyB, the lending volume drops by 1.3% per 1 pp increase in CCyB. On the contrary, for an increase of 2 pp in CCyB, lending drop is amplified to 1.9% per 1 pp of increase in CCyB.

	Target CET1	CET1	Lending to NFPS
CCyB increase by 0.5 pp	0.3 pp	0.2 pp	-0.6%
CCyB increase by 1 pp	0.7 pp	0.4 pp	-1.5%
CCyB increase by 1.5 pp	1 pp	0.6 pp	-2.6%
CCyB increase by 2 pp	1.3 pp	0.8 pp	-3.7%

Table 13: System-wide results from an increase in CCyB in all euro area countries

The non-linear response of system-level CET1 ratio and lending to CCyB policy arises due to bank heterogeneity. The impact of CCyB changes on bank-level target capital ratios is diverse, depending on their share of exposures to euro area jurisdictions. Irrespective of the scale of an initial increase in CCyB, a share of banks is only marginally affected, and the higher the increase, the flatter the distribution of changes in the target CET1 capital ratio, indicating an increasing heterogeneity of impact (see Figure 27).

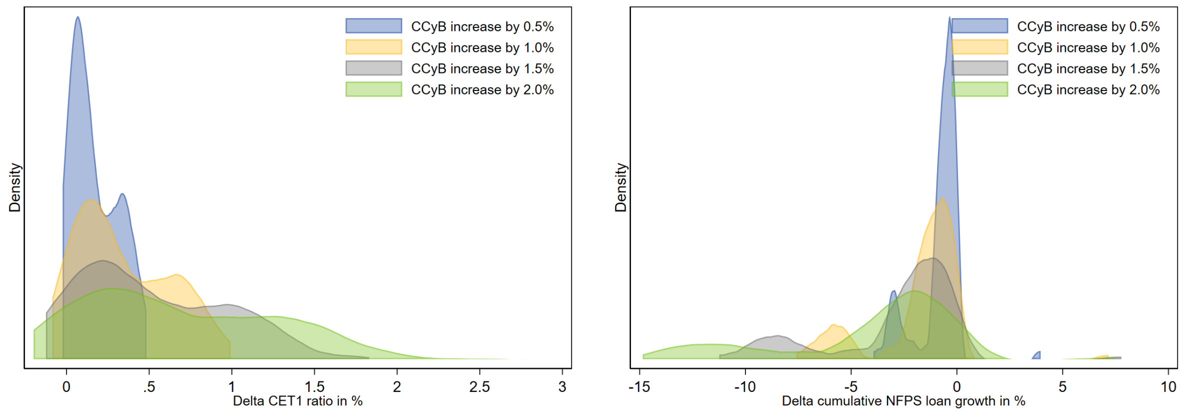


(a) CET1 ratio

Figure 27: Target regulatory CET1 ratio

The distribution of the impact on actual capital ratios is skewed to the left, with a substantial share of banks able to accommodate the policy change without substantial adjustments of their capital ratios (see Figure 28, left-hand side). The greater the increase in CCyB, the greater the share of banks that needs to substantially adapt their CET1 ratio, as reflected in the gradual flattening of the distribution. This heterogeneous response is a combination of the heterogeneous impact on target capital ratio, but foremost reflects different starting conditions (in terms of capital position but also profitability) of banks and their willingness to re-calibrate of management buffers.

The response in terms of lending is clearly bimodal. A share of banks responds very weakly, either being able to accommodate to changes in policy by adjusting their management buffer, or absorbing the increase in CCyB by retaining a higher share of profits. However, there is another, generally smaller group of banks that cuts lending substantially. These can be banks either particularly strongly affected, or with weak capitalisation and profitability, or with the balance sheet structure, which makes adjustment in lending easier, e.g. with a high share of short-term loans. Importantly for clarifying the non-linearity observed on the aggregate level, the stronger the change in CCyB policy, the higher the share of banks which adjust their lending substantially.



(a) CET1 ratio

(b) Loans to NFPS

Figure 28: CET1 ratio and lending volumes to the non-financial private sector (NFPS)

7.4 Forecasting performance

Many applications of the BEAST model are based on its ability to predict the evolution of the banking sector under specific macrofinancial conditions. One way to assess the quality of such predictions is to look at the forecast accuracy of the model. This section discusses the performance of model point forecasts and preliminary outcomes for interval forecasts.

The forecast evaluation relies on several forecast settings. The first, "in-sample" forecast looks at the predicted evolution of selected banking sector variables, namely the CET1 ratio, return on assets, ROA, and loans to the non-financial private sector, conditional on realised macrofinancial data. It speaks of the accuracy of the model in predicting banking sector information, netting out the confounding impact of (potential) inaccuracy of macrofinancial forecasts.

Two other settings allow us to assess forecast performance in close to out-of-sample conditions. They use the information available up to the reference date. The first setup takes on board the available 2 and a half to 3 year ahead ECB projections of macro-financial conditions.

This setup is closest to the most real life uses of the BEAST and shows how the model performs in such conditions; however, model performance can be tainted by any forecast error present already in macrofinancial ECB projections. The last setup includes model-specific forecasts of all endogenous variables, therein macrofinancial aggregates. Specific configurations are listed in Table 14, together with the main assumptions regarding the forward-looking banking regulation, feedback loop options, and interpretation.

The results in this section should be read recognising that they are based on relatively few observations and the period of evaluation has been plagued with numerous atypical events. The first historical data point in the model is 4Q 2017, and at the time of completing this article, the last is 3Q 2022. This results in less than 20 quarters of the available forecast evaluation periods (Table 15). We look both at 1 and 2 quarter ahead forecasts to learn about the model performance for a short-horizon window, and at 4 to 10 quarter ahead forecasts to learn about the model ability to predict the medium-run evolution of variables. The period of forecast evaluation includes sharp and largely unanticipated changes in economic activity, experiments with new policies put foreword during the COVID-19 pandemics, the outbreak of the Russian-Ukrainian war, and the phase-in of several new supervisory policies affecting the functioning of the euro area banking sector, e.g., the ECB NPL guidance.

	In-sample	Out-of-sample BMPE	Out-of-sample
How	Macro-financial variables correspond with actual data	Macro-financial conditions anchored at ECB economic projections	Model-specific forecasts of macro-financial variables
Regulation	Known a priori	Information up to the reference date	Information up to the reference date
Feedback loop	No banking sector real economy feedback loop	Feedback loop 1 or 2	Feedback loop 1 or 2
Interpretation	How well the model predicts banking sector aggregates given the information about the macro environment and changes in regulation?	How well does the model perform in real-life exercises?	How well does the model perform in conditions closest to out-of-sample setup?

Table 14: Forecast types and model settings

Horizon	1Q	2Q	4Q	6Q	8Q	10Q	Total
Observations	19	18	16	14	12	10	89

Table 15: Available observations per reference quarter

7.4.1 Point forecast metrics

We will rely on the two most common metrics to assess the model's point-prediction accuracy. For a point forecast $\hat{y}_{n+h}$ of the variable y_{n+h}, where n refers to the index of the reference quarter (the time at which the model starts simulating) and h the forecast horizon, we will first look at the root mean squared error ($RMSE$):

$$RMSE(h) = \sqrt{\frac{\sum_{n=0}^{N-h}(\hat{y}_{n+h} - y_{n+h})^2}{(N-h+1)}} \tag{322}$$

where N refers to the number of available reference quarters, and the statistic is calculated for horizons $h = \{1, 2, 4, 6, 8, 10\}$.

Although the RMSE is not interpretable directly, larger forecast errors will result in larger RMSE statistics. RMSE can be better evaluated compared to a naive benchmark provided by a random walk forecast of $\hat{y}_{n+h} = y_n$ (meaning that a naive forecast of any variable is equal to its last observed value). Effectively, the h-step ahead RMSE of a particular setup Θ (in-sample, out-of-sample BMPE, out-of-sample) of the BEAST is compared to the h-step ahead RMSE of the naive forecast as follows:

$$rRMSE(h) = \frac{RMSE(\Theta, h)}{RMSE(naive, h)} \tag{323}$$

If lower than 1, the relative RMSE (*rRMSE*) metric stipulates that the forecast error of the model is lower than that of a naive forecast.

The mean forecast error for the h-step ahead forecast error is:

$$ME(h) = \frac{\sum_{n=0}^{N-h}(\hat{y}_{n+h} - y_{n+h})}{(N-h+1)} \tag{324}$$

The mean of forecast errors is used to determine if predictions are biased compared to the true realisations, i.e., by how much, on average, a forecast deviates from the true realisation.

7.4.2 Point forecast error

The BEAST-based in-sample forecast of banking sector variables consistently outperforms their naive forecasts. Figure 29 summarises the RMSE ratios for the CET1 ratio, ROA, and lending for the in-sample, conditional, and unconditional out-of-sample forecasts. The in-sample *rRMSE* lower than 1 for all variables and most horizons. The model performs particularly well on the medium-term horizon, along with the expected relative strength of semi-structural models (see Kichian et al. [2010]).

The quality of the out-of-sample forecast is lower, as it reflects to a greater extent the forecasting problems in a highly dynamic environment. The forecast quality for *ROA* and loans to the non-financial private sector remains good, and most of the time better than that of a naive forecast (at least for the BMPE-based forecast). However, for the CET1 ratio, it deteriorates significantly the longer the underlying forecast horizon. For the aggregate CET1 ratio, the model does not perform systematically better than a simple random-walk forecast. Banks' CET1 ratios remained relatively stable during the evaluation period, which favours the naive forecasts.

The gap between the performance of the forecasts in- and out-of- sample evidences the role of COVID-19 disruptions and policies. The forecasting performance of the model is high as long as the forecast reflect full information about the magnitude of extraordinary shocks and the final calibration of public guarantees or supervisory policies like the dividend payout restrictions introduced during the pandemic. It degenerates in the absence of this information, reflecting the high macroeconomic uncertainty of the COVID-19 episode.

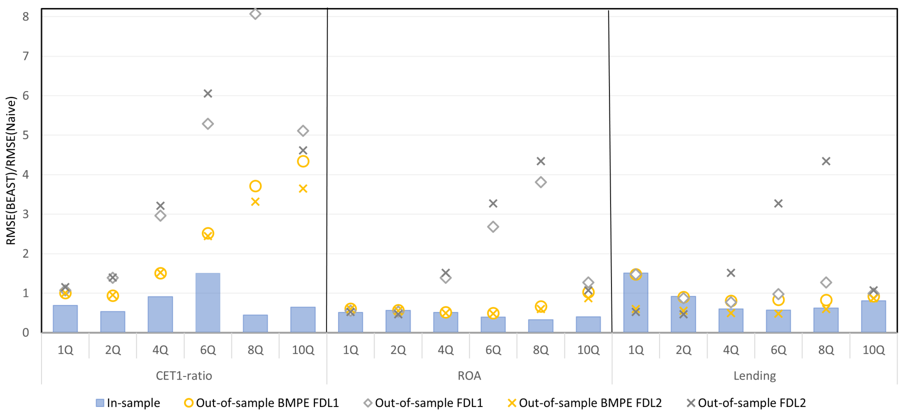


Figure 29: Root mean squared error of BEAST projections versus naive forecast: banking variables

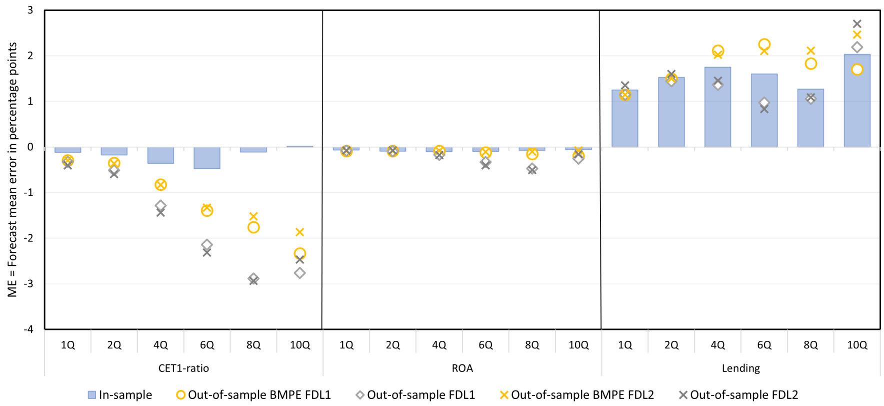


Figure 30: Mean forecast error of BEAST projections: banking variables

The mean forecast error statistics confirm the robust performance of BEAST in predicting banking sector variables once macrofinancial conditions are known. The in-sample statistics reveal a minimal negative bias present in the CET1 ratio and ROA forecasts, and a more substantial (around 1 pp) positive bias in forecasts of year-on-year lending volumes to the non-financial private sector. The out-of-sample forecasts are again performing worse, especially for the CET1 ratio. Out-of-sample forecasts of the CET1 ratio during and after the COVID-19 pandemics reflect that, as seen ex post, much of the deterioration of macrofinancial conditions during the pandemic had no significant impact on the banking sector, due to decisive and timely policy responses. This explains why the model predicts on average lower bank solvency.

7.4.3 Forecast interval metrics

The point forecast accuracy metrics are relatively easy to compute and understandable, and they are typically able to guide further actions by the forecast user (Christoffersen [1998]). However, since the BEAST model is also used to generate stochastic distributions of variables, one may be interested in measuring the quality of its interval forecasts. However, it should be kept in mind that the corresponding evaluation is even more negatively affected by the small and atypical evaluation sample than the evaluation of point forecasts.

In order to assess the accuracy of the interval forecast, we compare the share of actual values outside the forecast interval relative to their predicted share. For any variable y_t, $L_{n+h|n+h-1}(p)$

and $U_{n+h|n+h-1}(p)$ are, respectively, the lower and upper limits of the interval forecast at time $n+h$ made at time $n+h-1$ for coverage p. Let I_t be an indicator variable defined as:

$$I_{n+h} = \begin{cases} 1 & \text{if } y_{n+h} \in [(L_{n+h|n+h-1}(p), U_{n+h|n+h-1}(p))] \\ 0 & \text{if } y_{n+h} \notin [(L_{n+h|n+h-1}(p), U_{n+h|n+h-1}(p))] \end{cases} \tag{325}$$

In other words, I_t is 1 for any true realisation that lies within the interval and 0 if it lies outside it.

Assuming that the model perfectly replicates the true distribution of the variables under consideration, one would expect that a 95% confidence interval contains 95% of the realisations, while a 5% confidence interval covers 5% of the realisations. On the contrary, a 50% forecast interval that contains 90% of the realisations (more than it is expected to contain) is termed permissive, while a 50% forecast interval that contains 10% of the realisations (less than expected) is termed conservative.

Figure 31 illustrates the construction of figures that summarise the properties of interval forecasts. On the left side, there is a normally distributed true forecast density with mean 0 and standard deviation 0.5, and a normally distributed prediction forecast density with mean 0 and standard deviation 0.25. The yellow scatters represent stylised observations sampled from the true forecast density. For $p = 0.68$ on the right side, the predicted 68% forecast interval is narrower than the true 68% forecast interval. Collecting similar information for the entire range of p results in a curve bent towards the lower right side of the plot. It shows that for any coverage probability, the prediction forecast interval is more conservative, i.e. the actual share of realisations in each interval is lower than the theoretical coverage probability.

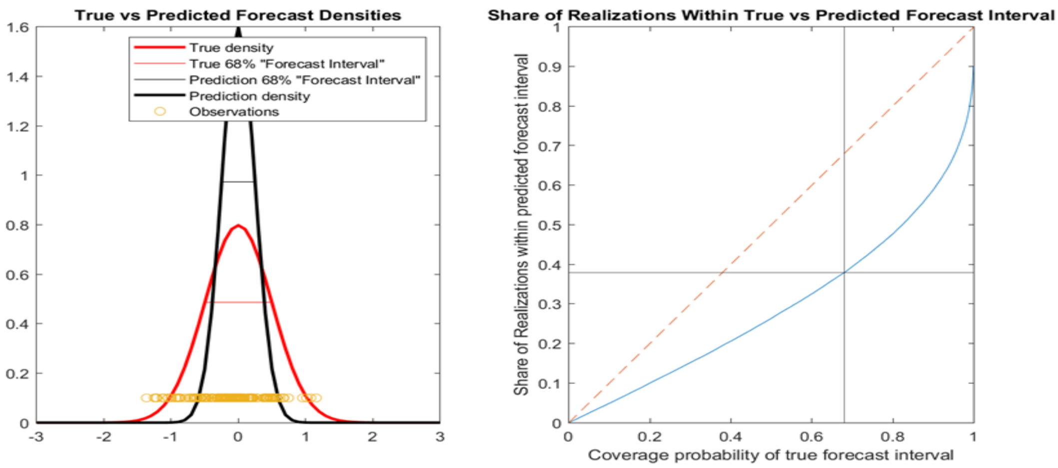


Figure 31: Two-sided interval forecast assessment - illustration

7.4.3.1 Two-sided interval forecast assessment

Figures 32 and 33 summarise the assessment of interval forecast for the euro-area CET1 ratio and loans to the non-financial private sector, respectively. Out-of-sample forecasts are derived around the ECB projection or unconditionally, using parametric sampling methods as in Section 6.3.1. Each forecast horizon, $h = \{1, 2, 4, 6, 8, 10\}$, is captured by a line. Because the consequences of a small evaluation sample become even more pronounced in the interval assessment, the figures also include the average over every $h-$step ahead forecast performance, denoted as full results.

For the CET1 ratio, the out-of-sample BEAST tends to produce conservative interval forecasts. The BEAST forecast intervals have smaller variance than the theoretical ones, given that most of the individual quarter-forward intervals lie more closely towards the lower right of the plots. More specifically, the full result shows that the spread of the forecast interval does not evolve as quickly as the confidence level, meaning that at higher confidence levels, the forecast interval will increasingly miss more realisations, which should have been included. On the contrary, the naive random walk forecast of the CET1 ratio (which has unlimited variance) would be very permissive, nesting most of the actual realisations, but compromising forecast accuracy.

Analogously, for year-on-year lending growth, only around 40% of the true realisations lie within the model's forecast interval with 100% confidence level. In contrast, the random walk forecast of the annual growth density with variance increasing over time is somewhat counterintuitively performing very well capturing loan volume realisations.

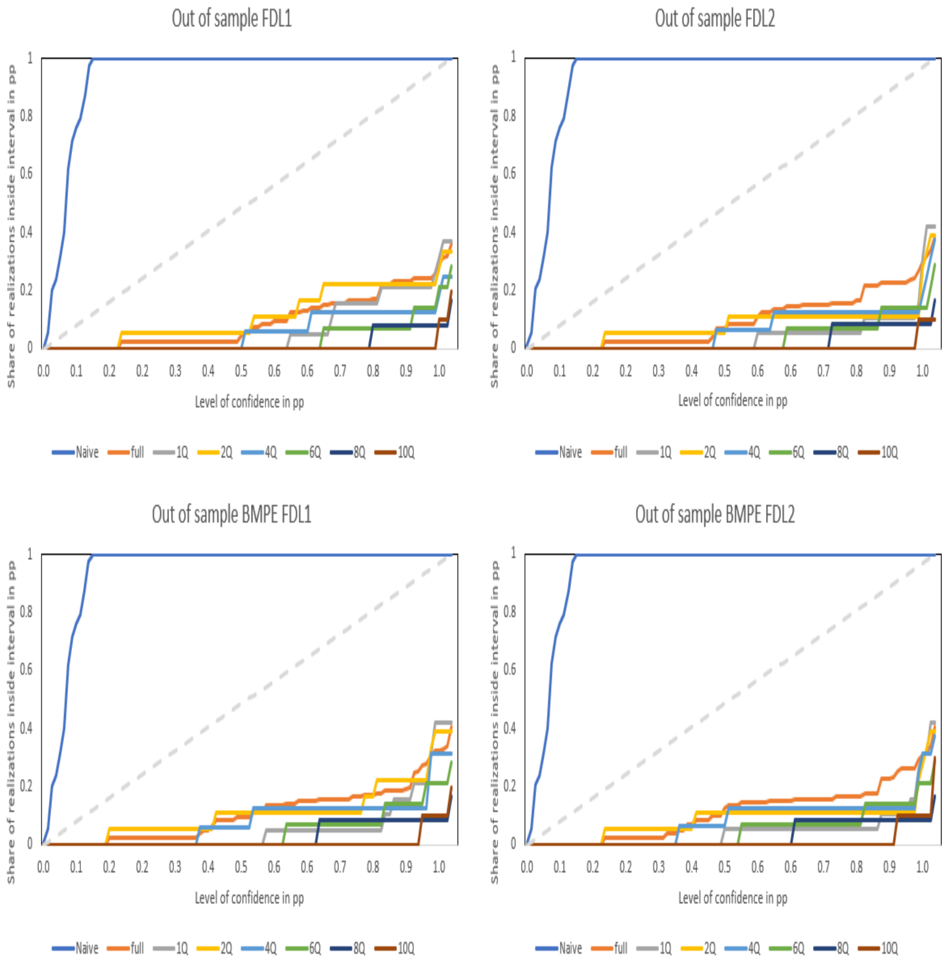


Figure 32: Two-sided interval forecast assessment - CET1-ratio

These results change only slightly between the feedback loop specifications and conditional versus unconditional out-of-sample forecasts. They substantiate that the model, as well as the official ECB projections, struggled to accurately forecast the future macrofinancial dynamics in very unstable times starting from the COVID-19 pandemics. However, the model point forecast accuracy based on the known macrofinancial environment has remained robust.

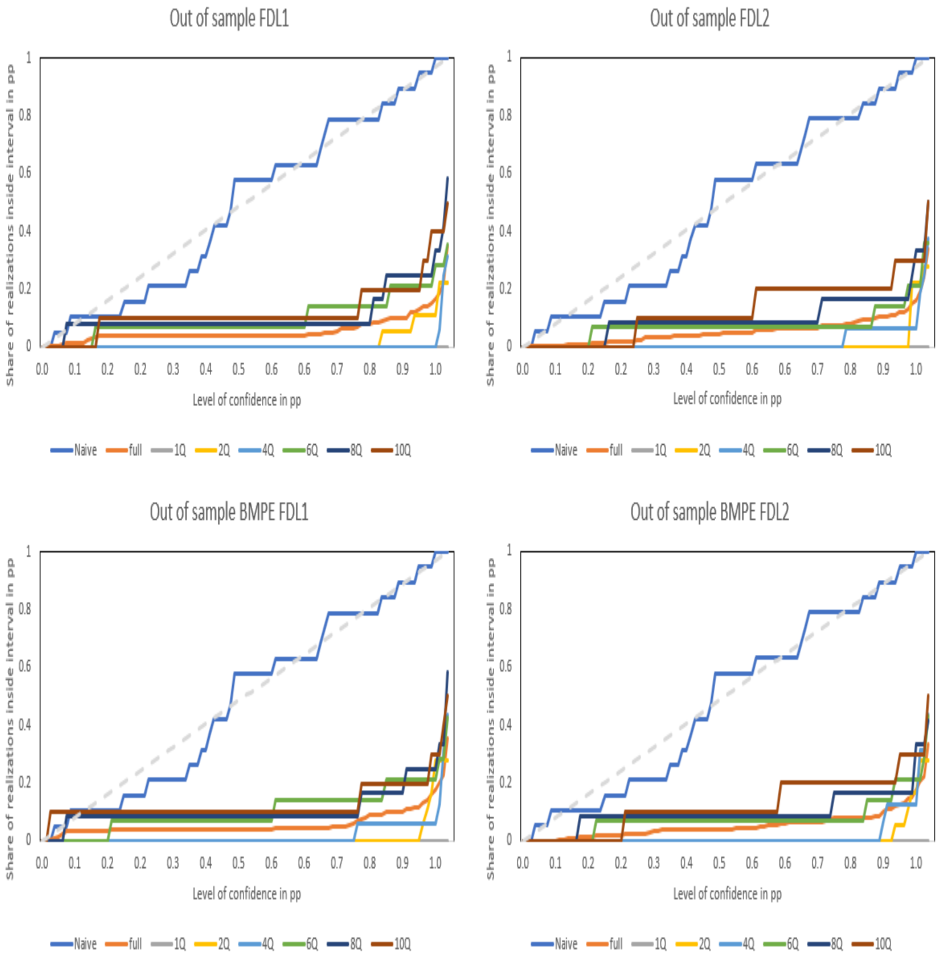


Figure 33: Two-sided interval forecast assessment - Lending growth (NFPS)

7.5 Modeling strategy

Building, updating or extending a large semi-structural model, with thousands of equations derived separately but solved jointly, requires a systematic approach to model development. Such a modelling and integration strategy is an essential element, which ensures the reliability and overall robustness of the final model. It also ensures that the results of the model are reproducible, that its properties are well understood, and that all parts of the model are meaningfully interconnected.

The BEAST modelling strategy has been developed gradually and tested over time. Today, it serves as a road map that outlines a sequence of well-defined steps used to incorporate or replace various components of the model, including data updates and biannual re-calibrations related to the availability of the EBA/SSM stress test results. Furthermore, since the development of such a model is a collaborative endeavour involving multiple team members, a well-defined modelling and integration strategy plays a crucial role in enhancing coherence and coordination among the team. By providing a common framework and guidelines, it helps streamline efforts and facilitates seamless integration of different, often developed in parallel, work elements.

The modelling and integration strategy is structured into four distinct but interconnected stages, each serving a specific purpose in the model development process:

1. Outside model quality checks

2. Stand-alone testing in a model block
3. Full model integration and checks
4. Economic evaluation

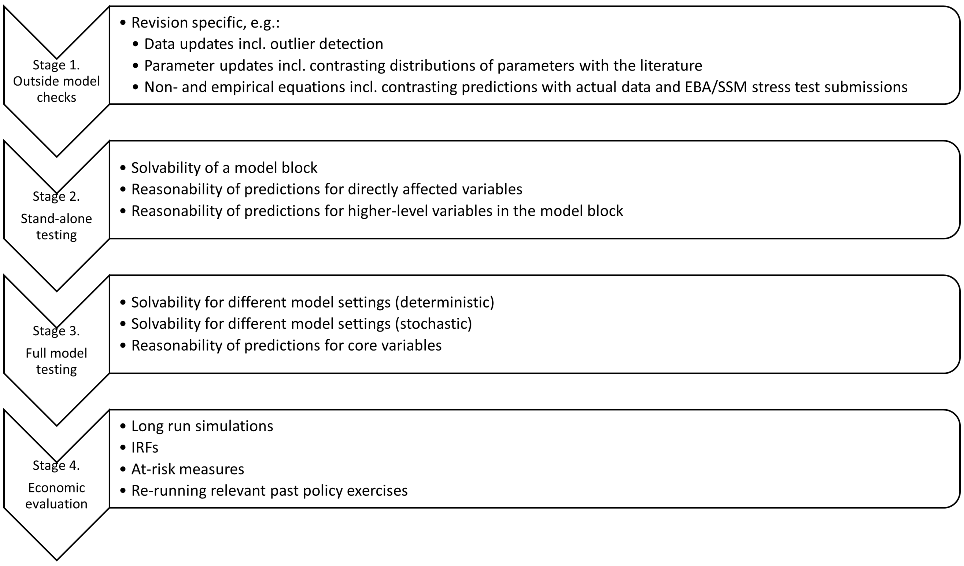


Figure 34: Modeling and integration strategy

The testing and evaluation processes are automated to a great extent, which reduces the resource implications of the process. A dedicated platform has been developed to produce statistics and comparisons involved in stages 2 through 4 and offer comprehensive summary reports to model developers. Some elements of stage 1, especially biannual on-boarding of new stress test data and quarterly on-boarding of supervisory reporting data, have also been substantially automated.

7.5.1 Outside model quality checks

The outside model quality checks are specific to the planned model change. In practise, these changes can concern:

- Starting point data updates
- Recalibration of existing parameters
- Updating or adding non-empirical formulas
- Updating or adding empirical equations

For data or calibrated parameters updates, quality checks would involve assessing the plausibility of variable or parameter values, for example, by inspecting their distributions, seeking outliers, contrasting them with the information in the related literature or available from experts. For new estimated equations, the first checks involve standard regression quality criteria, such as in-sample data fit, tailored econometric diagnostics for e.g. panel regression estimates, evaluating the dynamic properties of the equation (its long-run stability as implied by coefficient estimates) and its ability to replicate cross-sectional heterogeneity. For new empirical and non-empirical equations alike, the relevant aspect is their ex ante consistency with the economic literature and the remaining model parts.

The crucial part of outside model quality checks is the ability of new equations, parameters, or starting point data to deliver projections that match either or both of:

- The relevant bank submissions in the most recent EBA/SSM stress test in the baseline and adverse scenarios[105]
- Actual data realisations

To this end, the candidate model element is used to project selected endogenous model variables for a 3-year horizon conditional on the baseline and adverse scenarios of the last EBA/SSM stress test. For example, the performance of the new candidate equation for the transition probability matrix in equation (30) would be compared with respect to its dynamic and cross-sectional performance against bank submissions of transition rates (as in the first bullet) and additionally against selected information on default rates from supervisory reporting or Anacredit (the second bullet). The new candidate equation for e.g. lending volumes (equation (12)) or write-off rates (equation (34)), whose projected variables not available in banks' submissions, would be tested against the most actual data on lending from the supervisory reporting, individual Balance Sheet Items statistics, and challenged on the basis of expert knowledge and supplementary datasets such as Bank Lending Survey. The new data on the starting point for the lending volumes would be used jointly with the existing lending equation (12) to build projections later compared with the same actual lending data as would be the case for the new lending equation.

7.5.2 Stand-alone testing in a model block

In the second stage, the new elements are fully incorporated into the model structure and linked to other model variables and mechanisms. However, the tests are run only with the use of the most relevant model block. For instance, for transition and write-off rates, it is a loan-loss provisioning module as in Section 4.1.4, for new lending starting point data or equations, it is a block of loan volume dynamics and loan-loss provisioning jointly, that is, approximately equations in Sections 4.1.2 and 4.1.4. All other model blocks would be exogenized i.e. effectively replaced by stable projections or actual data of corresponding variables. Consequently, for banking sector changes the tests are run with known macrofinancial scenarios and bank-level variables not directly affected by the model change, and for macroeconomic module changes, with known and stable bank-level variables.

The role of this step is to understand the properties of the new model element in a real-life setting but excluding feedback mechanisms. It also concerns the ability of the new model parts to produce reasonable results. This step consists of checking:

- Solvability and the absence of numerical issues
- Reasonability and stability of the predictions of directly affected variables
- Reasonability and stability of the predictions of other and higher-level variables

The first criterion entails that the new, modified, or augmented model blocks must allow to be solved for any scenario horizon and (if applicable) under varying assumptions regarding the

[105]When possible these checks are also extended to past EBA/SSM stress test submissions and scenarios.

exact specification of the model block. The solvability can be disrupted due to numerical issues, such as division by zero or by values very close to zero, as well as coding errors.

Reasonability and stability criteria involve checking whether the variables directly or indirectly affected by the candidate model change remain in the relevant range, have stable dynamics, and produce economically reasonable results in the horizon of 5-10 years. For example, for transition and write-off rates, the projected variables must remain between zero and one and, at best, within their historical ranges and show no long-term upward or downward bias. Modification of transition and write-off rates equations should also guarantee stable dynamics of the banking sector and bank-level loan loss provisions.

The economic viability of the projections of directly and indirectly affected variables is once again assessed by exploring the last submissions to the EBA/SSM stress test for baseline and adverse scenarios, along with the available information on the actual realisations of the variables of interest.

7.5.3 Full model integration and checks

In the third stage, newly developed model parts are tested within the entire model structure. This is an indispensable step as it aims to evaluate the model's performance in a holistic and interconnected setting. This step focuses foremost on technical and numerical aspects; therein:

- Solvability and the absence of numerical issues for different model settings in a deterministic setup
- Solvability and the absence of numerical issues for different model settings in a stochastic setup with parameter and scenario uncertainty
- Reasonability of the predictions of core variables for different model settings in a deterministic setup

The criteria validated in this stage are similar to those applied in the earlier step, with the emphasis on testing the ability to run the model with its different options and in the horizon of 5-10 years. These options concern the use of different model versions, such as including or excluding the NPL coverage expectations, or different specification of the real economy - banking sector feedback loop, with different stochastic settings, such as with and without parameter uncertainty, applying parametric simulation or bootstrapping to scenario generation. For stochastic options, we additionally observe the speed of the solution and the number of simulations discarded either due to numerical issues or in the pruning process.

The reasonability of model predictions is tested mostly for macrofinancial variables, CET1 ratios, lending to the non-financial private sector, bank profitability and its main subcomponents, risk weights, and risk weighted assets. We also compare how model predictions change between different model settings, especially with and without the application of the real economy - banking sector and solvency - funding costs feedback loops.

7.5.4 Economic evaluation

This stage involves comprehensive checks of simulations from the full model and comparing them to the analogous simulations from the existing model without modification. This is the ultimate check of the model properties after a change, allowing a comprehensive understanding of its behaviour under real-life conditions. The criteria applied include the following:

- Long-term properties for core model variables as in Section 7.1
- Impulse response functions to preselected structural shocks (aggregate demand, supply, equity and real estate prices, government bond risk premium and two monetary policy shocks) as in Section 7.2
- At-risk measures for core model variables as in Section 6.4
- Replicating past policy exercises (see Section 8 for selected examples)

The last criterion involves replicating and comparing the results of two to three policy exercises. The exact selection of the policy exercises evolves over time (usually we return to most recent ones) and is adapted to the character of model change (we return to exercises that revealed related model weaknesses). However, at least one of the selected exercises must involve stochastic simulations and one must bring to forefront bank heterogeneity, either because it is at the core of the research question or because it has a substantial impact on the final results and their interpretation. While replicating the past policy exercises, we investigate whether the problem areas detected in the model were addressed appropriately and we evaluate qualitatively the model's forecasting performance.

8 Applications

The initial motivation for developing the BEAST model has been macroprudential stress testing. There was a need for a complementary approach to stress testing that could support the assessment of macrofinancial risks and adhere to the new ECB mandate. From the very beginning, BEAST marked a change in the macroprudential stress test philosophy. It included individual and heterogeneous banks but otherwise mimicked the logic of semi-structural models used by many central banks for inflation forecasting. It has relied on the simultaneous solution of economy-wide and bank-level equations, and as such it could capture the simultaneous nature of feedback loops and facilitated the use of conditional simulations. The model was an important ingredient that facilitated the shift toward a broader use of macroprudential stress test toolbox in the bank to:

- Provide a complementary metrics of the resilience of the banking sector (risk assessment)
- Evaluate and increase awareness of potential coordination failures in the banking sector and the economy (communication)
- Support the assessment of appropriateness and the calibration of macroprudential policy measures (policy evaluation)

The model has been put to risk assessment applications for five consecutive years, with a special role taken by the regular macroprudential stress test repeated in 2018, 2020 and 2021. The results of the macroprudential stress test could be read separately, as the assessment of system-wide resilience, or in tandem with the supervisory EU-wide stress test, as complementary metrics or additional validation.

In intermittent years, without an EU-wide stress test, the model served to provide a standalone risk assessment, often by employing the native scenario selection method (discussed in Section 6.5). For instance, in 2022, following the invasion of Ukraine and the turbulence in the energy markets, the model has been used to assess the impact on the banking sector of the most recent macroeconomic projections (June 2022) and a scenario with even higher gas prices, stronger interruption of trade links, and lower consumer and corporate confidence. Beyond that, the model has been well placed to provide topical risk assessments, such as the first climate stress test in 2020 or the sensitivity analysis to interest rate risks in 2022.

The model results on occasions entered the ECB communication and supported its policy stance. An example of such a model use is the communication by Enria [2020] encouraging banks to use available buffers to expand, or prevent contraction of, lending at the onset of the COVID-19 pandemics in 2020. The simulations of the model illustrated how buffer use and the overcoming of coordination failures can ward off the emergence of adverse amplification mechanisms in the banking sector and the economy.

Lastly, the model has been used extensively for analysing the impact assessment of regulatory, supervisory, or macroprudential policies applying various forms of ex ante cost benefit analysis of capital-based policies. The most demanding model application concerned the impact evaluation of the finalisation of Basel III reform. In contrast to the initial stage of Basel III reform, which involved mostly an increase in capital requirements compared to risk-weighted assets of banks, its finalisation is an intricate package aimed at increasing the comparability of risk-weighting practises across banks. It introduces multiple adjustments of risk weights on bank exposures and an occasionally binding output floor (a benchmark measure for risk-weighted assets based on a standardised approach). The high level of detail of the model allowed for a comprehensive and truthful evaluation of the package.

Risk assessment		
Macroprudential stress test 2018	Prepared on the back of the 2018 EBA/SSM EU-wide stress test, employing the dynamic balance sheet perspective and introducing the real economy-banking sector feedback loop.	Published as Budnik et al. [2019] and Budnik [2019]
Baseline and adverse scenario analysis 2019 in the Financial Stability Review	A stand-alone scenario analysis 2019 employing September 2020 ECB staff projections as a baseline and native adverse scenario selection method to reflect conjectural risks.	Published as ECB [2019]
Macroprudential stress test 2020	Prepared on the back of the 2020 SSM Vulnerability Analysis with model enriched with the solvency-funding costs feedback loop, taking account for COVID-19 mitigation policies and NPL coverage expectations.	Published in Budnik et al. [2021a]
Pilot macroprudential climate stress test 2020	The first ECB approach to model the impact of climate transition policies on the banking sector.	Published in ESRB [2020], see also Budnik et al. [2022b]
Macroprudential stress test 2021	Prepared on the back of the 2021 EBA/SSM EU-wide stress test, with the model featuring improved modelling of non-standard monetary policy transmission mechanisms.	Published as Budnik et al. [2021a], see also Budnik and Groß [2021]
Baseline and adverse scenario analysis 2022	A stand-alone adverse scenario analysis employing June 2022 ECB staff projections and native scenario selection method to reflect risks stemming from the Russian invasion on Ukraine.	-
Regular assessment of the macro at risk in support of monetary policy process	Quarterly evaluation of the growth-at-risk and inflation-at-risk 1-3 year ahead forecasts to assess changes in financial stability.	-
Interest rate sensitivity analysis 2022	Assessing the impact on the banking sector of the two interest rate scenarios, implying a parallel shift of the euro area yield curve or its steepening.	Budnik et al. [2022d]
Communication		
SSM communication on buffer use	Communication in support of the use of existing buffers by banks employing and comparing counterfactuals with and without buffer use.	Enria [2020], see also Borsuk et al. [2020]
Policy assessment		
Impact assessment of Basel III finalisation 2019	Applying growth-at-risk perspective to assess costs and benefits of the reforms.	Budnik et al. [2021b], see also: EBA [2019]
Impact assessment of Basel III finalisation 2021	Extending the costs and benefits assessment from 2019 to look at different designs of Basel III reforms.	Budnik et al. [2021d], see also: EBA [2021a]
Impact assessment of COVID-19 mitigation measures for the banking system	The impact of supervisory, macroprudential, public moratoria and guarantee policies introduced in response to the COVID-19 pandemic in the banking sector and real economy in three scenarios differing in the depth and duration of the recession.	Budnik et al. [2021c]
Impact assessment of the NPL coverage expectations	The impact assessment of the SSM coverage expectations for new and legacy NPLs on the banking sector and real economy.	Budnik et al. [2022c]
Exploring macroprudential policy space	The impact assessment of the releasability of capital conservation buffer at the instance of a future deep recession.	ECB [2022b]
Measuring macroprudential policy stance	Evaluation of the evolution of macroprudential stance, i.e. the balance between financial stability risks and calibration of macroprudential instruments over time.	Budnik et al. [2022a]
Assessing costs and benefits of capital buffer policies	The cost and benefits assessment of different calibration of CCyB and sectoral SyRB buffers in support of related policy discussions.	Examples in Budnik et al. [2022b]

Table 17: Overview of Macroprudential stress test and related analysis

At least two novel approaches to assess the cost and benefits of capital regulation have been developed within the BEAST setup. The costs of capital regulation have been always assessed by comparing the expected outcomes, e.g., growth rate of the EU or euro area economy, following the introduction of the policy package with the expected outcomes in the absence of the change. However, the approach to benefit measurement has been tailored to the case of structural changes, where capital regulation can include automatic stabilisers but, as a rule, is not subject to discretionary adjustments, and to the case of discretionary adjusted policies, such as cyclically recalibrated buffers.

The benefits of the Basel III finalisation have been based on the growth-at-risk-based measurement. They have been derived by comparing the lower percentile of the EU or euro area economy, following the introduction of the policy package, with the corresponding percentile in the absence of the change. The shift in the lower percentile of the growth distribution upward signified higher economic resilience, i.e., lower likelihood of very deep recessions. The idea of measuring the impact of policies on economic resilience by looking at the lower percentage of growth distribution has also been used to measure the benefits of NPL policies or changes in macroprudential stance.

An alternative approach to assess the benefits of capital regulation has been applied to releasable buffers. Such buffers are built in good times to be released to support bank lending in dire economic conditions. The benefits of building such buffers have been linked to the expected increase in output or lending during a stylised future economic recession that follows after a buffer is built. The advantage of the approach is the ability to tune the economic recession scenario to the specificity of a buffer, e.g., emphasise the contraction in house prices when assessing the impact of the release of a sectoral SyRB, or its extraordinary depth and correlation across countries, for the possible release of the conservation buffer.

Importantly, model development has always been intertwined with model use, and policy needs guide the choice of its development priorities. As such, model development has been a cumulative process in which each new application benefited from model extensions or improvements undertaken in support of its earlier use. For instance, the first application of the model to the impact assessment of policies, namely Basel III finalisation, pushed its development toward including more comprehensive representation of capital charges and liabilities, including the introduction of the funding costs – solvency feedback loop. These changes entered the macroprudential stress test in 2020, improving with exercise in 2018. The need to accommodate multiple policy adjustments during COVID-19 pandemic in the same stress test exercise resulted in a better preparation of the model to answer questions of the monetary policy domain.

8.1 Macroprudential stress testing

The regular application of BEAST is the biennial ECB macroprudential stress test carried out on the back of the EBA/SSM European Union (EU)-wide stress test[106] of the banking sector. The EU-wide stress test assesses the resilience of EU banks to a common set of adverse financial and economic shocks with the aim of informing supervisory decisions and increasing market discipline. It follows a constrained bottom-up approach which requires each participating bank to (independently) estimate the evolution of a common set of risks (credit, market, counter-

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

party, and operational risk) under the common baseline and a hypothetical adverse scenario.[107] To maximise the prudence of the exercise, the EBA/SSM stress test is carried out under the assumption of a static balance sheet.

In the macroprudential stress test exercise, the focus has routinely been on analysing the impact of the baseline and adverse scenario as used in the EBA/SSM EU-wide stress test (or in the SSM Vulnerability Analysis in 2020), while loosening the constraints embedded in the latter. It (i) relaxes the assumption of the constant balance sheet in order to study dynamic adjustments of banks' loans and liability structure, (ii) accounts for amplification mechanisms therein the feedback loop between the real economy and the banking sector, and (iii) removes a number of other assumptions such as zero write-offs or recovery rates, or various methodological caps and floors. By relaxing these constraints, the results of the macroprudential stress test enhance our understanding of how adverse conditions spread through the banking system and increase our awareness of systemic risks that can arise in the case of adverse macroeconomic developments. Furthermore, the macroprudential stress test assesses the resilience of the banking system as a whole and with assumptions that can be read as more realistic than those in the EBA/SSM stress test.

In the following, we review the three macroprudential stress test exercises based on the BEAST model from 2018, 2020 and 2021.[108] In addition, we discuss the evolution of the macroprudential stress test over time and, using the example of the last 2021 macroprudential stress test, we illustrate some systematic differences in the outcomes of a supervisory constant balance sheet and a macroprudential stress test.

8.1.1 Complementary assessment of bank solvency

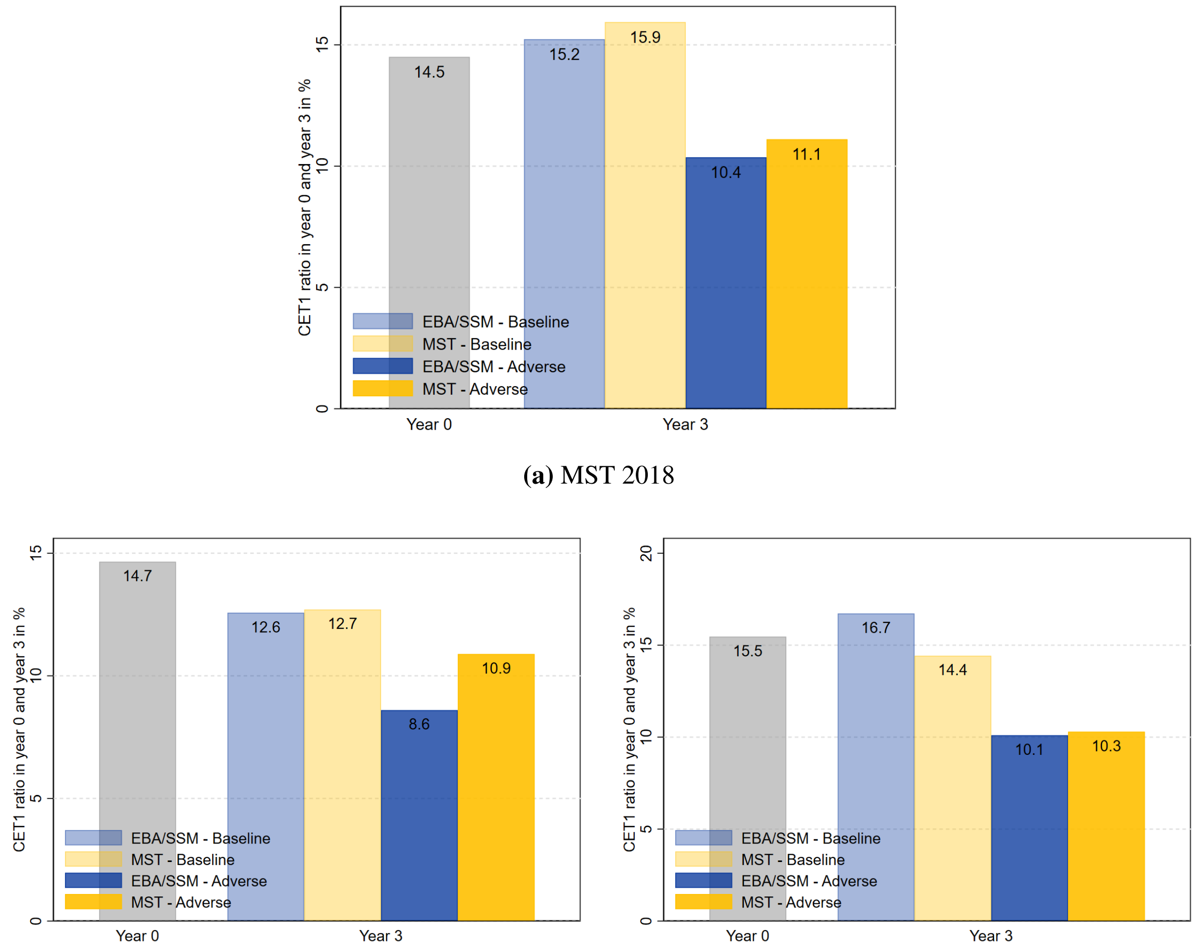
The ECB macroprudential stress test provides a complementary assessment of the evolution of the supervisory main result, i.e., banks' solvency. Figure 35 contrasts the transitional euro area CET1 ratio from the macroprudential ("MST") and EBA/SSM ("EBA/SSM") stress tests for the two scenarios ("Baseline" and "Adverse").[109]

There is no clear pattern of differences for baseline scenarios between the starting point and end-horizon CET1 ratio in the supervisory and macroprudential stress test. However, these stress test year-specific differences can reveal interesting information. The CET1 end-horizon ratio is above the starting point for both 2018 stress test exercises, reflecting the prolonged economic expansion in the 2018 baseline scenario, which translated into sound bank profitability. The system-level CET1 capital ratio decreases sharply in the baseline scenario in the 2020 stress tests, this time reflecting a large drop in economic activity in the first year of the scenario. This drop occurred on the back of measures imposed to counteract the spread of the COVID-19 pandemic and resulted in a pessimistic outlook of profitability. In the 2021 baseline scenario, a prolonged economic expansion again translated into good bank profitability. However, the

[107] The baseline stress test scenario corresponds to the most likely evolution of macro-financial environment to materialise, i.e., a forecast and is based on the latest Eurosystem staff macroeconomic projections. The adverse stress test scenario embeds the materialisation of risks to which the European Union (EU) banking system is assessed to be exposed at the time, reflecting the occurrence of a plausible, yet hypothetical low probability - tail - event. It draws on the main risks of financial stability for the EU banking sector identified by the General Board of the European Systemic Risk Board (ESRB).

[108] For more detailed description of the results please see Budnik et al. [2019] and Budnik [2019] for the macroprudential stress test 2018, and Budnik et al. [2021a] for macroprudential stress tests 2020 and 2021.

[109] Please note that the differences in solvency outcomes between supervisory and macroprudential stress tests over time cannot be solely attributed to the differences in main assumptions and underlying macrofinancial scenarios. In addition, they can be driven by a multitude of other factors related to the enhancements of the process or model and changes in the size and structure of the bank sample.



(a) MST 2018

(b) MST 2020

(c) MST 2021

Notes: The grey bars illustrate the system-wide CET1 capital ratio at the start of the stress test (i.e., the starting point). The blue and yellow bars reflect the projected system-wide CET1 capital ratio of the EBA/SSM stress test and the macroprudential stress test, respectively. The lighter-shaded blue and yellow bars depict the projected system-wide CET1 capital ratio under the baseline, while the darker-shaded bars represent the results under the adverse scenario.

Figure 35: Banks' solvency ratios across stress test exercises.

CET1 ratio at the end of the horizon in the 2021 macroprudential stress test is still lower than at the starting point, consistently with high dividend payout rates after the release of profit distribution restrictions. This change in the profit distribution policy has not been captured in the EBA/SSM stress test, which explains the discrepancy in the CET1 ratio between the two exercises.

In an adverse scenario, the system-wide CET1 ratio falls sharply (by around 3 percentage points) with respect to the starting point in all exercises, and remains systematically higher in macroprudential compared to supervisory stress test. Enabling banks to shrink their balance sheets and change the composition of their lending in response to falling loan demand and deteriorating asset quality helps them preserve higher CET1 ratios. In the macroprudential exercise of 2018, there is 0.8 percentage points positive difference between the system-wide CET1 ratio in the macroprudential (11.2%) and the supervisory stress test (10.4%). In the 2020 stress tests, this gap increases to 1.4 percentage points (10.2% versus 8.8%). In both macroprudential stress tests, the relaxation of constant balance sheet assumption has a substantially stronger impact on banks' solvency compared to the presence of an amplification mechanism (when compared with the corresponding supervisory exercises). Only in 2021, the gap between CET1 results in the two stress tests narrows to 0.2 percentage points. This happens on the back of a relatively strong negative impact of the banking sector-real economy feedback loop on the CET1 ratio in the macroprudential stress test, which is, however, counterbalanced with a larger positive solvency impact of the remaining COVID-19 mitigation policies compared to the supervisory exercise.

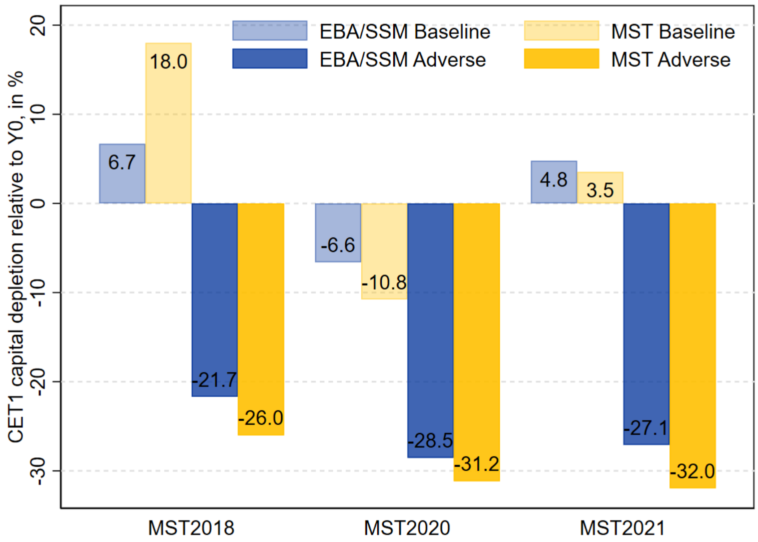


Figure 36: Capital depletion across stress test exercises

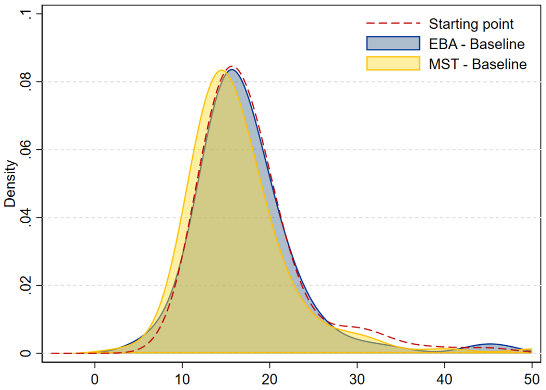
Despite higher CET1 capital ratios in adverse scenarios, the depletion of system-wide CET1 capital is greater in macroprudential compared to EBA/SSM stress tests. As shown in Figure 36, CET1 capital decreases by 21.7%, 28.5% and 27.1% compared to the starting point in the adverse scenarios of the EBA/SSM stress tests, while banks lose more than 26%, 31.2% and 32.0% of their CET1 capital in macroprudential stress tests for 2018, 2020 and 2021, respectively. Capital depletion represents a more relevant measure of stress test adversity compared to the CET1 ratio in the presence of the dynamic balance sheet. The latter metrics are positively affected by bank deleveraging and do not reflect the actual pressure on banks' CET1 capital.

The macroprudential stress test also results in a different distribution of bank-level solvency ratios compared to the EBA/SSM exercise.[110] Figure 37 looks at the distribution of solvency results of 2021 macroprudential and supervisory stress tests. In the baseline scenario, the median CET1 ratio moves from 16.3% in 2020 to 15.2% in 2023, a 1.1. percentage point decrease, compared to a decrease of 0.5 percentage points in the EBA/SSM stress test. This shift is more pronounced for larger banks with a above-median asset size as a starting point. There is also a moderate increase in the variation of bank solvency ratios in the macroprudential stress test, with the interquantile range increasing from 4.9% to 5.4% throughout the scenario horizon. On the contrary, the interquantile range remains constant at 5% in the EBA/SSM stress test.[111]

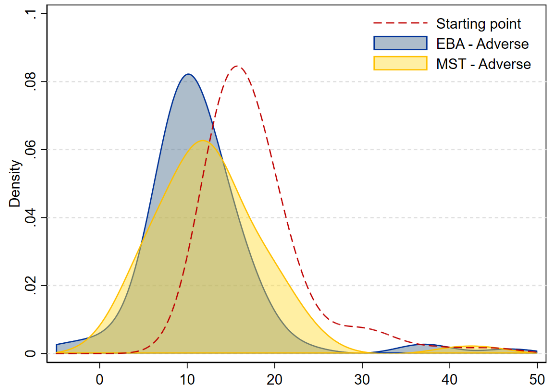
Differences in the distribution of the bank-level CET1 ratios between stress tests are more pronounced in the adverse scenario. Banks' CET1 ratios generally decline, shifting the distribution to the left. While in the EBA/SSM stress test the shape of the distribution of bank-level

[110]The following analysis recalls the main elements of the analysis published in Budnik et al. [2021a].

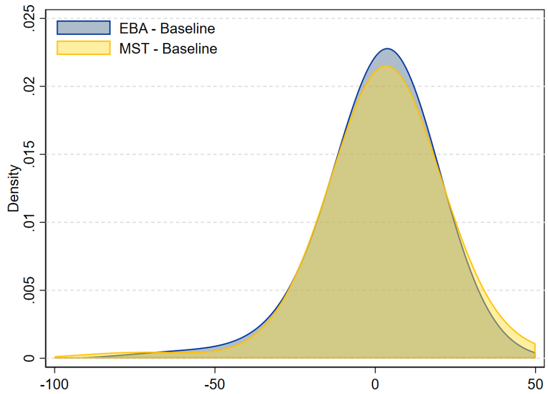
[111]The Kolmogorov-Smirnov test and Mann-Whitney U-test p-values for the null hypothesis that the CET1 ratios of the supervisory and macroprudential stress test sample from the same distribution in the baseline scenario are 7.8% and 7.9%, respectively.



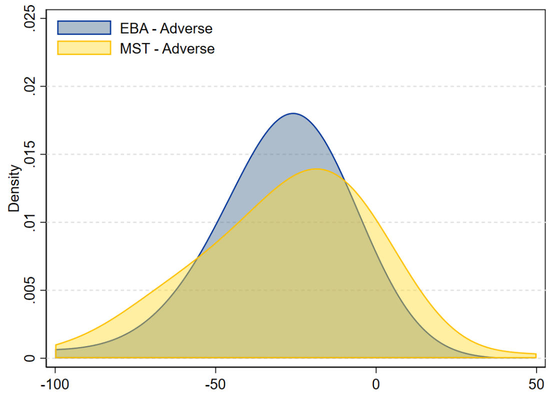
(a) CET1 ratio: Baseline



(b) CET1 ratio: Adverse



(c) CET1 capital change: Baseline



(d) CET1 capital change: Adverse

Figure 37: System-wide CET1 ratio and CET1 capital depletion of the stress test 2021

Notes: For CET1 ratio kernel density functions with bandwith equal to 3% are considered. The red dashed line represents CET1 ratio density at the end of year 2020. For CET1 capital change kernel density functions with bandwith equal to 15% are considered.

solvency rates remains close to their distribution in the starting point, it flattens in the macroprudential stress test. The interquantile range under the macroprudential stress test changes from 4.9% to 6.9%, a 2 percentage point increase, while it stays at 5% in the EBA/SSM stress test. The flattening of the distribution of the CET1 ratio at the bank level in the adverse scenario is more pronounced for smaller banks, with a below median asset size at the starting point. The observed increase in variability of the banks' CET1 ratio compared to the supervisory exercise can be attributed both to the dynamic balance sheet mechanism and the two amplification mechanisms used in the 2021 macroprudential stress test result.[112]

The distributional shape of CET1 capital depletion experiences an even greater change in the macroprudential stress test compared to the EBA/SSM counterpart. Figure 37 shows almost no difference in the distribution of individual bank-level capital depletion in the baseline scenario,[113] but the macroprudential stress test produces not only a flatter but also a more neg-

[112]For more results, see: Budnik et al. [2021a].

[113]The Kolmogorov-Smirnov test and Mann-Whitney U-test p-values for the null hypothesis that the values of capital depletion in the supervisory and macroprudential stress test are from the same distribution in the baseline

atively skewed distribution of capital depletion [114] in the adverse scenario. The interquantile range measures 20.4 percentage points in the EBA/SSM stress test, compared to 34.6 percentage points in the macroprudential stress test. This implies that large losses in capital (70% or higher) become more likely in the macroprudential stress test, particularly for larger banks, with total assets above the median in the starting point.

The bank-level results of the macroprudential versus the constant balance sheet stress test are generally positively correlated, but the former reveals vulnerabilities not captured by the supervisory exercise.[115] However, the end-point result in the EBA/SSM stress test can be better predicted using the initial CET1 ratio only compared to the end-point results of its macroprudential counterpart. For the former, the starting point solvency ratios account for 96% and 86% of the end point ratios in the baseline and adverse scenario, respectively. For the latter, the initial CET1 ratios account for 92% and 70% of the respective end points. Moreover, in both stress tests the ordering of banks' solvency ratios can change throughout the projection horizon, most noticeably in the adverse scenario. On average, banks tend to vary in their positional ranking to a greater extent in the macroprudential stress test (baseline: 10 points, adverse: 18 points) than in the EBA/SSM stress test (baseline: 8 points, adverse: 12 points).

8.1.2 Increasing the informativeness of baseline results

Stress tests traditionally emphasise the results in adverse scenarios, yet baseline scenarios, commonly incorporating the most likely future developments of an economy, can offer not less interesting insights. However, in constant balance sheet approaches, the interpretation of the baseline results is significantly hampered. The assumption of an unchanged asset size implies that banks are not allowed to benefit from good economic conditions and seize profit opportunities by expanding lending. The same assumption combined with zero cure rates leads to an increase of non-performing assets as compared to overall assets even in most favourable scenarios. Such results should thus be interpreted with great care, which is always the case with supervisory agencies, but less with the public not very familiar with the shortcomings of the methodologies.

The macroprudential stress test, with its dynamic balance sheet perspective and more realistic exposition of NPL management practises, offers economically sound insights in adverse and baseline scenarios alike.

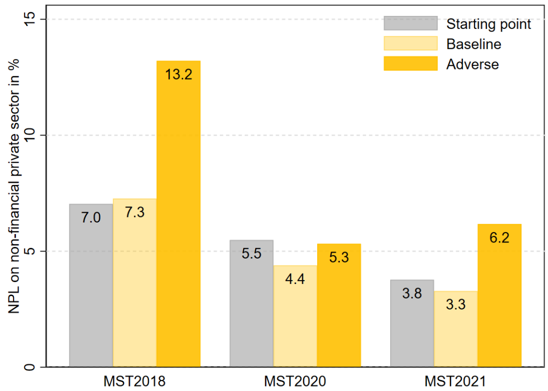
The euro area banks' NPL ratio, measured as the share of non-performing assets among outstanding loans to the non-financial private sector, generally decreases in the baseline scenario. As shown in Figure 38a, the NPL ratio in the macroprudential stress test 2018, increased subtly from 7.0% at the beginning of the exercise to 7.3% at the end of the projection horizon. In the macroprudential stress tests 2020 and 2021, the NPL ratio of the euro area for banks' exposures to the non-financial private sector evidently decreased from 5.5% and 3.8% at the start of the horizon to 4.4% and 3.3% at its end, respectively. Particularly in the 2020 exercise, the fiscal and supervisory COVID-19 mitigation policies[116] together with the NPL coverage expectations

scenario are 63% and 96%, and 11% and 22% in the adverse scenario, respectively.

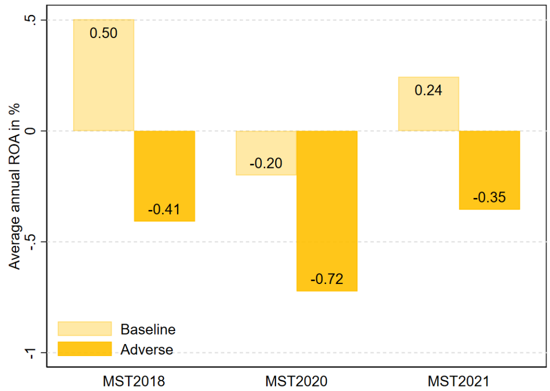
[114] The Pearson correlation coefficient for capital depletion in the adverse scenario is equal to -0.18 and -0.45 under the supervisory and macroprudential stress tests, respectively.

[115] The correlation of bank-level capital ratios at the end of the projection horizon (the Spearsman's rank coefficient) is 96% (74%) in the baseline scenario and 90% (68%) in the adverse scenario. The same correlation (Spearsman's rank coefficient) is less strong for bank-level capital depletion, with a baseline scenario correlation equal to 23% (41%) and an adverse scenario correlation equal to 51% (33%).

[116] For more details regarding the supervisory, macroprudential and government policies introduced in 2020, their introduction in the model as well as the assessment of their joint and individual impact on non-performing assets



(a) NPL ratio



(b) ROA

Figure 38: Profitability and NPL ratio across stress test exercises

limit the impact of the exceptionally negative economic outlook and allow a reduction in the NPL ratio of banks in the baseline scenario.

The share of non-performing assets on banks' balance sheet increases substantially in adverse scenarios. This happens on the back of high inflow of new defaulted loans (present also in constant balance sheet stress tests), lower write-offs and banks' deleveraging.

Looking at bank profitability in a macroprudential stress test provides additional insight into the health of banks. Figure 38b shows the outlook for profitability, measured by the return on assets, in the baseline and adverse scenarios in the 2018-2021 exercises. In adverse scenarios, profitability decreases in all macroprudential stress tests.

However, the profitability outlook in the baseline scenarios is more diverse between the exercises. Bank profitability is projected to remain stable and positive in the baseline scenario in the 2018 and 2021 macroprudential stress tests (0.5% and 0.24%, respectively), although relatively low in historical terms. The negative profitability in the 2020 macroprudential stress test is driven by the particularly negative macroeconomic outlook at the onset of the COVID-19 pandemic. At the same time, the lending margins in all of these exercises improved only marginally against the backdrop of the long-term low interest rate environment.

8.1.3 Additional information relevant for macroprudential purposes

Macroprudential stress test provides information about bank lending in different economic conditions. As such, it can assess the ability of the banking system to support economic growth over the scenario horizon.

Bank lending tends to expand in generally favourable baseline scenarios. The average annual loan growth to the non-financial private sector in the baseline scenario accelerates compared with the exercise's starting point, however, to a varying degree across the three stress test exercises (see Figure 39). Loans to the non-financial private sector were projected to grow by 8.8% cumulatively in the macruprudential stress test 2018. The strongest positive loan dynamic was observed in the 2021 exercise, while cumulative loans grew only marginally in the 2020 exercise. The macroeconomic outlook and the lagged impact of COVID-19 mitigation policies are prominent determinants of bank loans in both exercises. In particular, the positive outlook on lending would be much more muted in the absence of national and supervisory COVID-19

and bank profitability see Budnik et al. [2021c].

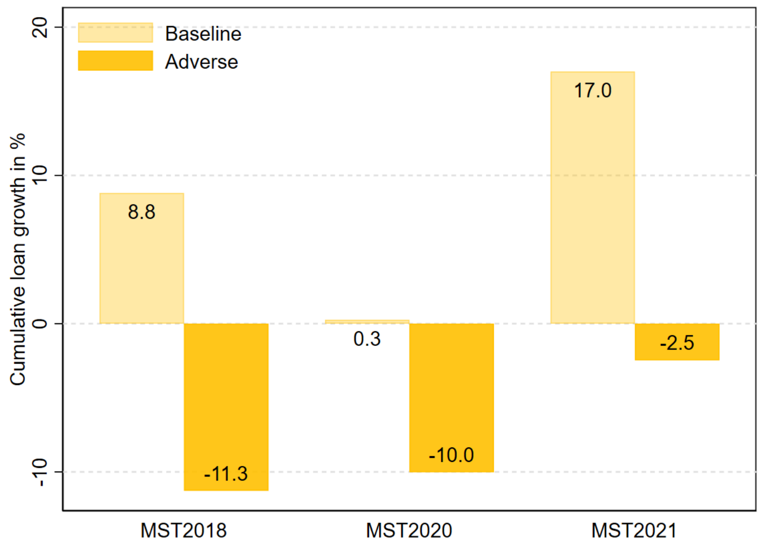


Figure 39: Lending across stress test exercises

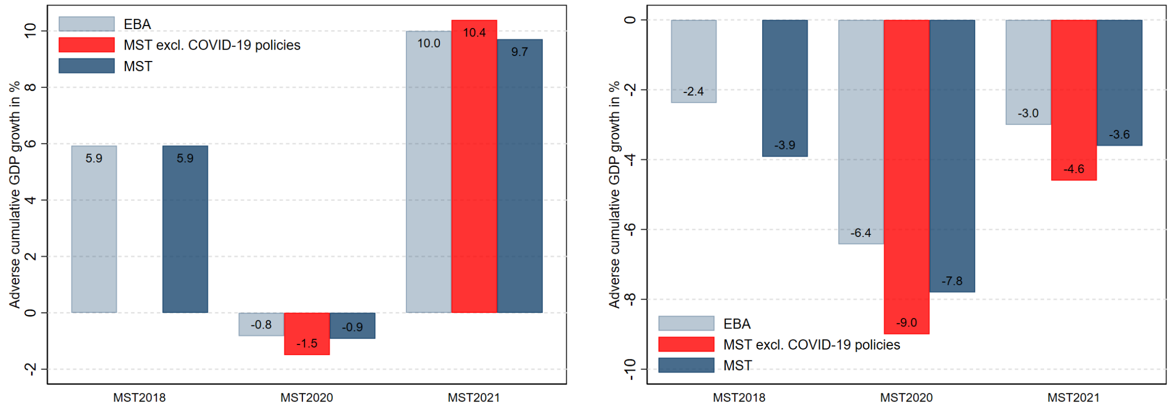
mitigating policies.

In all adverse scenarios, bank lending contracts. At the end of the scenario horizon, it would be expected that bank loan volumes have decreased by 11.3% and 10% in the 2018 and 2020 macroprudential stress tests, respectively. The modest drop of -2.5% in the macroprudential stress test 2021 can be attributed to the outstanding COVID-19 mitigation policies, which had a pronounced positive impact (close to 2pp in cumulative terms) on bank lending. A general decline in lending in adverse scenarios is in line with the deterioration in the asset quality, profitability, and capitalisation of banks' assets. Loan supply tensions are also observed in adverse scenarios in loan pricing. In adverse financial conditions, banks increase effective lending rates to the non-financial private sector to accommodate higher own funding costs.

An equally important and unique feature of the macroprudential stress test is its assessment of potential amplification effects in stress scenarios. Since 2020, the main results of the ECB macroprudential stress test ingrain the real economy - banking sector feedback loop for both baseline and adverse scenarios. This approach evolved over time, as in 2018, the main results built on the original EBA/SSM scenarios, while the assessment of the potential role in the adverse scenario was assessed separately. These reporting changes notwithstanding, in each of macroprudential stress tests we compared the results with and without amplification to learn about the relative role of the latter.

In favourable macrofinancial conditions the impact of the real economy - banking sector feedback loop on macrofinancial outcomes remains contained. It can be read by looking at the difference between cumulative GDP growth in the 3-year horizon in the EBA/SSM baseline scenario of 2021 and the same scenario from the ECB macroprudential stress test that includes the amplification effects in Figure 40a. The difference amounts to 0.3 percentage points of the euro area GDP growth, or a mere 4% of the cumulative growth projected in the original scenario.

The asymetric impact of the real economy - banking sector feedback loop across the business and financial cycle becomes apparent when looking at the difference between original adverse scenarios and adverse scenarios augmented with the amplification mechanism. The amplification of scenario adversity in the adverse scenarios of 2018 and 2021 amounts to a 1.6 percentage point additional reduction in the euro area GDP over the 3-year horizon. In the



(a) Baseline scenario **(b)** Adverse scenario

Figure 40: Feedback loop effect in macroprudential stress test exercises

baseline (or central scenario) of the 2020 macroprudential stress test (which still included the adverse impact of the COVID-19 pandemic), it was 0.7 percentage point additional reduction in the euro area GDP, and in the particularly severe adverse scenario of 2020, 2.6 percentage points.

In the unfavourable scenarios 2020 and 2021 the original negative impact of the real economy - banking sector feedback loop is partially offset by the positive impact of COVID-19 mitigation policies. In the baseline scenario 2020 the positive impact of COVID-19 mitigating policies amounts to 0.6% of the euro area real GDP. In the adverse scenarios 2020 and 2021, the positive impact of these policies was higher, 1.2% and 1% correspondingly. The final evaluation of the feedback-loop effect ,and its decomposition into the original impact and the effect of COVID-19 mitigation policies, emphasised the role of COVID-19 mitigation policies in containing the amplification through the banking sector.

8.1.4 Evolution of macroprudential stress testing over time

The BEAST model has continued to undergo important innovations aimed at further refinement of macroprudential analysis and stress tests, in particular. The following section provides an overview of the main changes of the model over time and through the lens of macroprudential analysis (for a general overview, see Figure 41).

In its first application in the 2018 macroprudential stress test, the priority of BEAST was to loosen two main methodological assumptions of the EBA/SSM stress test: constant balance sheet, and no feedback between banks' decisions and the real economy. The model has been developed with the emphasis on bank lending adjustment. Each bank adapted to the dynamics of loan demand in the domestic and other exposure markets, while its credit supply was simultaneously dependent on idiosyncratic factors, such as its solvency, profitability, and asset quality.

The second innovation concerned explicitly accounting for two-way linkages between banks and the macrofinancial environment. The integrated and simultaneous model mechanisms allowed the vulnerability of banks (i.e., banks suffering losses) to have negative repercussions on the macroeconomy. This was modelled in a non-linear fashion as the banking sector - real economy feedback loop in Section 5.2.

In addition, the macroprudential stress test 2018 lifted the caps and floors on different com-

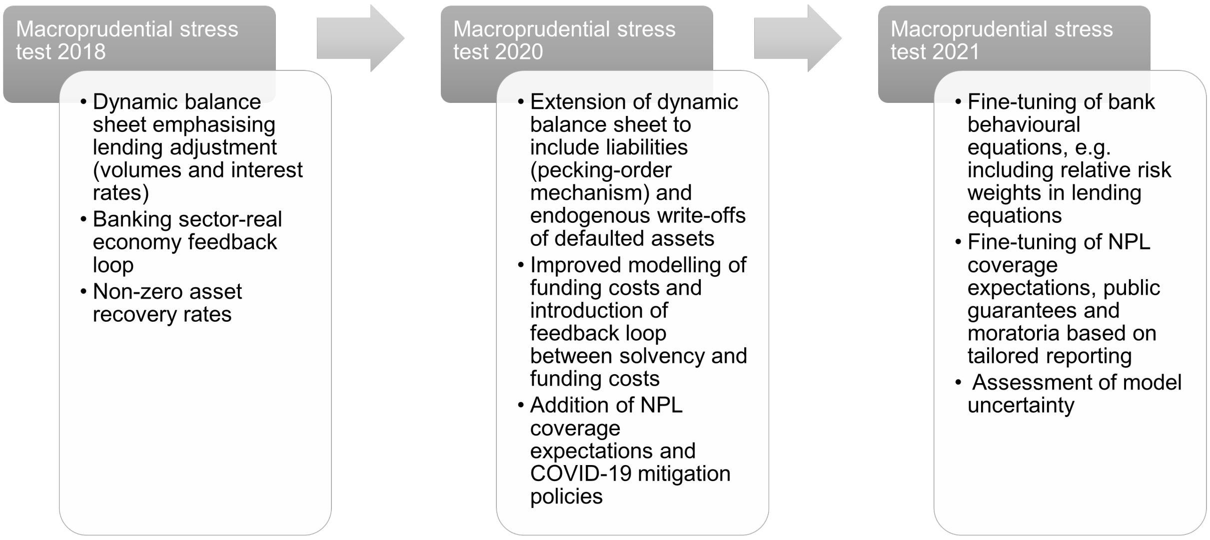


Figure 41: Macroprudential stress tests and model evolution

ponents of profit and loss, such as allowing for nonzero recovery rate for defaulted assets, which since then have been modelled jointly with other IFRS 9 transition probabilities.

The 2020 macroprudential stress test included several important extensions. The main innovation concerned the introduction of the pecking order mechanism in the adjustment of bank liabilities, in which banks turn to wholesale markets to close the funding gap arising from insufficient holdings of deposits from the non-financial sector and their own funds[117]. The extension of the model created a solvency-funding cost feedback loop, strengthening the interlinkages between the banking sector and the real economy in the model.

Other model extensions included the endogenous write-off decision for defaulted assets (Budnik et al. [2021c]) and a more detailed setup on risk weights, largely facilitated by the earlier application of the model to the impact assessment of the Basel III finalisation (Budnik et al. [2021b]). The stress test also included a richer set of policies. First, the model has been extended to map the workings of the NPL coverage expectations and later to capture the impact of public moratoria and national guarantee schemes.

The 2021 macroprudential stress test benefited from refined modelling of monetary policy transmission mechanisms, now specifically accounting for non-standard monetary policy measures. In addition, improved data availability fostered improvements in modelling of non-performing loans (NPL), allowing better calibration of bank-specific targets for NPL coverage. And finally, it evaluated for the first time the impact of parameter uncertainty on the main results.[118]

8.1.5 Break-down of mechanisms in the model

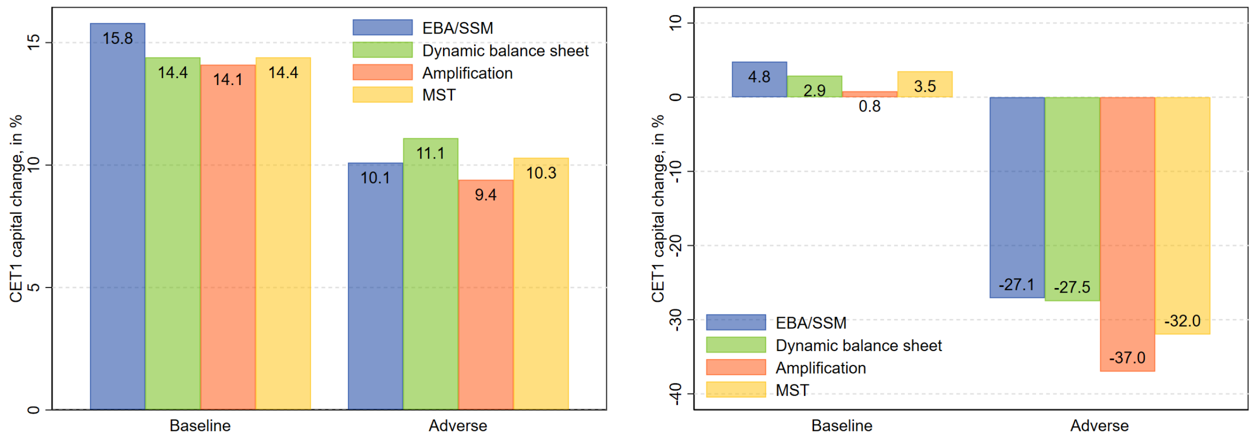
The following section aims to shed more light on how the two distinguishing characteristics of the macroprudential stress test vis-à-vis the supervisory stress test - the dynamic balance sheet and the presence of amplification mechanisms - impact the bank solvency outcomes.[119] In the

[117] For more details please see Section 4.2

[118] For more details please see Section 6.2.

[119] The analysis was originally detailed in Budnik et al. [2021a].

following, we leverage the ability of the model to add and remove different macroprudential mechanisms in simulations.



(a) CET1 ratio

(b) CET1 capital depletion

Figure 42: System-wide CET1 ratio and CET1 capital depletion of the stress test 2021

Figure 42a tracks the evolution of the transitional CET1 ratio in the euro area at the end of the scenario horizon in the 2021 EBA/SSM (leftmost bar) and the 2021 macroprudential stress test (rightmost bar). When banks are allowed to dynamically respond to favourable changes in macrofinancial conditions by adjusting their assets, liabilities and interest rates[120] in the dynamic balance sheet approach, they expand their balance sheets and their CET1 ratio drops by a 1.4 percentage point, compared with the constant balance sheet EBA/SSM stress test (light blue bar of Figure 42a).

However, in the adverse scenario, falling loan demand and deterioration in profitability and solvency prospects force banks to shrink their balance sheets. Cutting down and changing the composition of assets translates into a 1 percentage point increase in the CET1 ratio compared to the results of the 2021 EBA/SSM stress test.

Moving from the dynamic balance sheet stress test to the stress test that acknowledges the presence of solvency - funding costs and banking sector - real economy feedback loops (the light red bar in Figure 42a) does not markedly affect the CET1 ratios in the baseline scenario, but impacts them significantly in the adverse scenario. While banks take action to safeguard their solvency positions, they unintentionally trigger severe amplification mechanisms, which further worsen their situation. The system-wide CET1 ratio in a stress test involving the amplification mechanisms triggered by endogenous responses from banks falls by an additional 1.8 percentage points (of which 0.1 percentage points are related to the solvency-funding costs feedback loop) compared to a dynamic balance sheet stress test that ignores these feedback loops and is 0.7 percentage points below the EBA/SSM stress test solvency level.

Finally, activation of COVID-19 mitigation policies (the blue bar in Figure 42a) leads to an improvement in the solvency positions of banks. The impact of mitigation measures is more pronounced in the adverse scenario, adding 0.9 percentage points to the CET1 ratio compared to only 0.3 percentage points in the baseline scenario.

[120] Additionally, this model version incorporates a top-down assessment of credit risk including the model-specific implementation of NPL coverage expectations, amounting to 0.2 percentage point increase compared to the EBA/SSM stress test result.

A higher system-wide CET1 capital depletion in the adverse scenario of the 2021 macroprudential stress test compared to the constant balance sheet stress test can be attributed primarily to the amplification mechanisms present in the former stress test (see Figure 42b). The dynamic versus constant balance sheet perspective on its own does not affect this measurement of capital losses.

8.2 Policy impact assessment

The most recent applications of the model concern the assessment of the interaction between the monetary policy stance and financial stability. This section elaborates on an example from the end of 2021, where the discussion of the risk outlook centred around the consequences of a phase-out from pandemic asset purchases (PEPP). In the context of financial stability risk analysis, the main concern has been the interplay between the PEPP phase-out and potentially exacerbated market fragmentation. An acute market fragmentation could increase the costs of government debt financing in southern Europe and have a substantial impact on the banking sector.

The interplay between the phase-out from PEPP and market fragmentation has been studied on the basis of two alternative counterfactual scenarios. The first assumed the evolution of the ECB asset purchases along with market expectations, derived as a median of analysts' expectations. The second assumed lower than expected asset purchase, equivalent to the 10th percentile of market expectations (see Figure 43). The first scenario has been conditioned on the macrofinancial environment as in the December 2021 macroeconomic projections of the ECB (see Section 6.1) and the (market) expected path of asset purchases, while the second allowed deviations from the projections along with the macrofinancial impact of the lower than expected asset purchases.

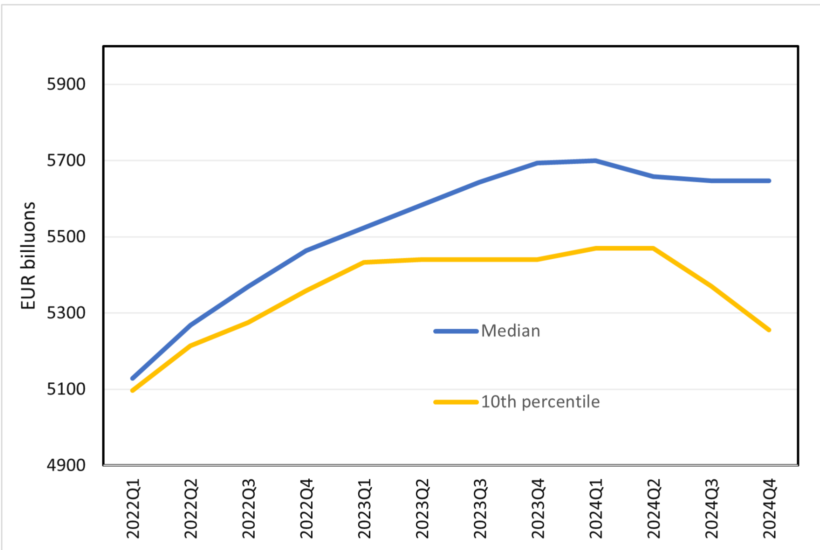
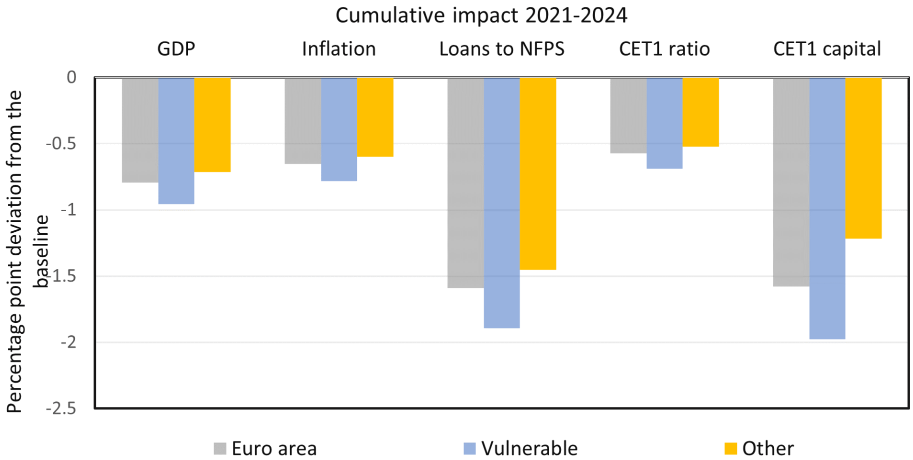


Figure 43: Euro system monetary policy portfolio 2022-2024 market expectations (end of 2021)

For both policy options, we looked at the full distribution of possible outcomes taking into account scenario uncertainty (see Section 6). The difference between the central paths of both distributions informed us of the expected impact of the withdrawal from the asset purchase programme.

Figure 44 summarises the expected impact of the PEPP phase-out on the macroeconomy and the banking sector. A gradual pullout from the asset purchase programme could be expected to lead to a moderate reduction in euro area output growth (0.3 pp annually) and lending (0.4 pp annually) in the three-year horizon. This would translate into a slightly below 0.6 pp reduction in the CET1 ratio at the end of the horizon. There are modest differences in impact between the vulnerable[121] and the remaining countries in the euro area, whereby the former are slightly more negatively affected.



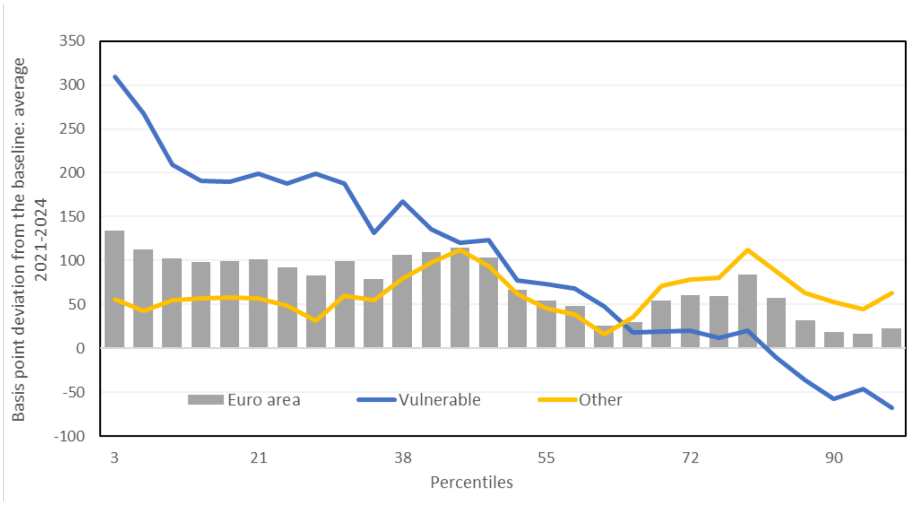
Notes: Vulnerable countries: Cyprus, Greece, Italy, Malta, Lithuania, Latvia, Spain, Portugal, and Slovakia at the end of 2024; Other countries: the euro area excluding countries classified as vulnerable.

Figure 44: Macrofinancial impact of lower than expected asset purchases

Next, we looked at the tails of the distribution conditional on the phase-out of asset purchases to assess the related financial stability risks. To arrive at a scenario that emphasises fragmentation risks, we sorted all scenarios in the distribution according to the two criteria: the average increase in the euro area bond yields and the spread between the vulnerable and other euro area countries (see Section 6.5). These criteria map the narrative of intensifying fragmentation risks, while the fact that all sorted scenarios are drawn from the distribution conditional on reduced PEPP policy paths emphasises the part of the narrative that speaks about the coexistence of changes in PEPP and fragmentation. Figure 45 shows the average yield of euro bonds (grey bars) and the yields of the bonds for the vulnerable (blue line) and other (yellow line) countries sorted according to the two criteria. The middle percentiles reflect a moderate, around 50 bp, increase in the average bond yields compared to the reference scenario, and a contained, around 20 bp, increase in the spread between the vulnerable and other countries. Moving to the left, one observes the intensification of fragmentation risks, with a stronger response of bond yields overall and higher spread.

We select a group of scenarios from the left tail of the distribution described on the two selection criteria (around the lower 30 percentile). For these scenarios, we average the results for other model variables of interest to derive information about the evolution of the main macrofinancial aggregates, expressed as deviations from the reference scenario. Figure 46 summarises this scenario with reference to the no policy change benchmark. There is a substantial reduction in output growth (0.4 pp annually) and lending (0.5 pp annually) with sharper differences between vulnerable and other euro area countries (0.7pp versus 0.2pp for GDP, 0.7pp versus 0.4 for lending). Around 40% higher bank capital losses, though a similar impact on capital ratios,

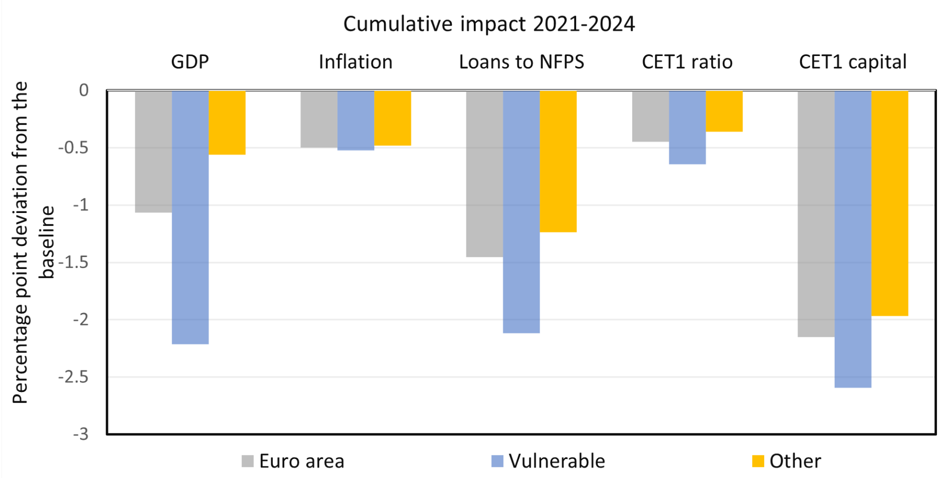
[121] This group includes Cyprus, Greece, Italy, Malta, Lithuania, Latvia, Spain, Portugal and Slovakia.



Notes: Euro area: the GDP-weighted average 10 year bond yields in the euro area at the end of 2024; Vulnerable: the GDP-weighted average 10 year bond yields in Cyprus, Greece, Italy, Malta, Lithuania, Latvia, Spain, Portugal, and Slovakia at the end of 2024; Other: the GDP-weighted average 10 year bond yields in the euro area excluding countries classified as Vulnerable at the end of 2024.

Figure 45: Sorting scenarios along with the criteria related to 10-year bond yields

consistent with stronger deleveraging in market fragmentation versus the benchmark scenario. Along with expectations, while the expected impact of "tapering" on lending and the solvency is moderate, it can become pronounced in and aggravate the macrofinancial effects of market fragmentation.



Notes: Vulnerable countries: Cyprus, Greece, Italy, Malta, Lithuania, Latvia, Spain, Portugal, and Slovakia at the end of 2024; Other countries: the euro area excluding countries classified as vulnerable.

Figure 46: Macrofinancial impact of lower than expected asset purchases in a fragmentation scenario

9 Conclusion

The paper describes the final development stage of the Banking Euro Area Stress Test (BEAST) model, laying out its structure, properties, and various analytical uses. The BEAST is the first semi-structural model linking the representation of macroeconomies with that of individual banks. A significant strength of the model is that it captures many aspects of bank heterogeneity.

This includes not only the different structures of the bank balance sheets, but also the banks' diverse reactions to economic conditions depending on their individual solvency situation, asset quality, and profitability performance. Thanks to its construct, it can describe in detail the propagation of macroeconomic conditions and different policies into the banking sector, and later their interplay with the real economy-financial sector amplification. Another advantage lies in its ability to solve for decisions of banks and the reactions of economies jointly, and period-by-period, which offers an appropriate framework for modelling feedback loops.

The BEAST model represents the culmination of a dynamic developmental journey within the realm of financial stability analysis. The origins of the model lie in macroprudential stress tests, but it has slowly grown into a workhorse model for applications in the field of risk and policy assessment, including the assessment of regulatory, macroprudential, and supervisory policies of their interactions with monetary policy. In doing so, BEAST bridges the divide between granularity and systemic perspective, accentuating its unique narrative capabilities and robust feedback mechanisms. It stands as a testament to the viability of constructing comprehensive models within policy institutions, surmounting numerical complexities.

Model applications and evaluations have revealed insightful dynamics within the intricate interplay between the real economy and the banking sector. A standout contribution is the macroprudential stress test, highlighting the model's prowess in deciphering potential amplification effects during stress scenarios. In favourable macrofinancial contexts, the feedback loop's influence remains contained. However, as adversity escalates in adverse scenarios, the amplification effect garners significance. In particular, during the 2018 and 2021 tests, an additional reduction of 1.6 pp in euro area GDP over a 3-year horizon surfaces, alongside a 2.6 pp reduction in the 2020 stress test.

Coupling the evaluation of the feedback loop's impact with prudential policies targeting the banking sector yields other intriguing insights. With instances like COVID-19 mitigation policies, these measures directly modify amplification effects, thereby influencing the feedback loop's magnitude. Consequently, the amplification of the adverse scenario is offset to some extent by the positive impact of COVID-19 mitigation policies.

A recurring observation is the asymmetry in response to smaller versus larger and positive versus negative shocks. Impulse response functions and stochastic simulations further emphasise the model's prowess in decoding nonlinearities within macrofinancial dynamics. Negative aggregate demand shocks induce more significant shifts in lending and GDP. Tightening monetary policy measures evoke a slightly more substantial impact than accommodative ones, suggesting nuanced dynamics between policy tools and the feedback loop. Larger increases in capital buffers generate proportionally stronger responses of lending volumes. Furthermore, the response of the bank in terms of lending to broad-based capital policies is clearly bimodal. A share of banks responds very weakly, either being able to accommodate to changes in policy by adjusting their management buffers, or retaining a higher share of profits. A smaller group of banks substantially cuts lending. Stochastic simulations depict a GDP distribution diverging from the normal pattern, marked by a right-skewed trend and moderately fatter tails. This observation points toward potential systemic vulnerabilities under specific conditions.

One of the less obvious lessons from the BEAST experiment is that the model illustrates well when very detailed bank-level heterogeneity is essential and when a more contained model can offer equally sound insights. As such, BEAST inspires further explorations of risk and policy assessment techniques that can balance the best computational intensity and economic relevance.

In the realm of policy decisions, the model showcases its utility in the shaping of forward-looking strategies. The model's robust forecast accuracy is notable within well-informed macrofinancial contexts, particularly on medium-term horizons, aligning well with the strengths of semi-structural models. Despite encountering challenges in forecasting macroeconomic variables during unprecedented events such as the COVID-19 pandemic, the model's performance remains consistent with the complexities faced by official ECB projections during highly volatile periods.

As each model, the BEAST has a number of shortcomings. It is a semi-structural model which balances information from the theory and data. However, it is not meticulously micro-founded and does not stipulate agents' optimisation problems. The empirical identification of equations is generally performed equation by equation (with different equations employing different datasets). It offers great flexibility and the ability to explore macroeconomic, bank-level and transaction-level data, but does not ensure statistical scrutiny of a joint estimation of all model equations. Other model limitations concern the focus on largest euro area banks only, which at times may compromise model accuracy regarding banking systems with a large share of smaller banks (e.g. Italy and Germany) or non-banking financial sector (e.g., the Netherlands). And lastly, the choice to concentrate on selected amplification mechanisms leaves aside other relevant aspects, e.g. interconnectedness. However, the BEAST model will likely continue to be improved further with re-estimation of its equations, and the availability of new datasets.

A very practical challenge of working with a non-linear model covering individual economies and individual banks is its size and numerical complexity. A lot of effort has been put into developing numerical solutions allowing the most efficient representation of model equations, then most efficient solutions, or organising the infrastructure and work processes in a way minimising operational risks and ensuring integrity of the model. This challenge, not fully reflected in the paper, is something which may discourage the construction and use of similar models and explain the popularity of hybrid approaches to e.g. macroprudential stress testing.

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A Data Sources

A.1 ECB statistical data warehouse (SDW)

The macroeconomic and financial time series are sourced from the official ECB statistical data warehouse[122] (SDW). The country-level time series sourced from this database include information on economic growth, inflation, unemployment and trade, and financial information related to interest and exchange rates and stock market developments. Most of the selected data are available since 1999 in either daily (e.g. interest rates), monthly (e.g. inflation), or quarterly (e.g. GDP) frequency.

The macroeconomic and financial time series are used to estimate the macroeconomic block in the model as described in the Appendix B, and often serve as explanatory variables in many of the bank-level models.

A.2 The macroeconomic projections of the Eurosystem/ECB staff ([B]MPE)

Forward-looking information on macroeconomic and financial time series is sourced from the internal ECB database with the Eurosystem and ECB staff projections[123] (BMPE). Macroeconomic projections cover the outlook for the euro area and the wider global economy and are published four times a year (in March, June, September, and December). The BMPE is conducted twice a year and involves staff from both the euro area NCBs and the ECB. It provides the short- and medium-term economic outlook for the euro area and for the individual euro area countries. Like the BMPE, the MPE is conducted twice a year and delivers the short- and medium-term economic outlook for the individual euro area countries and the euro area, the latter being consistent with the country aggregation. It covers the same variables as the BMPE but is produced mainly by ECB staff, with NCBs only contributing the short-term inflation projections.

A.3 Data from EBA/SSM stress test exercise

The main source of information on the balance sheets and profit and loss accounts of banks in the BEAST model is the EU-wide stress test templates defined and updated by the European Banking Authority (EBA) and shared on the dedicated website[124] prior to each biannual stress test exercise. The templates collect information on the starting year and three year ahead conditional projections (for baseline and adverse scenarios), on the banking and trading books of banks, their profit and loss accounts, and capital structure. The banking and trading book is represented at the granular sector and country portfolio level. The data are available at an annual frequency.

We used data from three consecutive EBA/SSM stress test exercises (2016, 2018 and 2021). The 2016 dataset contains starting point data for 2015 and three years of projections from 2016 to 2018. The 2018 dataset contains starting point data for 2017 and three years of projections for 2018 to 2020. Finally, the 2021 dataset contains starting point data for 2020 and three years of projections for 2021-2023. The data are provided at the highest level of consolidation for 93, 91 and 89 banking groups for 2016, 2018 and 2021 exercises, respectively.

[122] `https://sdw.ecb.europa.eu/`

[123] `https://www.ecb.europa.eu/pub/projections/html/index.en.html`

[124] `https://www.eba.europa.eu/risk-analysis-and-data/eu-wide-stress-testing`

The data are used to inform the model about the structure of banks' accounts, derive multiple model parameters, and for model estimations as described in Appendices D.1, D.2 and D.4.

A.4 COREP/FINREP

Common Reporting (COREP) and Financial Reporting (FINREP) templates are part of the EBA reporting framework,[125] which allows for consistent and integrated reporting of regulatory data that encompass enterprise risk and balance sheet information. COREP provides a standardised reporting framework for reporting credit, market, operational, and solvency reports across the EU. FINREP is based on International Accounting Standards (IAS) and International Financial Reporting Standards (IFRS). It covers a range of areas, including consolidated balance sheets (assets, liabilities, equities, and minority interest), and consolidated income statements.

The COREP/FINREP data are available from September 2014 at a quarterly frequency. The data are reported by all supervised banks in the EU, however, we only select the data reported by the systemically important (SI) institutions in our sample that are directly supervised by the single supervisory mechanism (SSM) (see Table 18).

Supervisory information is used to calibrate selected model parameters and estimate bank behavioural equations. The data feeds, for example, into the loan supply model (Appendix C.2), model for write-offs (Appendix C.3), lending interest rate model (Appendix C.4), debt security supply model (Appendix C.5), liquidity management (Appendix C.11), management buffer (Section C.12) and operating expense model (Appendix D.5).

In addition to the above uses, the COREP/FINREP data is used to update the bank-level information in the model (historical data) for quarters for which the information from the EU-wide stress test templates is not available (see Section A.3). The latter information is available only every two years, whereas multiple applications of the model benefit from taking into account the most up-to-date quarterly information. The main variables updated with information from COREP and FINREP are the following:

- P&L variables: Templates F 02.00, F 46.00, C 17.01.a
- Capital variables: Templates C 01.00, C 02.00, C 03.00, C 16.00, C 24.00, C 04.00
- Non-performing loan ratios: Template F 18.00.a
- Liability volumes: Template F 08.01.a
- Loan volumes: Templates C 07.00.a, C 08.01.a, C 08.02, C 09.01.a, C 09.01.b, C 09.02

A.5 iBSI/iMIR

The Monetary Financial Institutions (MFI) statistics have been originally set up to monitor monetary developments in the euro area and consists of two databases, the individual balance-sheet statistics (iBSI) and individual interest rate statistics (iMIR) databases. It is compiled by national central banks and the ECB for all euro area countries on a monthly basis. The individual MFI statistics rest on common reporting standards for all euro area member states, and the dataset has been continuously maintained from August 2007.

Currently, iBSI contains around 3000 banks for 150 balance sheet items and iMIR contains information on 250 banks for 54 interest rate related items. On most occasions, we selected

[125] https://www.eba.europa.eu/risk-analysis-and-data/reporting-frameworks

those who continuously provided information on variables of interest from August 2007 or at least for 8 years. Originally MFI statistics include the institutions selected on the basis of their residentship and includes resident headquarters, branches or subsidiaries of institutions headquartered abroad but exclude foreign subsidiaries or branches of resident institutions. At instances, we semi-consolidate MFI balance sheet and interest rate information, pooling credit institutions that belonged to the same banking group. Note that the resulting semi-consolidated data do not cover all entities entering a banking group, but only a subset of these entities which are included in our MFI sample (sub-consolidation level). MFI statistics are used to estimate bank behaviour models as described in the Appendices C.1, C.4, C.7, C.8.

A.6 S&P Capital IQ

S&P Capital IQ provides a variety of financial markets data from which we source information on credit default swaps (CDS). CDS spreads are available globally for sovereigns, non-financial corporates, and financial corporates, beginning from 2004. Spreads are available on daily frequencies and for maturities between overnight and 30 years (most commonly, however, they are available for integer-valued maturities between 1 and 10 years). Although a spread is available daily for each maturity, only 10% of the spreads are actually observed in a CDS market transaction. The rest are derived by Capital IQ from spreads actually observed at other maturities and dates. Most of the spreads are quoted conventionally. CDS data are used to estimate interest rates on debt security holdings and wholesale unsecured funding costs in Appendices C.6 and C.9.

A.7 Short Term Exercise

The Short Term Exercise (STE) is an ad hoc data collection developed by the ECB within the Single Supervisory Mechanism (SSM)[126]. The main focus of data collection is to supplement the data otherwise available for the Supervisory Review and Evaluation Process (SREP). The STE data collection covers all significantly important banks at their highest level of consolidation and a selected subset of subsidiaries of these institutions. Most parts of the STE are collected on an annual basis.

The elements of the STE used in the model relate to the collection of information on the implementation of the supervisory coverage expectations. They are used to calibrate the parameters of the related model and derive the variables necessary for the replication of the mechanics of the coverage expectations.

A.8 Capital requirement database

Information on bank-specific capital requirements from 2014 onwards is sourced either directly from COREP or from the internal database of capital requirements including detailed information on country-level (CCyB, SRB) and bank-level (OSII, GSII) macroprudential buffers, along with Pillar 2 requirements and Guidance.

[126] More details on the short term exercise can be found in the SSM Supervisory Manual: `https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.supervisorymanual201803.en.pdf`

A.9 MacroPrudential Policies Evaluation Database (MaPPED)

The MacroPrudential Policies Evaluation Database (see MaPPED) provides information on measures of macroprudential nature that have been implemented in European Union countries from 1995 onwards. It documents the outcome of a large-scale exercise to collect and classify such measures discussed in Budnik and Kleibl [2018]. This source allows us to construct longer time series of capital buffers and requirements.

A.10 S&P SNL Sector Financials dataset

The S&P SNL Sector Financials dataset covers financial data for financial institutions around the world. It specifically reports details on assets, deposits, loans, and regulatory capital ratios and performance coverage on more than a thousand banking institutions. The dataset covers all significantly important banks at their highest level of consolidation and reports figures on annual frequency. We obtain information on bank leverage, Tier 1 and CET1 capital ratios to backward-extend supervisory reporting information starting in 2014.

Type-0 Banks	Type-1 Banks
BAWAG Group AG	The Bank of New York Mellon SA
Erste Group Bank AG	Banque Degroof Petercam SA
Raiffeisenbankengruppe OÖ Verbund eGen	Aareal Bank AG
Raiffeisen Bank International AG	Deutsche Apotheker- und Ärztebank eG
Sberbank Europe AG	DekaBank Deutsche Girozentrale
Volksbanken Verbund	Münchener Hypothekenbank eG
Argenta Bank-en Verzekeringsgroep NV	Deutsche Pfandbriefbank AG
AXA Bank Belgium SA	J.P. Morgan Bank Luxembourg S.A.
Belfius Banque SA	Volkswagen Bank GmbH
KBC Group NV	RBC Investor Services Bank S.A.
Bank of Cyprus Holdings plc	State Street Europe Holdings Germany
Hellenic Bank plc	Bank of America Europe
RCB Bank LTD	Banque Internationale à Luxembourg S.A.
COMMERZBANK AG	Quintet Private Bank (Europe) S.A
Deutsche Bank AG	RCI Banque SA
DZ BANK AG	
HASPA Finanzholding	
Erwerbsgesellschaft der S-Finanzgruppe	
Landesbank Baden-Württemberg	
Bayerische Landesbank	
Landesbank Hessen-Thüringen Girozentrale	
Banco Bilbao Vizcaya Argentaria, S.A.	
Bankinter, S.A.	
Banco de Crédito Social Cooperativo, S.A.	
Ibercaja Banco, S.A.	
Kutxabank, S.A.	
Liberbank, S.A.	
ABANCA Corporación Bancaria S.A.	
Banco de Sabadell, S.A.	
Banco Santander, S.A.	
Unicaja Banco, S.A.	
OP Osuuskunta	
BNP Paribas S.A.	
BPCE S.A	
La Banque Postale	
Crédit Agricole S.A.	
Confédération Nationale du Crédit Mutuel	
HSBC Continental Europe	
Société générale S.A.	
Alpha Bank AE	
Eurobank Ergasias S.A.	
National Bank of Greece S.A.	
Piraeus Bank S.A.	
AIB Group plc	
Bank of Ireland Group plc	
Citibank Holdings Ireland Limited	
Ulster Bank Ireland d.a.c	
Banco BPM S.p.A.	
Banca Carige S.p.A.	
Credito Emiliano Holding S.p.A.	
Intesa Sanpaolo S.p.A.	
Mediobanca S.p.A.	
Banca Popolare di Sondrio, S.C. per Azioni	
UniCredit S.p.A.	
Bank of Valletta plc	
HSBC Bank Malta p.l.c.	
ABN AMRO Bank N.V.	
ING Groep N.V.	
Coöperatieve Rabobank U.A.	
Banco Comercial Português, SA	
Caixa Geral de Depósitos, SA	
Biser Topco S.à.r.l.	
Nova Ljubljanska Banka d.d. Ljubljana	
Hamburg Commercial Bank AG	
Nordea Bank Abp	
Novo Banco, S.A.	

Table 18: Bank sample (2021) and classification

B Behavioural equations in the macroeconomic block

B.1 Structural panel VAR

The estimation of model parameters reported in Section 3.1 relies on the following VAR specification:

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

or:

$$\overline{Y}_t^C = a^C + \sum_L A_L^C \overline{Y}_L^C + \sum_L E_L^C \overline{X}_{t-L}^C + v_t^C \tag{326}$$

where $\overline{Y}_t^C = [Y_t^{C'}, M_t^{C'}]'$ is a vector $N_Y \times 1$ of N_Y endogenous variables. For each country $a^C = [a_Y^{C'}, a_M^{C'}]'$ is a vector of N_Y constants $N_Y \times 1$ and A_L^C is a $N_Y \times N_Y$ matrix that group the parameters of the variables in $\overline{Y}_t^C$ in a conformable way. The vector $\overline{X}_t^C = [X_t^{C'}, Z_t^{C'}]'$ is a $N_X \times 1$ matrix that combines all exogenous variables and E_L^C is of size $N_Y x N_X$ that groups the parameters of the variables in $\overline{X}_t^C$ in a conformable way. $v_t^C = [v_t^{Y,C'}, v_t^{M,C'}]'$ denotes a $N_Y x1$ vector of stacked reduced-form residuals which are i.i.d. $N(0, \Sigma_C)$. Lastly, L denotes lag number and t is the time period, as in Section 3.1. The number of variables and time intervals that enter the estimation is the same for all countries in the panel (a balance panel). Further in the text, the country index C will be omitted when stating the dimension of the elements in the system. The panel VAR for the euro area region is estimated on the basis of a five-block Gibbs sampler. In this subsection, we describe the priors and provide a sketch of the sampling algorithm along with the conditional posteriors.

Priors and Posterior Sampling

The estimation of VAR combines the adaptation of the hierarchical prior model of Gelman [2006] to a panel framework by Jarocinski [2010] and the informative prior on the steady state of Villani [2009]. This combined approach allows us to flexibly choose the degree of prior cross-country parameter heterogeneity (if country basis, regional, or homogeneous), along with the precise inclusion of information about the long-run dynamics. Given that we specify priors for country-specific steady states (i.e. unconditional means), it is useful to rewrite the above model in terms of deviations of the variables from their unconditional means. This leads to the following two equivalent formulations for equation (326):

$$\underbrace{\overline{Y}_t^C - \Psi_Y^C}_{\equiv Y_{\Psi_t}^C} = \sum_L A_L^C \underbrace{\left(\overline{Y}_{t-L}^C - \Psi_Y^C\right)}_{\equiv Y_{\Psi t-L}^C} + \sum_L E_L^C \underbrace{\left(\overline{X}_{t-L}^C - \Psi_X^C\right)}_{\equiv X_{\Psi t-L}^C} + v_t^C \tag{327}$$

$$\overline{Y}_t^C = \Psi_Y^C d_t - \sum_L A_L^C \Psi_Y^C d_{t-L} + \sum_L A_L^C \overline{Y}_{t-L}^C + \sum_L E_L^C X_{\Psi t-L}^C + v_t^C \tag{328}$$

where in our case $d_t = 1$. $\Psi_Y^C = \mathscr{E}[\overline{Y}_t^C]$ is the vector $N_Y \times 1$ of the unconditional means of the endogenous variables, and $\Psi_X^C = \mathscr{E}[\overline{X}_t^C]$ denotes the vector $N_X \times 1$ of the unconditional means of the exogenous variables. The latter is assumed known and thus not estimated within the model.

In the following, we outline the Gibbs sampler used to characterise the joint posterior distribution of all parameters in the model. As will become clear below, the sampler cycles through five parameter blocks. Depending on which block of parameters the Gibbs sampler samples from, we resort to either of the equations (327) or (328) as needed.

Block 1: Drawing the VAR parameters for each country The first block involves the estimation of the VAR parameters. To sample the dynamic coefficients, we write the model equation (327) in terms of vectorised matrices. This involves stacking the rows of $Y_{\Psi_t}^C$ into a vector $T \times N_Y$ y_Ψ^C and stacking all variables on the right hand side into a $T \times (N_Y + N_X)L$ matrix Z_Ψ^C with the row t given by $\left(Y_{\Psi t-1}^{C'}, \ldots, Y_{\Psi t-L}^{C'}, X_{\Psi t-1}^{C'}, \ldots, X_{\Psi t-L}^{C'}\right)$. In addition, we put all the VAR coefficients in a matrix $(N_Y + N_X)L \times N_Y$ $\tilde{A}$ such that $\tilde{A} = [A', E']'$ and $\alpha^C = vec(\tilde{A})$.

The model then becomes:

$$y_\Psi^C = \left(I_{N_Y} \otimes Z_\Psi^C\right) \alpha^C + v^C$$

Following Jarocinski [2010] the prior distribution for α^C is normal, centred on a common mean in all countries of the euro area:

$$\alpha^C \sim \mathscr{N}(\alpha, \underline{\Omega}_\alpha)$$

and, for each country, the variance for the k^{th} coefficient in α^C in the n^{th} equation is specified as:

$$var(\alpha_{k,n}^C) = \lambda \left(\frac{\hat{\sigma}_n^2}{\hat{\sigma}_k^2}\right) \tag{329}$$

Larger values of λ imply less informative priors, which translates into a smaller degree of shrinkage of the coefficients toward the prior mean. The scaling factor λ is sampled from an inverse Gamma distribution, see B.1.[127]

These assumptions lead to the following normal conditional posterior distribution:

$$\alpha^C | \overline{Y}^C, \overline{X}^C, \alpha, \lambda, \Psi_Y^C, \Sigma_C \sim \mathscr{N}(\overline{\alpha}^C, \overline{\Omega}_\alpha^C)$$

$$\overline{\Omega}_\alpha^C = \left[\underline{\Omega}_\alpha^{-1} + \Sigma_C^{-1} \otimes \left(Z_\Psi^{C'} Z_\Psi^C\right)\right]^{-1}$$

$$\overline{\alpha}^C = \overline{\Omega}_\alpha^C \left[\underline{\Omega}_\alpha^{-1} \alpha + vec\left(Z_\Psi^{C'} Y_\Psi^C \Sigma_C^{-1}\right)\right]$$

Block 2: Drawing the unconditional means for each country Within this block, we make use of the second formulation of the model in equation (328). Furthermore, we define $W_t^C \equiv \overline{Y}_t^C - \sum_L A_L^C \overline{Y}_{t-L}^C - \sum_L E_L^C X_{\Psi t-L}^C$. Stacking in the usual way, we can thus bring the model in the form stipulated in Villani [2009]:

[127] Note that this setup is different compared to Jarocinski [2010] since we specify a common covariance matrix across all countries instead of scaling the country counterparts of $\hat{\sigma}_i^2$.

$$W^C = D\Theta^C + \nu^C$$

where $\Theta^{C'} = \left(\Psi_Y^C, A_1^C\Psi_Y^C, \ldots, A_L^C\Psi_Y^C\right)$. As shown in Villani [2009] to avoid a bad performance of the Gibbs sampler, a prior that is at minimum slightly informative is needed for the estimation of the steady-state parameter Ψ_Y^C. Its prior distribution is given by

$$\Psi_Y^C \sim \mathcal{N}(\underline{\Psi}_Y^C, \underline{\Omega}_\Psi^C)$$

The posterior then follows a multivariate normal distribution given by:

$$\Psi_Y^C | \overline{Y}^C, \overline{X}^C, \alpha^C, \Sigma_C \sim \mathcal{N}(\overline{\Psi}_Y^C, \overline{\Omega}_\psi^C)$$

$$\overline{\Omega}_\psi^C = \left[\underline{\Omega}_\psi^{C\,-1} + U'(D'D \otimes \Sigma_C{}^{-1})U\right]^{-1}$$

$$\overline{\Psi}_Y^C = \overline{\Omega}_\psi^C \left[\underline{\Omega}_\psi^{C\,-1}\underline{\Psi}_Y^C + U' vec(\Sigma_C{}^{-1}W^{C'}D)\right]$$

where $U' = (I_q, I_q \otimes A_1^{C'}, \ldots, I_q \otimes A_L^{C'})$ and $q = 1$ as we only include a constant in the model. The long run priors across the euro area in Block B.1 reflect country level of development, size, and perceived risk level. Table 19 provides an overview of the prior ranges as well as of the rationale behind their calibration. The mean of the prior level of short-term interest rates STN, the growth rate of the ECB balance sheet UMP and those of inflation HIC, are set uniformly across countries, reflecting the common monetary policy framework. Along with the same argument, the variance of priors for short-term interest rates STN and the growth rate of the ECB balance sheet UMP are identical across countries. However, for the inflation rate HIC the variance of the priors is set higher for smaller countries (allowing larger deviations from the target inflation) and tighter for larger countries. The size of a country for the calibration of the prior variance is measured by nominal GDP.

The long-term priors for all other price indices other than consumer prices are set uniformly for all countries. The mean prior growth of house prices is set at the same level as the mean prior consumer inflation. The mean growth of export prices is lower than the mean prior consumer inflation and is lower (by 0.5 pp annually) than the mean prior consumer inflation reflecting the assumption of slower medium-run growth of prices of tradable goods.

For the purpose of setting priors on GDP growth and later the growth rates of stock prices ESX, import MTR and lending volumes CPN, the euro area countries are subdivided into two groups broadly corresponding to their economic development and correlating with their time of accession to the EU or the euro area. The developed countries or old member states include Austria, Belgium, Cyprus, Spain, Finland, France, Greece, Italy, Luxembourg, the Netherlands and Portugal. The remaining countries include Estonia, Ireland, Lithuania, Latvia, Malta, Slovenia, and Slovakia. For the former countries, the average annual GDP growth is assumed to be around 1.5% annually, while for the latter it is twice as large. The variance of the prior is set to become tighter with a larger economy (as measured by nominal GDP). The mean prior growth of stock prices and lending volumes is set consistently with the mean prior growth of nominal GDP, while the mean prior growth of import prices reflects the faster growth in trade exchange between countries compared to their GDP. It is set as the prior growth in GDP multiplied by factor 1.6.

The setting of the remaining priors is informed by the data. The mean and variance of the prior distributions for lending margins BLR are set uniformly between countries. The uniform mean of 2.5% annually is calibrated in the middle of the interval spanned by the long-term average values of the sample for the country lending spreads of 1.5 to 4.5%. The mean prior for the spread between LTN and STN, *SPR*, is predicted from a non-linear regression of the spread on the public debt to GDP (and correcting for the margin between equilibrium and nominal interest rate for less developed EA countries). Finally, the mean prior for the unemployment rate *URX* is around the sample average unemployment rate. The variance of the *SPR* and *URX* priors is set so that the ratio between the standard deviation and the mean of the prior distributions for all countries remains the same.

	Variable	$\underline{\Psi}_Y^C$	$\underline{\Omega}_\Psi^C$	Rationale
Y_t	YER	[0.004 - 0.008]	[0.001- 0.006]	Level of development
	HIC	[0.005]	[0.001- 0.006]	Inflation target of 2% annually
	URX	[0.040 - 0.150]	[0.010- 0.038]	Sample average mean unemployment rate (country specific)
	IHX	[0.005]	[0.002]	Dynamic homogeneity with consumer inflation
	SPR	[0.004 - 0.036]	[0.0003 - 0.002]	Predicted country-risk based on public debt to GDP level
	ESX	[0.009 - 0.012]	[0.002 - 0.003]	Dynamic homogeneity with nominal GDP
	MTR	[0.006 - 0.012]	[0.003 - 0.006]	Faster growth of foreign trade compared to GDP
	XTD	[0.004]	[0.001]	Slower price growth of tradable (compared to consumer) goods
	BLR	[0.059]	[0.029]	Sample average lending sperad (across countries)
	CPN	[0.009 - 0.012]	[0.002 - 0.015]	Dynamic homogeneity with nominal GDP
M_t	STN	[0.034]	[0.003]	Common monetary policy
	UMP	[0.004]	[0.002]	Common monetary policy

Notes: Min-max range of predefined prior values for EA country-specific variables.

Table 19: Prior ranges of the macro VAR

Block 3: Drawing the error covariance matrix for each country We sample from the conditional posterior for Σ_C via the Stochastic Search Variable Selection (SSVS) approach of George et al. [2008]. The SSVS approach is a way to systematically impose restrictions on either the VAR coefficients and error covariance matrices (or both) without having to compare an unfeasible large number of different submodels. In our setup, the SSVS approach is only applied to the elements of Σ_C, for which the following decomposition is convenient:

$$\Sigma_C{}^{-1} = \Phi_C \Phi_C^{'}$$

with Φ_C being upper triangular. The SSVS approach in George et al. [2008] intuitively works as follows. The diagonal elements of Φ_C are assumed a priori to follow a Gamma distribution, ensuring that the diagonal entries are strictly positive and, therefore, any sampled $\Sigma_C{}^{-1}$ is positive definite. For the remaining off-diagonal elements, the idea is to specify the prior for the column elements as a mixture of two normal distributions. These are centred at a common mean of zero, but one has a small prior variance while the other has a large prior variance. The data then determine which of these distributions to draw from, thus selecting appropriate submodels for the data. Our implementation is identical to George et al. [2008] with variables appropriately adjusted to correspond to the system in equation (327).

Block 4: Drawing the common mean In contrast to the previous blocks, the common mean α is sampled from the entire panel dataset. As in Jarocinski [2010] the prior for α is non-informative:

$$p(\alpha) \propto 1$$

resulting in the following normal conditional posterior distribution:

$$\alpha|\overline{Y}^C, \alpha^1, \ldots, \alpha^C, \lambda \sim \mathscr{N}(M_\alpha, V_\alpha)$$
$$M_\alpha = \frac{1}{C}\sum_C \alpha^C$$
$$V_\alpha = \frac{1}{C}\underline{\Omega}_\alpha$$

Block 5: Drawing the common prior covariance scaling factor Lastly, we sample the common covariance scaling factor λ. Following Jarocinski [2010] the prior is specified as:

$$p(\lambda) \propto \lambda^{-\frac{1}{2}}$$

which corresponds to a non-informative prior on the standard deviation scaling factor $\sqrt{\lambda}$, resulting in an inverse gamma conditional posterior distribution:

$$\lambda|\overline{Y}^C, \alpha^1, \ldots, \alpha^C, \alpha \sim \mathscr{IG}\left(\frac{\overline{s}}{2}, \frac{\overline{v}}{2}\right)$$
$$\overline{s} = CN_y(N_y + N_x)L$$
$$\overline{v} = \sum_{c=1}^{C}\left((\alpha^C - \alpha)'\underline{\tilde{\Omega}}_\alpha^{-1}(\alpha^C - \alpha)\right)$$

where $\underline{\tilde{\Omega}}_\alpha$ is implicitly defined by $\underline{\Omega}_\alpha = \lambda\underline{\tilde{\Omega}}_\alpha$ (see equation (329)).

Selection of exogenous variables to control for COVID-19 and energy crisis episodes The country-specific vector Z_t^C includes two types of exogenous variables: dummy variables related to the COVID-19 episode and the energy price index. The sequence of extreme observations in the panel VAR in the period of the COVID-19 pandemic is treated by the inclusion of dummy variables for periods where we identify extreme observations.[128]

First, we determine at a country-by-country level which periods require a distinctive treatment based on the distribution of the reduced form errors. Concretely, the pre-treatment residuals are evaluated on the basis of the χ^2 distribution metrics:

$$\chi_t^{2C} = v_t^{C'}\Sigma_C{}^{-1}v_t^C$$

where v_t^C represents the reduced form residual in period t for country C and Σ_C is the variance-covariance matrix of the regression error for country C.[129]

[128] A range of methods have been put forward to deal with unprecedented fluctuations in key macroeconomic variables when performing inference in VAR frameworks. For example, Lenza and Primiceri [2022] or Carriero et al. [2021] capture these extreme observations by making adjustments in the stochastic volatility process of the VAR residuals. Schorfheide and Song [2021] excludes the pandemic observations from the estimation sample. Our approach resembles the latter.

[129] v_t^C are assumed to be i.i.d. $N(0,\Sigma_c)$, see equation (1).

Then dummies are set if the measure χ_t^{2C} exceeds the critical value of the χ^2 distribution at a level of significance of 1% with N degrees of freedom between 2020 Q2 – 2020 Q4.[130] Table 20 displays the countries and periods for which dummies were introduced.

Periods	AT	BE	CY	DE	EE	ES	FI	FR	GR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK
2020:Q2	x	x	x	x		x	x	x	x	x	x	x		x	x	x	x	x	x
2020:Q3						x		x											
2020:Q4					x														

Table 20: Exogenous variables to control for COVID-19

The exogenous country-specific fossil energy price index EPR_t^C is constructed as a weighted average of natural gas GAS, oil OIL, and solid fossil fuel SFF.

$$EPR_t^C = w_{GAS}^C GAS_t + w_{OIL}^C OIL_t + w_{SFF}^C SFF_t$$

with w^C reflecting the share of natural gas, oil and solid fossil fuels in the country C mix of fossil energy.

Structural Shock Identification

The identification of structural shocks is based on the methodology of Arias et al. [2018]. It comprises both sign restrictions and zero restrictions. The restrictions are binding on impact and up to the first quarter, respectively.

The structural shocks identified by the sign restriction summarised in table 3 and capture the following share of the variable variation:

	Credit Supply	Credit Demand	Monetary Policy	Unconventional Monetary Policy	Stock Price	Yield	Resident. Price	Aggregate Demand	Aggregate Supply
Real GDP	13	6	1	1	4	12	16	10	8
HICP	18	7	1	1	1	2	4	16	15
Unemp. rate	4	1	5	6	5	12	18	11	9
Short-term rate	3	1	1	0	0	15	25	14	8
Interest rate spread	14	4	5	6	5	7	17	10	8
Import volume	16	6	3	4	4	10	16	10	7
Export price	17	7	5	6	6	9	12	10	5
Residential prop. prices	39	13	5	5	5	5	6	5	4
Bank lending rate	25	13	1	0	0	9	14	11	5
Bank loan volume	18	9	1	2	2	10	17	7	8
Equity price index	16	7	2	3	3	9	14	13	6
Eurosystem's assets	2	1	2	2	2	14	22	12	8

Table 21: Forecast error variance decomposition for a 2 year horizon in percentage

Data Most of the euro area variables are sourced from SDW. Table 22 summarises the original sources of the series. SPR entering the panel, VAR is computed as the difference STN and LTN. FDR is calculated as a weighted average of import volumes (originally sourced from Eurostat and equivalent to the variable MTR) of countries to which the reference country exports.

[130] We also study the distribution of errors for 2021 Q1 but our measure didn't point towards the inclusion of a dummy variable for any of the countries.

The weights are proportional to the share of exports to a country in the total export volumes of the reference country. CXD is calculated as a weighted average of export prices (sourced from Eurostat and equivalent to the variable XTD of the reference country's trading partners. The weights are proportional to the share of imports from a country in the total import import volumes from the reference country. The index of the price of fossil fuels EPR is calculated as a weighted mean of gas GAS, oil OIL and solid fuel SFF. For natural gas Dutch TTF Natural Gas Forward Day Ahead prices, for oil brent spot prices are used, both sourced from Refinitiv. Solid fossil fuel price data is sourced from the Organisation for Economic Cooperation and Development (OECD). The weights underlying each country's energy index are proportional to the country's dependence on gas, oil, and solid fossil fuels on fossil energy according to the International Energy Agency (IEA).

Variables	AT	BE	CY	DE	ES	FI	FR	GR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK	
YER										Eurostat									
HIC										Eurostat and EC									
URX										Eurostat									
IHX	ECB	Banque Nationale de Belgique	Eurostat	Verband Deutscher Pfandbriefbanken	Eurostat	Eurostat	Eurostat	Eurostat	Eurostat	Eurostat	Eurostat	Eurostat	Central Statistical Bureau of Latvia	Central Bank of Malta	Eurostat	Eurostat	Statistical Office of the Republic of Slovenia	Eurostat	Eurostat
STN										Refinitiv									
LTN										Refinitiv									
ESX	Datastream	Datastream	Datastream	Datastream	Refinitiv	Datastream	Refinitiv	Datastream	Datastream	Datastream	Datastream	Datastream	Datastream	Bloomberg Finance	Datastream	Datastream	Datastream	Refinitiv	
MTR										Eurostat									
XTD										Eurostat									
BLR										NCBs and ECB (BSI statistics)									
CPN										NCBs and ECB (BSI statistics)									
UMP										ECB									
FDR										ECB									
CXD										ECB									
OIL										Refinitiv and ECB									
GAS										Refinitiv and ECB									
SFF										Hamburg Insitute of International Economics (HWWI)									

Notes: NCBs refers to the National Central Banks of all EU Member States.

Table 22: Sources of Macroeconomic Variables

B.2 Rest of the world VARs

Methodology

In reference to equation (4), the VARs for 18 rest of the world economies are estimated for each country separately, applying a maximum likelihood estimator. The specifications for Bulgaria (BG), Czech Republic (CZ), Denmark (DK), Croatia (HR), Hungary (HU), Poland (PL), Romania (RO), Sweden (SE), Switzerland (CH), Norway (NO) Brazil (BR), China (CN), Japan (JP), Mexico (MX), Russia (RU), Sweden (SE), Turkey (TK), United Kingdom (UK) and United States (US) include varying number of endogenous variables depending on availability of historical data and macrofinancial projections from the ECB. These are summarised in Table 23.

Variables	BG	BR	CH	CN	CZ	DK	HR	HU	JP	MX	NO	PL	RO	RU	SE	TK	UK	US
MTR	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
XTD	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
YER	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
URX							x	x			x	x	x		x			x
HIC					x	x		x	x		x	x	x		x		x	x
STN							x		x		x							x
LTN									x									x
IHX					x	x	x					x						
ESX					x	x						x			x			

Table 23: Rest of the World macroeconomic variables

Data

The data sample starts with 2002 Q2 and ends in 2020 Q4. The data for the non-euro area European Union countries are sourced from Eurostat. For other countries, the data sources are summarised in Table 24. The country-VAR variables are transformed similarly to the transformations applied to the corresponding variables in countries in the euro area as in Table 2.

Variables	BR	CH	CN	JP	MX	NO	RU	TK	UK	US
MTR	Instituto Brasileiro de Geografia e Estatística	State Secretariat for Economic Affairs	National Bureau Statistics and ECB calculations	Cabinet Office of Japan	Instituto Nacional de Estadística Geografía e Informática	Statistiska Sentralbyra	Russia Federal State Statistics Service	Turkish Statistical Institute	Office for National Statistics	Bureau of Economic Analysis
XTD	Instituto Brasileiro de Geografia e Estatística	State Secretariat for Economic Affairs	National Bureau Statistics and ECB calculations	Cabinet Office of Japan	Instituto Nacional de Estadística Geografía e Informática	Statistiska Sentralbyra	Russia Federal State Statistics Service	Turkish Statistical Institute	Office for National Statistics	Bureau of Economic Analysis
YER	Instituto Brasileiro de Geografia e Estatística	State Secretariat for Economic Affairs	National Bureau Statistics and ECB calculations	Cabinet Office of Japan	Instituto Nacional de Estadística Geografía e Informática	Statistiska Sentralbyra	Russia Federal State Statistics Service	Turkish Statistical Institute	Office for National Statistics	Bureau of Economic Analysis
URX										Bureau of Labor Statistics
HIC					Ministry of Internal Affairs and Communications	Statistiska Sentralbyra			Office for National Statistics	Bureau of Labor Statistics
STN				Refinitiv		x				Refinitiv
LTN				Refinitiv						Refinitiv
IHX							x			
ESX							x	x		

Table 24: Overview of Rest of the World variable sources

B.3 Yield curve

Methodology

The parametric three-factor yield curve model of Nelson and Siegel [1987] is estimated for 19 countries in the individual euro area, the euro area and the United States. Each yield curve is assumed to be described by four parameters: level, slope, curvature, and decay rate. The estimation focuses on the curvature factor and exponential decay rate, while the level and slope parameter are pinned down by the level of the short- and long-term interest rates projected in the macrofinancial block.

The two-step grid search procedure proposed by Nyholm [2008] is used to estimate the curvature factor and exponential decay rate based on the historically last available data points. First, the level, slope, and curvature are determined for a fixed exponential decay rate value by applying a maximum likelihood approach. This step is repeated for a range of exponential decay rate values. In a second step, we select an exponential decay rate that minimises the sum of squared residuals between the estimated yield curve and the real yields.

Data

In order to estimate parameters related to the shape of the yield curve, we use maturities from 3 months up to 30 years. For example, in the case of the German sovereign yield curve, the following maturities are used to estimate the exponential decay rate and the curvature: 3, 6-month, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 20 years. Table 25 summarises the maturities used for each country. The data used refer to Q2 2022 and are sourced from Refinitiv.

Results

The results of the slope and the curvature estimation are summarised in Table 26. Figure 47 illustrates the estimation of the yield curve at six selected time points that exhibit a wide range

Countries	1 Month	3 Month	6 Month	9 Month	1 Year	2 Years	3 Years	4 Years	5 Years	6 Years	7 Years	8 Years	9 Years	10 Years	15 Years	20 Years	25 Years	30 Years
AT		x			x	x	x	x	x	x	x	x	x	x	x	x		x
BE		x	x		x	x	x	x	x	x	x	x	x	x		x		x
CY		x													x			
DE	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x
ES		x	x		x	x	x	x	x	x	x	x	x	x	x	x		x
FI		x				x	x	x	x			x		x	x		x	x
FR	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x
GR		x	x											x	x	x		
IE		x			x			x	x	x	x			x	x			
IT		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		x
LT		x					x		x					x				
LV		x				x	x		x									
MT		x	x		x		x		x					x		x		
NL		x	x			x	x	x	x	x	x	x	x	x		x		x
PT		x	x		x	x	x	x	x	x	x	x	x	x	x	x		x
SI		x				x			x					x				
SK		x							x			x		x				
EA		x			x	x	x	x	x	x	x	x	x	x				
US	x	x	x		x	x	x		x		x			x				x

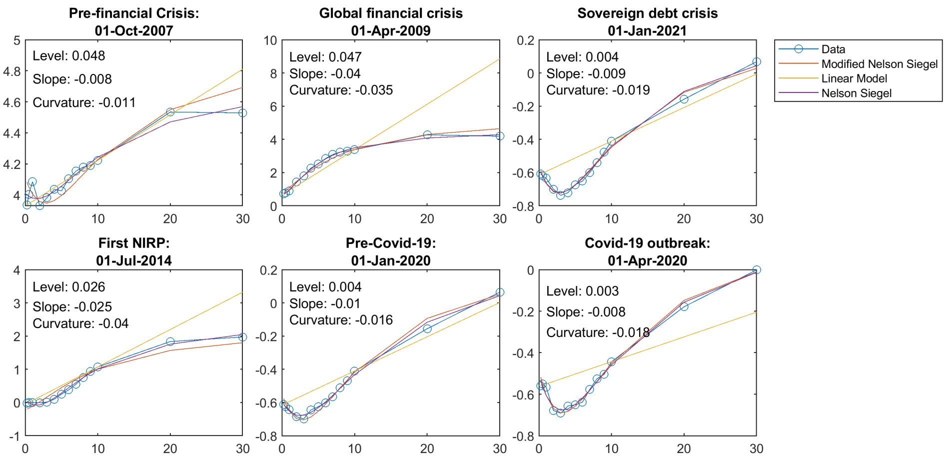
Table 25: Maturities used for determining the curvature factor and the exponential decay rate.

of different economic situations – before a crisis, during a crisis, and in the course of a recovery. As a result, the shape of the yield curve differs materially depending on the time point. The Nelson-Siegel yield curve approximates the yield curve data reasonably well independently of the exact shape of the curve. Compared to a simple linear approximation by a straight line using only the 3 month and the 10 year rate, the benefits are particularly strong if the curvature is large.

Variables	AT	BE	CY	DE	ES	FI	FR	GR	IE	IT	LT	LU	LV	MT	NL	PT	SI	SK	EA	US
Curvature	0.000	0.000	1.121	0.000	0.000	0.019	0.000	0.197	0.036	-0.037	0.000	1.121	18.833	0.000	-0.015	0.000	1.121	0.000	0.000	0.020
Exp. decay rate	0.495	0.365	0.548	0.760	0.420	0.275	0.425	0.110	0.170	1.170	0.975	0.548	0.015	0.395	1.260	0.385	0.548	0.345	0.485	1.260

Table 26: Yield curve parameters kept constant over time

Given that relatively little yield curve variation is attributed to the curvature factor, keeping this parameter constant over time should represent a sensible approximation Diebold and Rudebusch [2013] also indicated by Figure 47. The modified Nelson-Siegel approximation (red line in Figure 47) , which assumes a constant curvature, approximates the yield curve data better compared to a linear approximation and is only marginal worse compared original Nelson-Siegel approximation.



Notes: The exponential decay rate is set to 0.305 and the curvature to -0.018 for the modified Nelson Siegel model. The maturity is displayed on the x-axis and the yield is displayed on the y-axis in %.

Figure 47: German yield curve data at different time points, 3 factor Nelson-Siegel model, Linear model and a modified Nelson Siegel model

C Empirical models of bank behaviour

C.1 Loan demand

Methodology

Estimation of the bank loan demand function (see equation (11)) involves two steps. The first step is to build a bank-level indicator that approximates the evolution of bank-specific loan supply changes. The second step is to estimate sector-specific loan demand equations that include the indicator derived in the first step as a control variable.

To enable a consistent identification of bank-level loan demand, it is necessary to take into account changes in credit supply. Due to the lack of historical data on bank solvency or profitability from 2008 (i.e., the starting point of the sample used to estimate loan demand equations), we derive a sector-specific structural loan supply shock using semi-consolidated information on banks' outstanding lending volumes from iBSI and lending rates on new lending from iMIR. More precisely, for each ultimate parent bank, we estimate on the highest level of consolidation an SVAR model as in Altavilla et al. [2016]:

$$Y_{i,t}^{S} = c_i + \sum_{p} A_{i,p} Y_{i,t-p}^{S} + \sum_{p} B_{i,p} X_{i,t-p} + \varepsilon_{i,t} \tag{330}$$

where Y^S is a vector that includes the natural logarithm of lending volumes and the first difference in the average lending rate for new loans to sector $S \in \{NFC, HH, TOTAL\}$ at time point t for bank i. c_i is a vector of bank-specific intercepts. $X_{i,t}$ is a vector of exogenous variables that includes the logarithm of exposure weighted real GDP and changes in short-term rates in the euro area STN. $A_{i,p}$ is a bank-specific matrix of autoregressive coefficients, p is the number of lags set $p = 1$, and $\varepsilon_{i,t}$ is a vector of reduced–form residuals.

Relying on these banking group specific SVARs we identify credit supply shocks by using the algorithm of Arias et al. [2018] and imposing sign restrictions as illustrated in Table 27:

	Credit supply
Loan volumes	–
Avg. interest rate	+

Table 27: Summary of identifying restrictions

In a second step, the lending demand equations for each sector-country portfolio $S = \{NFC, HHCC, HHHP, SOV, FIN\}$ are estimated separately using a fixed-effect panel regression of bank-level loan growth rates on the economic conditions in a country of exposure. Thereby we postulate the following functional relationship for the quarterly growth rate of bank i loan volumes to sector S in country C at time t denoted by $TotalLoans\_gr_{i,t}^{S,C}$:

$$\begin{aligned} TotalLoans\_gr_{i,t}^{S,C} = \beta_{0,i}^{S} + \sum_{p} (\beta_{1,p}^{S}\, TotalLoans\_gr_{i,t-j}^{S,C} + \beta_{2,p}^{S}\, YERgr_{t-p}^{C} + \beta_{3,p}^{S}\, HICgr_{t-p}^{C} \\ + \beta_{4,p}^{S}\, \Delta URX_{t-p}^{C} + \beta_{5,p}^{S}\, \Delta STN_{t-p}^{C} + \beta_{6,p}^{S}\, SPR_{t-p} \\ + \beta_{7,p}^{S}\, \Delta EIRAssetNew_{i,t-p}^{S,C}) + \beta_{8}^{S}\, SupplyShock_{i,t}^{S} + \beta_{9}^{S}\, PG_{t}^{C} + \varepsilon_{i,t}^{S,C} \end{aligned}$$

where $EIRAssetNew$ corresponds to the effective lending rate. Macroeconomic control variables include the GDP growth rate $YERgr$, inflation $HICgr^C$, unemployment rate URX^C, 3-month EURIBOR rate STN and the spread between long- and short-term rates SPR, all in the country of exposure C. A dummy variable PG controls the introduction of public loan guarantees during the outbreak of the COVID-19 pandemic and is equal to one if a guarantee programme was initiated in the country C and the time point t. β stand for regression coefficients, therein $\beta_{0,i}$ stands for fixed effects of the bank. To control for bank-specific supply factors, the specification includes the cumulative supply shock index $Supplyshock$ from equation (330) accordingly:

$$Supplyshock_{i,t}^{S} = \begin{cases} Supplyshock_{i,t}^{NFC} \text{ if } S = NFC \\ Supplyshock_{i,t}^{HH} \text{ if } S \in HHHP, HHCC \\ Supplyshock_{i,t}^{TOTAL} \text{ if } S \in SOV, FIN \end{cases}$$

The sets of regressors differ for the non-financial private sector $S \in \{NFC, HHCC, HHHP\}$ and the sovereign and financial sectors $S \in \{SOV, FIN\}$. For the first, information on bank lending rates $EIRAssetNew$ can be obtained from iMIR and captures the effect of price for each bank. For the latter, this information is not available, and the regressions aim to capture the direct transmission of short-term market rates ΔSTN and the spread between long- and short-term rates SPR in sovereign and financial lending volumes. Furthermore, to smooth the effect of the very large and sudden drop in economic activity during the first year of the COVID-19 pandemic, GDP growth rates are transformed into annual moving average growth rates ($\overline{YERgr}_{t-1}^{4q}$) for non-financial private sectors $S = \{NFC, HHCC, HHHP\}$.

Regressions are estimated with standard errors clustered at the banking group level. To exclude insignificant variables and their lags, a general to specific procedure is applied starting from two lags $p = 2$ for all covariates. Panel specifications are estimated subject to dynamic homogeneity restrictions (see Jensen [1994]) to ensure a stable long-term relationship between nominal GDP and loan growth. This condition imposes that nominal credit growth equals nominal GDP growth in the long run.

Data

The estimation of the loan demand regressions relies on a large unbalanced panel of quarterly data including bank lending rates on new business from iMIR, outstanding amount of loans from iBSI and macroeconomic variables for the country of exposure from the SDW (information in Table 28 is provided in decimals). The stocks of outstanding loan volumes from iBSI are transformed into indices of notional stocks taking into account revaluations of securities, reclassifications, loan write-offs/write-downs, and net flows of loans securitized or otherwise transferred.

The first stage of the analysis is based on semi-consolidated loan and interest rate information, while the second stage uses individual reporting of banking group branches and subsidiaries per country. Loan and interest rate data were seasonally and outlier adjusted using the X-12-ARIMA algorithm Bureau [2011] separately for the data sets at the individual branch and consolidated bank level.

The originally monthly iMIR/iBSI data are then transformed to quarterly time series by taking the last-month observations for the stock of loans and the three-month average of monthly lending rates. Due to the very high volatility of bank lending volumes to the sovereign and financial sectors, the corresponding variables are transformed into annual moving average growth rates. The current historical sample covers bank-level data from 2007 Q4 until 2020 Q4.

Variables	Observations	Mean	Median	Standard deviation
$TotalLoans\_gr\ NFC$	5811	0.0035	0.0032	0.0384
$TotalLoans\_gr\ FIN$	7216	0.0086	0.0058	0.2829
$TotalLoans\_gr\ HHHP$	4348	0.0023	0.0015	0.0246
$TotalLoans\_gr\ HHCC$	4485	-0.0027	-0.0019	0.0293
$TotalLoans\_gr\ SOV$	2970	-0.0045	-0.0071	0.1005
$\Delta EIRAssetNew\ NFC$	5811	-0.0007	-0.0004	0.0035
$\Delta EIRAssetNew\ HHCC$	4485	-0.0007	-0.0006	0.0041
$\Delta EIRAssetNew\ HHHP$	4348	-0.0007	-0.0006	0.0024
$YERgr$	7228	0.0013	0.0030	0.0285
$HICgr$	7363	0.0027	0.0030	0.0044
ΔSTN	7228	-0.0011	-0.0001	0.0035
SPR	7228	0.0203	0.0156	0.0228
ΔURX	7228	0.0003	-0.0005	0.0054
$SupplyShock\ TOTAL$	7228	0.1303	0.0729	0.6949
$SupplyShock\ NFC$	4060	0.1591	0.1526	0.5011
$SupplyShock\ HH$	4485	0.0294	0.0156	0.4334

Table 28: Summary statistics: loan demand regressions

Figure 48 illustrates the median quarterly loan growth for non-financial corporations and households (in the left panel) together with the respective shock indices of credit supply per banking group (in the right panel). Lending dynamics differs between sectors. Lending volumes to non-financial corporations is generally more volatile than lending volumes to households. Credit supply indices mirror recent financial turmoils, such as the Lehman crisis in 2008 or the European sovereign debt crisis. The indices reached their peak in 2012 and slowly moderated in the expansionary period with stable financial markets from 2016 to 2020.

Figure 48: Lending volumes and loan supply shocks for NFC and household lending

Results

Table 29 summarises the estimates for all economic sectors. Table 30 outlines the estimates for the impact of the public guarantee policy on NFC lending in each country. The dummies are equal to one for the periods between Q1 and Q4 2020, in case a guarantee programme was active. The policy dummies are significant for Spain, Portugal, Greece, Italy and Luxembourg.

	(1) NFC	(2) HHHP	(3) HHCC	(4) SOV	(5) FIN
$TotalLoans\_gr_{t-1}$	0.192**	0.645**	0.327**	0.768**	0.711**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$TotalLoans\_gr_{t-2}$	0.148**	0.226**	0.229**		
	(0.000)	(0.000)	(0.000)		
$\overline{YERgr}^{4q}_{t-1}$	0.660**	0.129**	0.443**		
	(0.000)	(0.000)	(0.000)		
$YERgr_{t-1}$				0.0860**	0.141**
				(0.000)	(0.000)
$YERgr_{t-2}$				0.146**	0.148**
				(0.000)	(0.000)
$HICgr_{t-1}$	0.287**	0.0909**	0.226*	0.232**	0.289**
	(0.000)	(0.007)	(0.010)	(0.000)	(0.000)
$HICgr_{t-2}$	0.373**	0.0377	0.217*		
	(0.000)	(0.224)	(0.015)		
ΔSTN_{t-1}				-0.397^{+}	0.295
				(0.083)	(0.231)
SPR_{t-1}				-0.0810^{+}	-0.355**
				(0.055)	(0.002)
ΔURX_{t-1}				0.603**	0.401
				(0.003)	(0.125)
$\Delta EIRAssetNew_{t-1}$	-0.176	-0.366**	-0.288**		
	(0.111)	(0.000)	(0.000)		
$SupplyShock_t$	-0.0095**	0.0012	-0.004**	-0.0077**	-0.00604*
	(0.000)	(0.111)	(0.007)	(0.029)	
Obs	5811	4348	4485	2973	7222
Banks	67	59	60	40	70
R^2	0.078	0.539	0.165	0.607	0.500

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 29: Loan demand regressions: 2007 Q4 – 2020 Q4

	(1) AT	(2) BE	(3) DE	(4) ES	(5) PT	(6) FR	(7) GR	(8) IE	(9) IT	(10) LU	(11) NL
$PG-Dummy$	-0.0057	0.0013	-0.0008	0.0270**	0.0317**	0.0092	0.0256**	-0.0005	0.0192*	0.0036**	-0.0191
	(0.391)	(0.871)	(0.884)	(0.009)	(0.000)	(0.112)	(0.000)	(0.886)	(0.012)	(0.003)	(0.090)

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 30: Public guarantee dummies for NFC model in 2020Q1-Q4

C.2 Loan supply

Methodology

To identify factors that influence banks' lending supply (12), we rely on a pooled bank-level regression inspired by Khwaja and Mian [2008]. A bank counterparty is a specific lending segment such as a corporate sector in one of the jurisdictions.[131] Using data for counterparties that borrow from at least two banks, we can identify counterparty-time fixed effects related to the evolution of the macroeconomic environment and loan demand factors. The salient assumptions behind this methodology are that all entities within the same sector-counterparty class face the same demand for loans and that loan demand is counterparty-specific.

The general regression specification is as follows:

$$
\begin{aligned}
TotalLoans\_gr_{i,t}^{S,C} = {} & \beta_1^S CET1SurShortfall_{i,t} \times I(Type_i = 0) \times I(HomeForeign_i^{S,C} = 0) \\
& + \beta_2^S CET1SurShortfall_{i,t} \times I(Type_i = 0) \times I(Home_i^{S,C} = 1) \\
& + \beta_3^S CET1SurShortfall_{i,t} \times I(Type_i = 1) \times I(Home_i^{S,C} = 0) \\
& + \beta_4^S CET1SurShortfall_{i,t} \times I(Type_i = 1) \times I(Home_i^{S,C} = 1) \\
& + \beta_5^S LEVRSurShortfall_{i,t} \times I(Type_i = 0) \\
& + \beta_6^S LEVRSurShortfall_{i,t} \times I(Type_i = 1) \\
& + \beta_7^S netNPLR_{i,t}^{S,C} \times I(\Delta_4 NPLR_{i,t}^{S,C} < 0) \\
& + \beta_8^S ROA_{i,t} + \beta_9^S EIRLiab_{i,t} \\
& + \beta_{10}^S RRW_{i,t}^{S,C} \\
& + \beta_{11}^S CET1SurShortfall_{i,t} \times I(CET1SurShortfall_{i,t} < 0) \\
& + \beta_{12}^S netNPLR_{i,t}^{S,C} \times I(\Delta_4 NPLR_{i,t}^{S,C} > 0) \\
& + \beta_{13}^S RRW_{i,t}^{S,C} \times I(CET1SurShortfall_{i,t} < 0) + \varepsilon_{i,t}^{S,C}
\end{aligned}
$$

where $TotalLoans\_gr$ is the quarterly log change of sector S loans to the counterparty (country) C, $CET1SurShortfall$ is a measure of CET1 capital surplus or shortfall (see equation (201) for its definition) [132] and leverage ratio shortfall $LEVRSurShortfall$ compared to bank specific leverage ratio targets (see equation (204)). $netNPLR$ is sector-counterparty specific share of non-performing loans net of provisioning, ROA is return on assets, RRW is the sector-counterparty specific relative risk weight derived as the sector-country specific risk weight of the counterparty relative to the average risk weight of a bank, $RRW_{i,t}^{S,C} = RW_{i,t}^{S,C}/RW_{i,t}$. $\beta_{0,t}^{C}$ are counterparty-time fixed effects.

In addition to the linear effect of capital surplus or shortfall, we are interested in three types of non-linearities. First, a bank close to its regulatory requirements may be more likely to substantially deleverage. To capture this effect, we interact $CET1SurShortfall$ and RRW with a dummy variable equal to one if bank i experiences a capital shortage in time t denoted by $I(CET1SurShortfall < 0)$. Second, when in trouble, banks may deleverage primarily on non-domestic exposures. To pin down this home-bias effect, we interact $CET1SurShortfall$ with a dummy variable $Home$ that turns one for exposures to the domestic market $I(Home) = 1$ and zero for foreign markets $I(Home) = 0$. Finally, we distinguish between the cases where the share of bank NPLs increased in the last year and the cases where such a share decreased and introduce the interactions with the corresponding dummies $I(\Delta_4 NPLR > 0)$ and $I(\Delta_4 NPLR > 0)$.

[131] Similar approach is used by Mésonnier and Monks [2015] in their study of the effect of the 2011 EBA capital exercise.

[132] Several studies have shown an importance of the link between bank capital and lending activity (see for example Gambacorta and Mistrulli [2004], Jonghe et al. [2016] and Aiyar et al. [2016]). A general finding of these studies is that less-capitalised banks provide fewer funding sources for the real economy.

An additional indicator variable *Type* allows one to distinguish banks with the special nature of their business model (special lenders) or ownership structure (state-owned) (see Table 5 for the classification of banks in the sample). The indicator *Type* is interacted with $CET1SurShortfall$ and $LEVRSurShortfall$ to acknowledge that empirically these banks exhibit significantly lower elasticity of lending to their capitalisation changes.

The estimated equations are partitioned into *LoanSupplyLin* (see equation (13)) and *Loan Supply_NonLin* (see equation (14)), where the latter contains interaction terms with dummies related to capital shortfall and NPL changes. Furthermore, in BEAST, the fixed effects of counterparty time are removed and effectively replaced by the loan demand equation.

Regressions are estimated separately for four sectors $S \in \{NFC, HH, SOV, FIN\}$ where the data for sectors $HHHP$ and $HHCC$ are combined to arrive at estimates for the overall household sector. To identify the possibly different sensitivity of $HHHP$ and $HHCC$ lending to bank solvency, the regression for HH includes additional interaction variables.

Data

The estimation relies on COREP / FINREP reporting (see A.4) for the period 2014–2020. These data are supplemented with information on combined capital requirements of banks from COREP, internal capital database, and MaPPED, from which we derive our measure of $CET1SurShortfall$ (see equation (201)). All variables (ratios and growth rates) are reported in decimals.

Variables	Observations	Mean	Median	Standard deviation
$TotalLoans\_gr\ NFC$	12075	0.0129	0.0014	0.1477
$TotalLoans\_gr\ HH$	4274	0.0038	0.0064	0.0361
$TotalLoans\_gr\ SOV$	4841	-0.0027	0.0000	0.0835
$TotalLoans\_gr\ FIN$	9189	0.0145	0.0020	0.2773
$CET1SurShortfall$	12075	0.0401	0.0348	0.0346
ROA	11304	0.0043	0.0042	0.0103
$LEVRSurShortfall$	12075	0.0642	0.0539	0.0297
$EIRLIAB$	12075	0.0018	0.0017	0.0043
$netNPLR$	12075	0.0864	0.0183	0.2039
RRW_NFC	12075	1.8364	1.6829	1.0282
RRW_HH	4274	1.3160	1.1568	0.7216
RRW_SOV	4624	0.6180	0.1020	1.8647
RRW_FIN	9189	1.1034	0.7630	1.5371

Table 31: Summary statistics: loan supply regressions

Results

Table 32 presents the estimation results for the corporate, household, sovereign, and financial sectors. The effect of a CET1 shortfall with respect to regulatory requirements leads to a strong reduction in loan supply for corporate and consumer loans, while it has a positive effect on sovereign and domestic mortgage loans. This provides empirical validation of a substitution effect, where banks with the CET1 shortfall shift their lending from corporate and consumer loans to sovereign and partially also to mortgage loans with relatively lower risk profile.

Second, the lending effect of CET1 is amplified when a bank experiences a capital shortage. As expected, this non-linearity is more pronounced for riskier corporate loans. Third, the effect of capital surplus or shortfall is stronger for foreign exposures. Banks with capital shortages first reduce their loan supply abroad, and only later in the domestic market. Lastly, the negative effect of NPLs on lending is stronger for banks that recently experienced an increase in the share of their NPLs.

C.3 Write-offs

Methodology

The write-off rate $WriOffr$ (see equation (34)) is modelled following a tobit specification, which accounts for the non-linear nature of its dynamics:

$$WriOffr_{i,t}^{S,C} = \Phi\left(\frac{WriOffrLin_{i,t}^{S,C}}{\sigma}\right) \times \left[WriOffrLin_{i,t}^{S,C} + \sigma \times \frac{\phi(\frac{WriOffrLin_{i,t}^{S,C}}{\sigma})}{\Phi(\frac{WriOffrLin_{i,t}^{S,C}}{\sigma})}\right]$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, $\phi(\cdot)$ the standard normal probability density function, σ is the standard error estimated from the tobit regression and $WriOffrLin$ is the underlying linear projection, which evolves with the following equation:

$$\begin{aligned}
WriOffrLin_{i,t}^{S,C} = \beta_0^S + \beta_1^S NPLR_{i,t-1}^{S,C} + \beta_2^S NPLR1Y_{i,t-1}^{S,C} + \beta_3^S ProvCovr_{i,t-1}^{S,C} \\
\beta_4^S ColCovr_{i,t-1}^{S,C} + \beta_5^S ROA_{i,t-1} + \beta_6^S NPLR1Y_{i,t-1}^{S,C} \times ProvCovr_{i,t-1}^{S,C} \\
\beta_7^S ProvCovr_{i,t-1}^{S,C} \times ROA_{i,t-1} + \beta_8^S ProvCovr_{i,t-1}^{S,C} \times NPLR_{i,t-1}^{S,C} \\
\beta_9^S ColCovr_{i,t-1}^{S,C} \times ROA_{i,t-1} + \varepsilon_{i,t}^{S,C}
\end{aligned}$$

The write-off ratio will depend on the share of non-performing loans $NPLR$, share of defaulted exposure older than one year $NPLR1Y$, coverage of defaulted exposure with loan loss provisions $ProvCovr$ (see equation (36)), coverage of defaulted exposure with collateral $ColCovr$, return-on-assets ROA, and lastly, the interaction terms between these variables.

In order to accommodate the relative scarcity of the time period for which we can collect data on write-off rates, the regression is estimated jointly for all sectors $S \in \{NFC, HH, SOV, FIN\}$. Sector-specific coefficients $beta^S$ are derived by interacting the observations with a set of four sector dummies and following the general-to-specific methodology where both the significance and the equality of the coefficients are tested at each step before arriving at the final empirical specification. We also tested for the difference between the constant between the $HHHP$ and $HHHC$ sectors by interacting the regression constant with the bank-specific share of $HHHP$ exposures in total HH exposures $ShareHHHP_i$.

Data

The propensity for bank writeoff is estimated on the basis of quarterly data from supervisory statistics (FINREP). Templates F 04.04.1 and F 12.00 provide information on banks' write-offs of defaulted loans since 2018 as well as the underlying provisioning. The estimation sample

	(1) NFC	(2) HH	(3) SOV	(4) FIN
$CET1SurShortfall_{t-1} \times I(Home=0) \times I(Type=0)$	0.146*		0.115	0.162*
	(0.030)		(0.455)	(0.015)
$CET1SurShortfall_{t-1} \times I(Home=0) \times I(Type=1)$	0.0246		0.0196	0.046
	(0.746)		(0.710)	(0.164)
$CET1SurShortfall_{t-1} \times I(Home=1) \times I(Type=0)$	0.0997		0.166	-0.0845
	(0.366)		(0.493)	(0.385)
$CET1SurShortfall_{t-1} \times I(Home=1) \times I(Type=1)$	0.0109		0.0462	-0.0442
	(0.901)		(0.689)	(0.323)
$CET1SurShortfall_{t-1} \times I(Home=0) \times I(Type=0)$		0.113**		
$\times I(Sector=HHHP)$		(0.004)		
$CET1SurShortfall_{t-1} \times I(Home=0) \times I(Type=1)$		0.0271		
$\times I(Sector=HHHP)$		(0.817)		
$CET1SurShortfall_{t-1} \times I(Home=1) \times I(Type=0)$		0.0762+		
$\times I(Sector=HHHP)$		(0.100)		
$CET1SurShortfall_{t-1} \times I(Home=1) \times I(Type=1)$		0.0233		
$\times I(Sector=HHHP)$		(0.710)		
$CET1SurShortfall_{t-1} \times I(Home=0) \times I(Type=0)$			0.171**	
$\times I(Sector=HHCC)$			(0.001)	
$CET1SurShortfall_{t-1} \times I(Home=0) \times I(Type=1)$			0.0658	
$\times I(Sector=HHCC)$			(0.642)	
$CET1SurShortfall_{t-1} \times I(Home=1) \times I(Type=0)$			0.105*	
$\times I(Sector=HHCC)$			(0.028)	
$CET1SurShortfall_{t-1} \times I(Home=1) \times I(Type=1)$			-0.000448	
$\times I(Sector=HHCC)$			(0.994)	
$CET1SurShortfall_{t-1} \times (CET1SurShortfall_{t-1} < 0)$	0.936*	0.553**	-0.35	-0.507+
	(0.043)	(0.000)	(0.611)	(0.067)
RRW_{t-1}	-0.00234	-0.00251**	-0.00221	
	(0.104)	(0.008)	(0.344)	
$RRW_{t-1} \times CET1SurShortfall_{t-1}$	-0.00292	-0.0019		
	(0.547)	(0.464)		
$netNPLR_{t-1} \times (\Delta_4 NPLR_{t-1} \leq 0)$	-0.0486**	-0.0258**	-0.0527	-0.0269
	(0.000)	(0.000)	(0.178)	(0.275)
$netNPLR_{t-1} \times (\Delta_4 NPLR_{t-1} > 0)$	-0.0667**	-0.0290**	-0.058	-0.0624
	(0.000)	(0.000)	(0.250)	(0.108)
ROA_{t-1}	0.435**	0.0467	0.424	0.368*
	(0.005)	(0.374)	(0.005)	(0.037)
$LEVRSurShortfall_{t-1} \times I(Type=0)$	0.145**	0.0236	0.161	0.211**
	(0.008)	(0.470)	(0.855)	(0.848)
$LEVRSurShortfall_{t-1} \times I(Type=1)$	0.0284	0.00751	0.0309	0.0184
	(0.764)	(0.902)	(0.855)	(0.848)
$EIRLiab_{t-1}$	-0.715*	-0.188+	-0.197	
	(0.030)	(0.063)	(0.785)	
Obs	12075	4274	9189	4841
Banks	110	93	114	115
$R^2(adj.)$	0.11	0.30	0.05	0.05

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 32: Loan supply regressions: 2014 Q1 –2020 Q4

covers quarterly observations from 2018Q1 to 2020Q2.[133] Table 33 provides information about the sample, and all the ratios included are expressed in decimals.

Variables	Observations	Mean	Median	Standard deviation
WriOffr *HH*	505	0.0093	0.0008	0.0154
WriOffr *NFC*	598	0.0141	0.0059	0.0178
WriOffr *SOV*	155	0.0048	0.0000	0.0121
WriOffr *FIN*	369	0.0037	0.0000	0.0124
ROA	505	0.0042	0.0038	0.0044
ColCovr	505	0.5369	0.5791	0.1887
ProvCovr	505	0.1032	0.0838	0.0861

Table 33: Summary statistics: write-off rate regressions

Results

The estimations of the regression parameters are provided in Table 34. Banks with higher non-performing loan ratios *NPLR* tend to write off a higher share of their defaulted exposures. The write-off rate is reduced by the amount of collateral underlying the average sector loan. Furthermore, higher bank profitability is associated with lower write-off rates. Regarding the interaction terms, the coefficient estimates indicate that banks write off a higher share of defaulted loans when their overall NPL burden is larger and when defaulted loans have a relatively high coverage with loan-loss provisions. The estimate for σ is positive and stands at 0.0006 compared to a standard deviation of the dependent variable equal to 0.015 (see Table 33).

C.4 Lending interest rate

Methodology

The regression mapping the adjustments in bank interest rates on new loans *EIRAssetNew* aims to account for the lending demand and supply factors simultaneously. The dependent variable is an effective interest rate margin *EIRmargin* defined by the spread between the respective lending rate *EIRAssetNew* for each sector-country portfolio and the overall funding costs per bank *EIRLiab* (see equation (55)).[134] The assumption that banks pursue a direct pass-through of an increase in their funding costs ensures that bank funding distress feeds back into the credit market, with possible spillover effects on financial conditions in the real economy.[135] Further, it is assumed that bank pricing strategy differs for short- and long-term maturity loans $D = \{Short, Long\}$. Short-term maturity buckets are defined by the cut-off duration of less than 2 years for loans to *NFC* and *HHCC*, and less than 5 years for mortgage lending to households *HHHP* generally characterised by longer maturities.[136]

[133] By cutting the sample at the beginning of the COVID-19 pandemics, we circumvent potential problems estimating the write-off rates during the COVID-19 pandemics.

[134] The modelling approach was revised compared to the version in Budnik et al. [2020].

[135] ECB [2017] demonstrates that cost of funding for banks and bank balance sheet characteristics are important driving forces behind changes in pass-through mechanism from policy rates to bank lending rates, and as nominal interest rates move closer to their effective lower bound, the likelihood of non-linear bank transmission channels increases.

[136] The break-down of interest rates into short- and longer-term maturities is justified by findings by e.g. Mojon et al. [2005] that banks interest rates with different maturities depend differently on changes in the yield curve and

	(1)
$NPLR_{t-1}$	0.178^{***}
	(0.009)
$NPLR1Y_{t-1} \times I(Sector = FIN)$	-0.0221^{***}
	(0.007)
$ColCovr_{t-1}$	-0.0119^{**}
	(0.009)
$ProvCovr_{t-1} \times I(Sector = HHCC)$	0.0350^{***}
	(0.000)
$ProvCovr_{t-1} \times I(Sector = NFC)$	0.0375^{***}
	(0.002)
$ProvCovr_{t-1} \times I(Sector = SOV)$	-0.0128^{*}
	(0.096)
ROA_t	-0.787^{*}
	(0.009)
$NPLR_{t-1} \times ProvCovr_{t-1}$	-0.302^{**}
	(0.009)
$NPLR1Y_{t-1} \times ProvCovr_{t-1}$	0.0346^{***}
	(0.009)
$ColCovr_{t-1} \times ROA_{t-1}$	1.238^{*}
	(0.009)
$ProvCovr_{t-1} \times ROA_{t-1}$	2.409^{***}
	(0.009)
$const.$	-0.0058^{*}
	(0.009)
$const. \times I(Sector = FIN)$	-0.0222^{***}
	(0.000)
$const. \times ShareHHHP \times I(Sector = HH)$	-0.0146^{*}
	(0.068)
σ	0.0006^{***}
	(0.009)
Obs	1627
R^2	-0.157

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 34: Write-off regressions: 2018Q1 – 2020Q2

The regression specification for the non-financial private sectors $S = \{NFC, HHCC, HHHP\}$ corresponding to equation (56) reads as follows:

$$\begin{aligned}
\Delta EIRmargin_{i,t}^{D,S,C} &= \beta_1^{S,D} \Delta EIRmargin_{i,t-1}^{D,S,C} \\
&+ \beta_2^{S,D} \Delta STN_{i,t-1}^{EA} + \beta_3^{S,D} \Delta LTN_{i,t-1}^{C} \\
&+ \beta_4^{S,D} \Delta YERgr_{i,t-1}^{C} + \beta_5^{S,D} \Delta HICgr_{i,t-1}^{C} \\
&+ \beta_6^{S,D} CET1SurShortfall_{i,t-1} + \beta_7^{S,D} \Delta LevRaTa_{i,t-1} + \varepsilon_{i,t}^{D,S,C}
\end{aligned}$$

The specification acknowledges that the pass-through of monetary policy stance, therein market short- and long-term interest rates, to bank lending rates depends both on macrofinancial factors (Gambacorta [2008], Memmel et al. [2018]) and bank specific characteristics (Holton and Rodriguez d'Acri [2018]). Regressions are estimated in a standard OLS framework using heteroskedasticity-consistent standard errors.

Data

The estimation framework for the lending rate model uses a large unbalanced panel of quarterly data. Information on bank lending rates for new businesses is sourced from iMIR statistics. Interest rate data were adjusted seasonally and for outliers using the X-12-ARIMA algorithm Bureau [2011] where we generally assume that individual branch level information approximates the lending rates of the ultimate parent bank to sector S in the country C. The originally monthly iMIR data are then transformed into quarterly time series by taking the average rate within the quarter. Bank-specific information on solvency and leverage ratio is sourced from COREP templates and the S&P SNL Sector Financials dataset. The latter data set is used to backward extend the historical time series for bank capitalisation. Information on bank-specific capital requirements is sourced from COREP, the internal capital database, and the MaPPED database. The macroeconomic time series are sourced from the SDW. The current historical sample covers bank-level data from 2007 Q4 to 2020 Q4, and Table 35 provides the summary statistics for the included variables.

Results

Table 36 presents the estimation results for the segments of the corporate, household consumption, and mortgage markets. The first three columns represent the estimates for short-term rates *Short*, while the last three correspond to the longer maturities *Long*. Since the model is estimated in the first differences, the autoregressive margin component enters with a negative sign for all sectors except *HHHP-Long*.

It appears that the pass-through of changes in the short- and long-term market rates differs substantially between the individual sectors and the maturity classes. The 3 month EURIBOR pass-through rate is highest for short-term lending rates *Short*, and the long-term bond yield pass-through is the highest for *Long*-maturity buckets. Although the impact of the leverage ratio *LevRaT* is insignificant for most sectors, banks' capital buffer or shortfall with respect to their capital targets $CET1SurShortfall$ triggers additional adjustments in the lending rate, that is, banks experiencing a shortfall in solvency further increase their lending rates, especially in *Long*-maturity market segments.

macroeconomic conditions.

Variables	Observations	Mean	Median	Standard deviation
$EIRmargin\ NFC\ Long$	3210	0.0099	0.0091	0.0181
$EIRmargin\ HHHP\ Long$	2925	0.0127	0.0128	0.0184
$EIRmargin\ HHHC\ Long$	4902	0.0296	0.0272	0.0305
$EIRmargin\ NFC\ Short$	4118	0.0070	0.0070	0.0168
$EIRmargin\ HHHP\ Short$	2664	0.0092	0.0088	0.0180
$EIRmargin\ HHHC\ Short$	5363	0.0195	0.0192	0.0273
$CET1SurShortfall$	4459	0.0436	0.0429	0.0355
$LevRaT$	4459	0.0602	0.0586	0.0226
$HICgr$	4459	0.0024	0.0027	0.0041
$YERgr$	4459	0.0015	0.0038	0.0329
ΔSTN	4459	-0.0005	-0.0001	0.0021
ΔLTN	4459	-0.0010	-0.0010	0.0038

Table 35: Summary statistics: lending rates regressions

	(1) NFC-S	(2) HHHP-S	(3) HHCC-S	(4) NFC-L	(5) HHHP-L	(6) HHCC-L
$\Delta EIRmargin_{t-1}$	-0.247**	-0.107*	-0.228**	-0.272**	0.120**	-0.0813*
	(0.000)	(0.033)	(0.000)	(0.000)	(0.004)	(0.023)
ΔSTN_{t-1}	0.237**	-0.0355	0.0913	0.0730	-0.0909**	-0.0798*
	(0.000)	(0.406)	(0.108)	(0.252)	(0.001)	(0.018)
ΔLTN_{t-1}	0.0828**	0.136**	0.0723**	0.191**	0.170**	0.126**
	(0.000)	(0.000)	(0.005)	(0.001)	(0.000)	(0.000)
$\Delta YERgr_{t-1}$	0.0036+	0.0000	0.0031	0.0003	0.0011	0.0041*
	(0.069)	(0.985)	(0.203)	(0.877)	(0.384)	(0.036)
$\Delta HICgr_{t-1}$	0.0277+	-0.0287	0.00633	0.0313	-0.005	-0.0098
	(0.050)	(0.120)	(0.743)	(0.208)	(0.727)	(0.574)
$\Delta LevRatTa_{t-1}$	0.0056	0.0416	0.004	0.004	0.0086	0.0841+
	(0.811)	(0.174)	(0.901)	(0.943)	(0.696)	(0.091)
$CET1SurShortfall_{t-1}$	0.000746	-0.0026+	-0.0004	-0.0033*	-0.003*	-0.0033+
	(0.523)	(0.092)	(0.829)	(0.033)	(0.014)	(0.066)
Obs	4118	2664	3628	3210	2925	3288
$R^2(adj.)$	.074	.025	.052	.082	.056	.017

p-values in parentheses
$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$

Table 36: Bank lending rate regressions: 2007 Q4 – 2020 Q4

C.5 Debt security holdings

Methodology

Banks adjust their holdings of debt securities from non-financial, financial corporates, and sovereigns taking into account their solvency and liquidity conditions and analogously to how they adapt their loan supply (Appendix C.2). The empirical specification of the bank propensity to hold debt securities defined in equation (74) is specified as follows:

$$\begin{aligned}\Delta VolAssetSupply_{i,t}^{S,C} = & \beta_t^{S,C} + \beta_1^S CET1SurShortfall_{i,t} \\ & + \beta_2^S CET1SurShortfall_{i,t} \times I(Type_i = 1) \\ & + \beta_3^S LEVRSurShortfall_{i,t} \\ & + \beta_4^S LEVRSurShortfall_{i,t} \times I(Type_i = 1) \\ & + \beta_5^S netNPLR_{i,t} + \beta_5^S ROA_{i,t} + \beta_6^S EIRLiabWhsl_{i,t} + \varepsilon_{i,t}^{S,C}\end{aligned}$$

where $\Delta VolAssetSupply$ corresponds to the quarterly log change in the holdings of the bank debt security of sector $S \in \{SNFC, SFIN, SGOV\}$ in the counterparty (country) C. $CET1SurShortfall$ and $LEVRSurShortfall$ are analogously defined as in Section C.2, $netNPLR$ corresponds to a bank's net NPL ratio, ROA to return on assets, and $EIRLiabWhsl$ to bank's overall wholesale funding costs.

The estimation is based on a pooled bank-level regression inspired by Khwaja and Mian [2008]. A bank counterparty here is a specific sector in one of the jurisdictions that issues debt securities. By using data for sector-country exposures that concern at least two banks, we can account for the variation in the evolution of the macroeconomic environment and the demand for debt funding by including a set of counterparty time fixed effects $\beta_t^{S,C}$. . The salient assumptions behind this methodology is that each counterparty-sector has a similar propensity to issue a debt security and the supply of its debt instruments is not bank-specific, i.e., it is equal across all banks that lend to a counterparty.

The regression further classifies the bank sample with an additional indicator variable $Type$, where $Type = 1$ identifies banks that due to the nature of their business model (special lenders) or ownership structure (state owned) exhibit significantly lower elasticities of lending to bank capitalisation measures (see Table 5 for bank sample classification). The indicator $Type$ is interacted with $CET1SurShortfall$ and $LEVRSurShortfall$.

Data

The bank-level information about debt security holdings, profitability, solvency, leverage ratio, and wholesale funding costs are sourced from supervisory statistics (FINREP/COREP). To be precise, the information regarding banks security holdings to individual euro area countries is sourced from template F 20.04. The estimation sample covers quarterly observations from 2016Q3 to 2020Q2 and for 117 banks. The summary statistic in Table 37 is reported in decimal (growth) rates.

Variables	Observations	Mean	Median	Standard deviation
$\Delta VolAssetSupply\ SGOV$	12527	0.0068	-0.0003	0.1805
$\Delta VolAssetSupply\ SFIN$	11817	0.0107	-0.0005	0.1699
$\Delta VolAssetSupply\ SNFC$	5936	0.0122	0.0001	0.1975
ROA	5936	0.0040	0.0042	0.0108
$CET1SurShortfall$	5936	0.0564	0.0401	0.0691
$LEVRSurShortfall$	5936	0.0612	0.0544	0.0248
$EIRLiabWhsl$	5936	0.0014	0.0009	0.0117

Table 37: Summary statistics: security holdings regressions

Results

The estimation results outlined in Table 38 indicate that banks' debt security holdings depend positively on their leverage, except for state-owned or special lender bank debt security holdings towards the NFC sector, and positively on their profitability. Furthermore, higher rates in the wholesale funding market are associated with a reduction in their debt securities. In case a bank experiences a CET1-ratio shortfall, i.e., the CET1 ratio falls below the regulatory requirements, it reduces its debt security holdings for the non-financial and financial sector, while increasing the holdings for more saver government debt securities.

	(1) SNFC	(2) SFIN	(3) SGOV
$CET1SurShortfall_{t-1}$	0.293***	0.0264	-0.00662
	(0.001)	(0.272)	(0.779)
$CET1SurShortfall_{t-1} \times (Type = 1)$	-0.203**		
	(0.010)		
$netNPLR_{t-1}$	0.197***	0.126***	0.0210
	(0.000)	(0.000)	(0.389)
ROA_{t-1}	0.472***	0.472***	0.472***
	(0.000)	(0.000)	(0.000)
$LEVRSurShortfall_{t-1}$	0.161*	0.333***	0.364***
	(0.077)	(0.000)	(0.000)
$LEVRSurShortfall_{t-1} \times I(Type = 1)$	-0.276***	-0.276***	-0.276***
	(0.000)	(0.000)	(0.000)
$EIRLiabWhsl_{t-1}$	-0.625***	-0.146	-0.0359
	(0.006)	(0.430)	(0.779)
Obs	30280	30280	30280
$R^2(adj.)$	.03	.03	.03

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 38: Debt security supply regressions: 2016 Q3 – 2020 Q2

C.6 Debt security interest rates

Methodology

The interest rates on non-financial corporate $SNFC$ and sovereign bonds $SGOV$ securities held by a bank depend on a risk-free component and a credit spread (see equation (62)). The specification of the credit spread is log-multiplicativewith a linear component $LinSpread_t$ (see equation (63)). This linear function is estimated indirectly, using the logarithm of quarterly single-name credit default swaps (CDS) of individual non-financial corporations (for sector $SNFC$) or sovereigns (sector $SGOV$).

For credit spreads on sovereign bonds, we apply the following specification for quarterly frequency CDS spreads CDS of individual euro-area sovereigns C with maturities τ:

$$
\begin{aligned}
log(CDS_t^{SGOV,C}(\tau)) = \beta_1\, log(CDS_{t-1}^{SGOV,C}(\tau)) \\
+ \beta_2\, YERgr_t^C + \beta_3\, ESXgr_t^C \\
+ \beta_4\, \Delta SPR_t^C + \beta_5\, \Delta STN_t^{EA} + \varepsilon_{\tau,t}^C
\end{aligned}
$$

Credit spreads on sovereign bonds depend on a variety of macrofinancial indicators, therein GDP growth rate YER, the stock market growth rate ESX and the spread SPR between long- and short-term rates in the country of exposure C. The sovereign bond rate regression is estimated using a feasible generalised least squares (FGLS) to account for autocorrelation. The maturities τ and the countries C are pooled before regression, implying country- and maturity-independent parameters β.

The linear function for the corporate risk spread component is mapped by regression:

$$
\begin{aligned}
log(CDS_t^{SNFC,C}(\tau)) = \beta_1 log(\tau) \\
+ \beta_2\, YERgr_{i,t}^C + \beta_3\, YERgr_{i,t-1}^C + \beta_4\, YERgr_{i,t-2}^C \\
+ \beta_5\, ESXgr_{i,t}^C + \beta_6\, ESXgr_{i,t-1}^C + \beta_7\, \Delta URX_{i,t}^C \\
+ \beta_8\, \log(\tau) \times \Delta LTN_{i,t-1}^C + \varepsilon_{\tau,t}^C
\end{aligned}
$$

The corporate bond interest rate regression is estimated in log levels, using a generalised linear model (GLM) with log-link and poisson-distributed outcomes.

Data

Variables	Observations	Mean	Median	Standard deviation
CDS SGOV	7,534	1.13%	0.69%	1.21%
CDS SNFC	11,814	1.45 %	0.98 %	1.84 %
$YERgr$	23,100	0.0047	0.0058	0.0222
$ESXgr$	14,700	0.0122	0.0183	0.0934
ΔURX	16,800	0.0001	-0.0007	0.0061
ΔSTN	16,330	-0.0004	-0.0	0.0033
ΔLTN	16,330	-0.0006	-0.0007	0.0065
ΔSPR	16,330	-.0011	-.0003	.0067

Table 39: Summary statistics: security interest rates regressions

Sovereign bond CDS spreads of 23 euro-area sovereigns are aggregated up to a quarterly frequency by averaging over all daily closing spreads within the quarter. For each quarter and country, we observe CDS spreads for maturities $\{0.5, 1, 2, \ldots, 10\}$ years. For selected quarters and country combinations, we can include maturities up to 30 years and shorter maturities up to overnight in the sample. In total, 6,830 country-time-maturity data points are used in the estimation of *SGOV* spreads observed over the period from 2012Q3 to 2018Q4.

CDS spreads for non-financial corporate bonds are calculated using daily CDS spreads of 166 euro area non-financial firms listed on S&P Capital IQ (formerly Credit Market Analysis) between 2005Q2 and 2020Q3. These corporate titles are aggregated up to country level, yielding average non-financial corporate CDS spreads in 12 countries. For 11 of these 12 countries, data are available from at least 2005Q2. For one country, data are available starting only from 2011Q3. For each available country-time combination, we include CDS spreads for maturities in $\{1, 2, \ldots, 10\}$ years. In total, 7,632 country-time-maturity data points are in the estimation sample.

Results

Table 40 reports the results of the estimation. Sovereign CDS spreads depend positively on changes in EURIBOR and on country-specific government bond yield spreads. The risk of sovereign default decreases with increases in GDP and stock indices.

Non-financial corporate CDS are negatively correlated with GDP, stock market indices, and positively with the level of unemployment. Additionally, the slope of the non-financial corporate yield curve depends on the firm's home country's 10 year sovereign bond rates.

	log of CDS Spread (in %)	
	SGOV	SNFC
$log(CDS_{t-1})$	0.128**	
	(0.000)	
$YERgr_t$	-0.138	-3.504**
	(0.160)	(0.000)
$YERgr_{t-1}$		1.747**
		(0.006)
$YERgr_{t-2}$		-16.724**
		(0.000)
$ESXgr_t$	-0.244**	-1.29**
	(0.000)	(0.000)
$ESXgr_{t-1}$		-2.308**
		(0.000)
ΔURX_t		3.209**
		(0.000)
ΔSTN_t	27.09**	
	(0.000)	
ΔSPR_t	13.37**	
	(0.000)	
$ln(\tau)$		0.321**
		(0.000)
$ln(\tau) \times \Delta LTN_t$		2.258**
		(0.000)
Issuers	23	166
Obs	6,830	7,632

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 40: Sovereign and non-financial corporate CDS spreads: 2005 Q2 – 2020 Q3

C.7 Deposit supply model

Methodology

The deposit supply equations (160) are estimated using a fixed effect panel regression, with bank-level deposit growth rates on the left side and the economic conditions in a deposit origination country on the right side. The model is estimated separately for the sectors $S = \{HHS, NFCS, DEPT\}$. We postulate the following functional relationship for the quarterly deposit growth rate $VolLiabTotal\_gr$ of bank i from the counterparty sector S in country C at time t:

$$\begin{aligned} VolLiabTotal\_gr_{i,t}^{S,C} = \beta_{0,i} + \sum_{p}(\beta_{1,p}^{S} VolLiabTotal\_gr_{i,t-j}^{S,C} + \beta_{2,p}^{S} YERgr_{t-p}^{C} + \beta_{4,p}^{S} HICgr_{t-p}^{C} \\ + \beta_{4}^{S} \Delta URX_{t-p}^{C} + \beta_{6,p}^{S} \Delta EIRLiabNew_{i,t-p}^{S,C} \\ + \beta_{7}^{S} DepSpread_{i,t-p}^{S,C}) + \varepsilon_{i,t}^{S,C} \end{aligned} \tag{331}$$

where $EIRLiabNew$ corresponds to the bank i deposit rate offered, and $DepSpread$ the spread between the deposit rate and the 3-month EURIBOR for the respective sector-country-bank combination $DepSpread = EIRLiabNew_{i,t-1}^{S,C} - STN_{t-1}$. $YERgr$ represents the real GDP growth in the country C, $HICgr$ inflation rate in the country C, ΔURX the change in the unemployment rate. The specification is estimated with bank fixed effects $\beta_{0,i}$ and clustered standard errors at the level of the banking group. To exclude insignificant variables and their lags, we apply a general to specific procedure starting from three lags $p = 3$ for all covariates. The regression specifications are subject to dynamic homogeneity restrictions (see Jensen [1994]) to ensure a stable long-term relationship between nominal GDP and deposit growth.

Data

Historical deposit volume and rate information is sourced from iBSI (volumes) and iMIR (rates). They are seasonally adjusted using the X-12 ARIMA algorithm and converted from the original monthly series to quarterly series by taking the last month stock of deposits and the average deposit rate per quarter. The macroeconomic variables are sourced from the SDW. Table 41 provides an overview of the summary statistics of the underlying sample in decimal points. The sample includes the time span from 2008Q1 until 2019Q2.

Variables	Observations	Mean	Median	Standard deviation
$VolLiabTotal\_gr\ HHS$	6389	0.0144	0.0176	0.0697
$VolLiabTotal\_gr\ NFCS$	6294	0.0201	0.0186	0.1049
$VolLiabTotal\_gr\ DEPT$	5942	-0.0222	-0.0177	0.1046
$\Delta EIRLiabNew\ HHS$	6114	-0.0003	-0.0001	0.0008
$\Delta EIRLiabNew\ NFCS$	6012	-0.0003	-0.0001	0.0010
$\Delta EIRLiabNew\ DEPT$	5808	-0.0008	-0.0004	0.0032
$DepSpread\ DEPT$	5808	0.0084	0.0064	0.0097
$YERgr$	7238	0.0023	0.0032	0.0126
$HICgr$	7238	0.0031	0.0033	0.0042
ΔURX	7238	0.0001	-0.0010	0.0047

Table 41: Summary statistics: private deposit volume regressions

Results

Table 42 shows the estimates for sectors $S = \{NFCS, HHS, DEPT\}$. The offered bank deposit rates $EirLiabNew$ have a relatively strong positive impact on the supply of term deposits, while they have a less pronounced but still positive impact on short-term deposit volumes, especially for the supply of sight deposits from households. The estimated autoregressive coefficients indicate a relatively low inertia in deposit volumes, while the coefficients on GDP growth and inflation suggest a strong positive business cycle component in the dynamics of private sector deposits.

	(1) DEPT	(2) NFCS	(3) HHS
$VolLiabTotal\_gr_{t-1}$	0.249**	0.0716**	0.163^{+}
	(0.000)	(0.000)	(0.078)
$VolLiabTotal\_gr_{t-2}$	0.0940**	0.245**	0.223**
	(0.000)	(0.010)	(0.003)
$YERgr_{t-1}$	0.230*	0.614**	0.216^{+}
	(0.010)	(0.000)	(0.052)
$YERgr_{t-2}$	0.428**	0.315**	0.398**
	(0.000)	(0.000)	(0.000)
$HICgr_{t-1}$	0.657**	0.928**	0.614**
	(0.000)	(0.000)	(0.000)
$\Delta EIRLiabNew_{t-1}$	2.991**		
	(0.000)		
$\Delta EIRLiabNew_{t-2}$	2.081**		
	(0.000)		
$\Delta EIRLiabNew_{t-3}$			1.578
			(0.128)
$DepSpread_{t-1}$	-0.193		
	(0.263)		
ΔURX_{t-1}	0.937**		
	(0.000)		
const.	-0.0041**	0.0025**	0.0023**
	(0.000)	(0.000)	(0.000)
Banks	144	159	158
Obs	5942	6294	6389
R^2	0.130	0.001	0.069

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Homogeneity constraint: nominal GDP growth = deposit growth

Table 42: Deposit supply regressions: 2008 Q1 – 2019 Q2

C.8 Deposit interest rates

Methodology

The empirical specifications of interest rates on sight and term deposits put special emphasis on the pass-through of the short-term rate and the role of deposit market competition. For the sight deposit rates, the empirical counterparts of equation (174) estimated separately for $S = \{NFCS, HHS\}$ read as follows:

$$\begin{aligned}\Delta EIRLiabNew^{S,C}_{i,t} =&\beta^S_{0,i} + \beta^S_1 \Delta EIRLiabNew^{S,C}_{i,t-1} + \beta^S_2 \Delta EIRLiabNew^{S,C}_{i,t-2}\\ &+\beta^S_3 YERgr^C_{t-1} + \beta_4 YERgr^C_{t-2}\\ &+\beta^S_5 HICgr^C_{t-1} + \beta_6 HICgr^C_{t-2}\\ &+\beta^S_7 \Delta SpreadLTN^C_{t-1} + \beta^S_8 \Delta SpreadLTN^C_{t-2}\\ &+\beta^S_9 STN\_PT^{S,C}_{i,t-1} + \beta^S_{10} EIRLiabConv^{S,C}_{i,t-1} + \varepsilon^{S,C}_{i,t}\end{aligned}$$

The regression relies on an unconstrained panel setup with fixed bank effects $\beta_{0,i}$ and heteroskedastic robust standard errors. The specification includes an autoregressive term, the change in GDP growth rate $YERgr$ that approximates the business cycle conditions, and the spread between the domestic 10-year government bond yield and the German bund (10Y) that captures the sovereign risk:

$$SpreadLTN^C_t = LTN^C_t - LTN^{DE}_t$$

The variable STN_PT reflects the state-dependent pass-through of changes in the 3-month EURIBOR STN defined as:

$$STN\_PT^{S,C}_{i,t} = \Delta STN^C_{i,t} \times f(EIRLiabNew^{S,C}_{i,t})$$

and:

$$f(EIRLiabNew_{i,t}) = \left(\frac{2}{1+e^{-25\times max(EIRLiabNew_{i,t},0)}} - 1\right)$$

The pass through of the 3-month EURIBOR on deposit rates reflects the limited ability of banks to lower deposit rates as the latter approach zero (see Demiralp et al. [2019]). The last term $EIRLiabConv$ takes into account the competitive pressure in each market segment (S,C) and measures the impact of the market average deposit rate $\overline{EirLiabNew^{S,C}}$ on individual bank pricing decisions.

$$EIRLiabConv^{S,C}_{i,t} = EIRLiabNew^{S,C}_{i,t} - \overline{EIRLiabNew^{S,C}_{i,t}} \tag{332}$$

The dynamics of term deposit rates from equation (175) follows the specification:

$$\begin{aligned}\Delta EirLiabNew^{DEPT,C}_{i,t} =&\beta_{0,i} + \beta_1 \Delta EirLiabNew^{S,C}_{i,t-l} + \beta_2 \Delta EirLiabNew^{S,C}_{i,t-2} +\\ &\beta_3 YERgr^C_{t-l} + \beta_4 YERgr^C_{t-2} + \beta_5 HICgr^C_{t-l}\\ &\beta_7 \Delta SpreadLTN^C_{t-1} + \beta_8 \Delta SpreadLTN^C_{t-2}\\ &+\beta_9 0.125 \times \Delta_8 STN^C_t + \varepsilon^C_{i,t}\end{aligned}$$

The macroeconomic variables and risk spreads enter the regressions analogously as in the regression of sight deposits. The specification assumes a slow (introducing a two-year moving average of EURIBOR rather than its reference period value) but full long-term pass-through of the short-term interest rate into deposit rates (imposing the dynamic homogeneity condition of $\beta_1 + \beta_2 + \beta_9 = 1$) and the pass-through is linear. The estimates are based on a constrained bank fixed-effect regression model with robust heteroskedastic standard errors.

Data

Regressions of bank deposit rates are estimated in a large unbalanced panel of quarterly bank deposit rates data from iMIR. Deposit rates were adjusted seasonally and for outliers using the X-12-ARIMA algorithm Bureau [2011] where we generally assume that information at the individual branch level approximates the deposit rates of the ultimate parent bank to the sector S in the country C. The originally monthly iMIR data are then transformed to quarterly time series by taking the average deposit rates within each quarter. The macroeconomic time series are sourced from SDW. The current historical sample covers bank-level data from 2007 Q4 until 2020 Q4. Table 43 provides the summary statistics of all variables in decimal points.

Variables	Observations	Mean	Median	Standard deviation
$EIRLiabNew\ HHS$	4979	0.0033	0.0012	0.0054
$EIRLiabNew\ NFCS$	4913	0.0036	0.0013	0.0061
$EIRLiabNew\ DEPT$	3465	0.0093	0.0055	0.0107
$YERgr$	6297	0.0012	0.0031	0.0251
$HICgr$	6297	0.0029	0.0032	0.0044
$SpreadLTN$	6297	0.0117	0.0031	0.0238
ΔSTN	6297	-0.0009	-0.0001	0.0032

Table 43: Summary statistics: deposit rate regressions

Results

Table 44 presents the results of the estimation of sight deposit rates for the sector of households HHS and companies $NFCS$. The spread between the domestic long-term rate and the German BUND ($SpreadLTN$) impacts deposit rates positively while the pass-through of short-term market rates is relatively stronger in corporate deposits. The market correction term $DeprCor$ enters significantly and negatively both sector regressions.

The coefficient estimates for term deposits (including deposits from households and non-financial corporations) are shown in the last column of Table . The pass-through of the two-year moving average short-term rate is estimated at 0.67, and the inflation rate enters the specification statistically significant and positive.

C.9 Unsecured wholesale funding yield curve

Methodology

The bank-specific yield curve for unsecured wholesale funding combines, as in equation (179), a risk-free yield curve and a bank-specific credit risk spread. The risk margin is specified log-linearly with the log-difference of a credit spread equal to a linear function $LinSpread$ (see equation (63)). The latter function is estimated indirectly, using bank-specific credit default swap (CDS) spreads.

The use of CDSs to model changes in funding costs relies on the argument of Duffie [1999], Hull et al. [2004] that any deviation of the CDS from the credit spread should open up opportunities for arbitrage. The close empirical relationship between CDSs and credit spreads has been empirically evidenced, e.g. Blanco et al. [2004], Hull et al. [2004].[137]

[137] Some authors find credit spreads account not only for the risk of default, but also other drivers, such as liquidity

	(1) HHS	(2) NFCS	(3) DEPT
$\Delta EIRLiabNew_{t-1}$	0.133*	0.0736	0.203**
	(0.034)	(0.173)	(0.000)
$\Delta EIRLiabNew_{t-2}$			0.123**
			(0.000)
$YERgr_{t-l}$	0.00229**	0.00233**	0.00463**
	(0.001)	(0.001)	(0.000)
$YERgr_{t-2}$	0.00216*	0.00231*	0.00458**
	(0.012)	(0.025)	(0.003)
$HICgr_{t-1}$			0.0255**
			(0.008)
$SpreadLTN_{t-2}$	0.00821**	0.00598	0.0842**
	(0.009)	(0.119)	(0.000)
STN_PT_{t-1}	1.112**	1.528**	
	(0.000)	(0.000)	
$EIRLiabConv_{t-l}$	-0.0995**	-0.140**	
	(0.000)	(0.000)	
$0.125 \times \Delta_8 STN^C_{t-1}$			0.674**
			(0.000)
Banks	126	129	137
Obs	4979	4913	4421
$R^2(within)$	0.273	0.385	-

p-values in parentheses

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$

Constr.regression with homogeneity condition on long STN pass-through

Table 44: Retail deposit rate regressions: 2007 Q3 – 2020 Q4

The use of CDSs as opposed to the use of bond yields has a number of advantages. First, CDS are traded at variable maturities on OTC markets by third parties. Therefore, they provide information on the theoretical yield for all maturities independently of the maturities of bonds actually issued by a firm. Second, CDS can be used to estimate theoretical risk margins even for firms that are currently unable or unwilling to issue securities on wholesale markets. The actual credit spreads observed in the unsecured wholesale funding market are subject to considerable selection bias. Firms will tend to issue securities in the wholesale funding market when they expect beneficial credit spreads. This implies that credit spreads for firms that did not select into the wholesale funding market will likely be underestimated if calculated on the basis of the observed bond yield data. CDS spreads, which are traded by third parties, are not beset by these issues. Third, CDS markets tend to be more liquid than corporate bond markets, and data are available in greater abundance and frequency. Last, the use of CDS data allows us to avoid a number of other confounding factors inherent to the use of bond yields such as coupon effects or residual maturity effects (see Annaert et al. [2013] for a comprehensive review).

Movements in the bank-specific yield curve at each maturity are specified log-linearly, using a GLM model with log-link and poisson-distributed outcomes (see also equation (180)):

risk (Longstaff et al. [2005]) or tax considerations (Elton et al. [2001]). In our modelling approach, these factors are omitted and market liquidity or tax effects are not considered.

$$\begin{aligned}log(CDS_{i,t}(\tau)) =& \beta_0 + \beta_1\, SUBS_i + \beta_2\, LABA_i \\ & + \beta_3\, LevRaTa_{i,t} + \beta_4\, netNPLR_{i,t} + \beta_5\, TA_{i,t} + \beta_6\, YERgr_t^{C_i} \\ & + log(\tau) \times (\beta_7\, LevRaTa_{i,t} + \beta_8\, netNPLR_{i,t} + \beta_9\, TA_{i,t} + \beta_{10}\, LTN_t^{C_i}) + \varepsilon_{i,\tau,t}\end{aligned} \quad (333)$$

where C_i denotes the country in which bank i is headquartered.

The log-linearized CDS spread of a bank depends on macroeconomic factors and bank-specific factors. For the former, these are the GDP growth YER and the 10-year rate of sovereign debt LTN of the bank's country of origin. For the latter, we include the bank leverage ratio $LevRatTa$, net NPL ratio $netNPLR$, and the size of the bank's balance sheet approximated with the total assets of the bank TA, arguing that each of these factors influences the (real and perceived) risk of credit default involved in lending to the bank, thereby driving CDS spreads. Furthermore, the idiosyncratic risk margins of subsidiary banks and state-owned banks are captured by dummies $SUBS$ and $LABA$, respectively.

Data

CDS risk margins are estimated using daily CDS spreads of 112 euro area banks sourced from S&P Capital IQ data (formerly Credit Market Analysis). The sample covers the period from 2003 to 2020, and contains 52,998 daily CDS quotes, of which 15,822 quotes for 52 euro-area bank CDS are used in the final regression. For the bank-maturity-days without a completed trade, a spread is inferred from bid-ask and recently completed trades at close maturities. Such an inference takes place in 91.6% of bank-maturity-days observations. Since independent variables include bank and country-level variables available only at a quarterly frequency, these CDS spreads are aggregated accordingly by averaging over all days within a quarter.[138]

For each bank, spreads are observed along the entire yield curve, so that the data constitute a (unbalanced) three-dimensional panel across banks, maturity, and quarters. For each quarter and country, we observe CDS spreads for $\{0.5, 1, 2, \ldots, 10\}$ years to maturity. For selected quarters and country combinations, there exist CDS spreads with maturities up to 30 years and shorter maturities up to overnight. 5Y CDS are traded most frequently, making up just under half of all maturities traded across all banks and quarters. 3Y, 7Y and 10Y CDS each contribute around 15% of all deals. Maturities below one year constitute most of the remaining 5% of observed maturities.

Variables	Observations	Mean	Median	Standard deviation
SUBS	21489	0.0361	0.0000	0.1866
LABA	28074	0.0952	0.0000	0.2935
netNPLR	19028	0.0884	0.0395	0.1137
TA	27644	546730	210744	714139
LevRaTa	27442	0.0565	0.0538	0.0203
$YERgr$	50489	0.0007	0.0034	0.0295
LTN	50461	0.0238	0.0177	0.0272

Table 45: Summary statistics: unsecured wholesale funding costs

[138] Since we aggregate the data up to bank-maturity-quarters, inclusion or exclusion of inferred spreads does not significantly affect our estimation results.

Results

Table 46 summarises the estimation results. Most variables enter the regression of the default risk with the expected signs. An increase in the leverage ratio and a reduction in the non-performing loan ratio (net of provisions) decrease the perceived default risk of a bank. Both have a more pronounced effect on the short end of the bank's unsecured yield curve, and their effect attenuates with increasing tenor of issued debt. Larger banks generally have lower CDS spreads and this effect is again most pronounced for the short-end of the yield curve. Subsidiary institutions and *Landesbanken* both have lower CDS spreads than their non-subsidiary or non-landesbank counterparts.

Higher levels of GDP growth reduce risk spreads along the entire yield curve. Increases in country-specific sovereign bond yields LTN increase bank-specific risk spreads in the long term.

	log of CDS Spread (in %)
$SUBS$	-0.512*
	(0.026)
$LABA$	-1.015**
	(0.000)
$LevRaTa_t$	-20.93**
	(0.000)
$netNPLR_t$	6.735**
	(0.000)
TA_t	-0.0000**
	(0.000)
ΔYER_t	-1.279*
	(0.045)
ΔYER_{t-1}	-4.229**
	(0.000)
$log(\tau)$	-0.0741
	(0.305)
$log(\tau) \times LevRaTa_t$	3.900**
	(0.000)
$log(\tau) \times netNPLR_t$	-1.002**
	(0.000)
$log(\tau) \times TA_t$	0.0000*
	(0.021)
$log(\tau) \times LTN_t$	1.881*
	(0.027)
$const.$	1.569**
	(0.000)
Banks	52
Obs	15822

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 46: Bank CDS spreads regressions: 2003 Q4 – 2020 Q3

C.10 Unsecured wholesale funding maturity

Methodology

The maturity-at-issuance of financial term deposits FIN and securities $UNSEC$ defined in equation (182) is projected based on the shape of the idiosyncratic yield curve facing the bank. To this end, the level and slope of the linear component *LinSpread* of the yield curve are regressed with respect to the maturity of corporate bonds issued by financial institutions in the euro area.

The specification of $NewDurationLiab$ for FIN and $UNSEC$ is estimated on the level and slope of the predicted yield curve. In this way, a bank can react to changes in the shape of its yield curve by issuing shorter or longer-term debt.

$$NewDurationLiab^S_{i,t} = \beta_0 + \beta_1\, log(CDS_{i,t-1}(\tau = 1)) + \beta_2\, \frac{\partial log(CDS_{i,t-1}(\tau))}{\partial log(\tau)} + \varepsilon^S_{i,t}$$

Data

The duration model is estimated using bond issuance data from 24 euro area banks sourced from S&P Capital IQ data (formerly Credit Market Analysis). The sample covers the period 2015Q1 to 2017Q4 and contains 590 single-name bonds issued by banks in that period. For each individual bank, the data are aggregated by calculating a quarterly average duration of bonds issued by the bank, weighted by the volume of each bond. The intercept and slope of the log-linearized yield curve are calculated by evaluating the relevant parts of equation (333) for each bank-quarter combination. In particular, the intercept term $log(CDS(\tau = 1))$ is calculated as the sum of components independent of τ, and the slope term $\frac{\partial log(CDS(\tau)}{\partial log(\tau)}$ is the sum of components corresponding to coefficients $\beta_7 - \beta_{10}$ that multiplies $\log(\tau)$.

Variables	Observations	Mean	Median	Standard deviation
$NewDurationLiab$	290	7.6874	6.8740	5.4300
$log(CDS(\tau = 1))$	290	-3.1502	-3.5452	1.4398
$\frac{\partial log(CDS(\tau)}{\partial log(\tau)}$	290	0.1771	0.1794	0.0487

Table 47: Summary statistics: Unsecured wholesale duration model

Results

The empirical results summarised in Table 48 show that banks increase their funding maturities when log-linearized CDS spreads increase along the entire yield curve. Similarly, when the slope of the yield curve increases, maturities-at-issuance also become longer.

C.11 Liquidity management

Methodology

Three equations introduced in Section 4.2.3.3 characterise a bank funding mix across the four categories of wholesale funding. The first regression maps the proportion of secured funding

	$NewDurationLiab^{S}_{i,t}$
$log(CDS_{i,t-1}(\tau=1))$	1.099^{**}
	(0.000)
$\frac{\partial log(CDS_{i,t-1}(\tau))}{\partial log(\tau)}$	4.964
	(0.307)
$const.$	10.74^{**}
	(0.000)
Banks	24
Obs	290

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 48: Duration of newly issued financial bonds: 2015 Q1 – 2017 Q4

(secured short-term debt, that is, repos, $SECST$ and secured long-term debt, that is, ABS or covered bonds $SECLT$, jointly) within wholesale funding:

$$\begin{aligned} logit(\gamma^{SEC}_{WHSL,i,t}) = \beta_0 + &4\beta_1\, SpreadST_{i,t} + 4\beta_2\, SpreadLT_{i,t} \\ &+\beta_3\, log(max(LCR_{i,t-1} - TLCR, 0)) + \varepsilon_{i,t} \end{aligned}$$

where:

$$SpreadST_{i,t} = EirLiabNew^{FINS}_{i,t} - EirLiabNew^{SECST}_{i,t}$$

$$SpreadLT_{i,t} = EirLiabNew^{UNSEC}_{i,t} - EirLiabNew^{SECLT}_{i,t}$$

denote the spread between the cost of unsecured and secured funding at the short maturity end,and the spread between the cost of unsecured and secured funding at the long maturity end, respectively. LCR denotes the liquidity coverage ratio of a bank and $TLCR$ is the regulatory minimum liquidity coverage ratio.

The second equation expresses the proportion of long-term debt in secured debt:

$$\begin{aligned} logit(\gamma^{LT}_{SEC,i,t}) = \beta_0 + &4\beta_1 SpreadSEC_{i,t} \\ &+\beta_2 log(NSFR_{i,t-1} - TNSFR) \\ &+\beta_3 EncumberableGovBuffer_{i,t} \\ &+\beta_4 EncumberableLoanBuffer_{i,t} + \varepsilon_{i,t} \end{aligned}$$

where:

$$SpreadSEC_{i,t} = EirLiabNew^{SECLT}_{i,t} - EirLiabNew^{SECST}_{i,t}$$

denotes the spread between the cost of long-term and short-term secured funding, $EncumberableGovBuffer$ the volume of unencumbered sovereign bonds relative to the demand of a bank for wholesale funding over one year, and $EncumberableLoanBuffer$ the volume of unencumbered loans eligible for use as collateral in the creation of asset-backed securities relative to a bank's demand for wholesale funding over one year, $NSFR$the net stable funding ratio of a bank, and $TNSFR$ stands for the regulatory minimum net stable funding ratio.

The third and final equation explains the proportion of long-term debt in unsecured debt:

$$logit(\gamma^{LT}_{UNSEC,i,t}) = \beta_0 + 4\beta_1 SpreadUNSEC_{i,t} + \beta_2 log(NSFR_{i,t-1} - TNSFR) + \varepsilon_{i,t} \tag{334}$$

where:

$$SpreadUNSEC_{i,t} = EirLiabNew^{UNSEC}_{i,t} - EirLiabNew^{FINS}_{i,t}$$

denotes the spread between the cost of long-term and short-term unsecured funding.

The three equations are estimated separately using a pooled logistic regression.

Data

The volumes of overall (encumbered and unencumbered) sovereign bond holdings and loans are sourced from FINREP templates 04 and 05. Data from COREP 72 on high-quality liquid assets are then used to find the degree of encumberance for sovereign bonds and loans. The level of LCR is taken from COREP 76, and NSFR from COREP 84 (where the information on $NSFR$ is available only from 2021Q2 onwards). Relative prices within the available categories of wholesale funding are taken from COREP 69. Data are available for 82 banks in the euro area from 2016Q3 to 2021Q4.

Regressions are estimated only for banks that use two types of funding corresponding to the relevant binary decision. In the regression of γ^{SEC}_{WHSL}, we use information on 70 banks that issue both secured and unsecured funding (12 banks that do not issue secured funding are excluded from the estimation).[139] In the regression of γ^{LT}_{SEC}, we use data on 23 banks that issue repos and ABS or covered bonds (we exclude 47 banks that issue no ABS or covered bonds).[140] In the regression of γ^{LT}_{UNSEC} we use the full sample of 82 banks.

Variables	Observations	Mean	Median	Standard deviation
$\gamma\ SEC\ WHSL$	1,723	0.2990	0.1479	0.3382
$\gamma\ LT\ SEC$	1,230	0.0689	0.0000	0.2159
$\gamma\ LT\ UNSEC$	1,701	0.1454	0.0265	0.2569
$SpreadST$ (in bps)	1,723	30.0297	23.5299	46.6995
$SpreadLT$ (in bps)	1,723	34.7975	10.0000	81.3459
$SpreadSEC$ (in bps)	1,723	30.0297	23.5299	46.6995
$SpreadUNSEC$ (in bps)	1,723	19.0526	4.9517	95.0155
$log(NSFR - TNSFR)$	239	-1.0402	-1.0536	0.6071
$log(LCR - TLCR)$	1,723	-0.1475	-0.2662	0.8253
$log(EncumberableGovBuffer)$	1,723	-0.6188	-0.6362	1.5943
$log(EncumberableLoanBuffer)$	1,278	1.4338	1.7940	1.7974

Table 49: Summary statistics: liquidity management regressions

Results

Table 50 presents the results of the estimation. Bank propensity to issue secured rather than unsecured debt increases with the premium a bank pays to attract financial sight deposits as opposed to repos and, to a smaller and statistically less significant degree, with the premium on

[139]In the model their share of secured funding for the excluded banks is always 0%.

[140]The share of long-term secured funding for these banks is set to 0% in the model.

unsecured versus secured funding. Additionally, the larger bank's excess short-term liquidity coverage, the more likely the bank is to issue secured funding.

The proportion of long-term funding within secured funding depends on the available pool of encumberable assets that are needed to create the different types of secured funding. If the available stock of encumberable government bonds increases, the share of long-term secured funding decreases in favour of more repos. On the other hand, if the volume of encumberable loans increases, the proportion of these long-term securities also increases. Furthermore, the higher the NSFR, the more likely a bank is to issue short-term funding. Lastly, the higher the maturity premium, the more likely a bank is to issue long-term funding.

The proportion of long-term funding within unsecured funding is empirically linked to the net stable funding ratio. The larger the excess stable funding beyond regulatory requirements, the more likely the bank will be to fund itself at shorter maturities. The effect of the maturity premium is statistically insignificant.

	(1) γ_{WHSL}^{SEC}	(2) γ_{SEC}^{LT}	(3) γ_{UNSEC}^{LT}
$SpreadST_t$	0.004^{**}		
	(0.001)		
$SpreadLT_t$	0.0001		
	(0.855)		
$SpreadSEC_t$		0.027^{+}	
		(0.082)	
$SpreadUNSEC_t$			-0.003
			(0.341)
$log(LCR_{t-1} - TLCR)$	0.195^{**}		
	(0.006)		
$log(NSFR_{t-1} - TNSFR)$		-1.823	-0.662^{*}
		(0.124)	(0.043)
$EncumberableGovBuffer_t$		-1.925^{**}	
		(0.005)	
$EncumberableLoanBuffer_t$		2.173^{*}	
		(0.010)	
$const.$	-0.724^{**}	-11.997^{**}	-2.491^{**}
	(0.000)	(0.001)	(0.000)
Banks	70	23	82
Obs	1,339	49	237

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 50: Liquidity management regressions: 2016 Q3 – 2021 Q4

C.12 Management buffer

Methodology

The management buffer from equation (295) represents an internal target for the CET1 ratio in addition to regulatory requirements and buffers. The empirical equation reads as follows:

$$
\begin{aligned}
log(ManBuf_{i,t}) =& \beta_0 + \beta_1\, log(TA_{i,t}) + \beta_2\, \frac{FCI_{i,t}}{TA_i} + \beta_3\, netNPLR_{i,t} \\
&+ \beta_4\, CovbonRatio_i \times \frac{VolLiabTotal^{SECLT}_{i,t}}{VolLiabTotal_{i,t}} + \beta_5\,(1 - CovbonRatio_i) \times \frac{VolLiabTotal^{SECLT}_{i,t}}{VolLiabTotal_{i,t}} \\
&+ \beta_6\, \frac{VolLiabTotal^{NFPS}_{i,t}}{VolLiabTotal_{i,t}} + \beta_7\, \frac{VolLiabTotal^{SOV}_{i,t}}{VolLiabTotal_{i,t}} + \beta_8\, \frac{VolLiabTotal^{WHSL}_{i,t}}{VolLiabTotal_{i,t}} + \varepsilon_{i,t}
\end{aligned}
$$

where TA represents total bank assets, $\frac{FCI}{TA}$ is a ratio of gross fee and commission income to total assets, $netNPLR$ is an NPL ratio net of loan loss provisions. Furthermore, the structure of bank funding is mapped by the proportion of funding sourced from the issuance of covered bonds $CovbonRatio \times VolLiabTotal^{SECLT}$, other long-term secured funding such as asset-backed securities $(1 - CovbonRatio) \times VolLiabTotal^{SECLT}$, funding from the retail sector $VolLiabTotal^{NFPS}$, sovereigns $VolLiabTotal^{SOV}$, and the unsecured wholesale market $VolLiabTotal^{WHSL}$ in total bank debt funding $VolLiabTotal$.

The equation is specified log-linearly, and estimated in a pooled OLS setting.

Data

We do not have information on actual bank management buffers. For this reason, we need to construct a proxy quantity by observing the capital surplus of banks paying out positive dividends. If a bank pays out dividends strictly larger than zero, but strictly smaller than their distributable profit (a condition we term *unrestricted*), we assume that the next period's capital surplus reflects an internal capital target.[141] [142]

The calculation of proxy management buffers is performed based on end-of-year data sourced from COREP/FINREP. For the construction of capital ratios in excess of requirements, we use COREP 03.00 (on capital adequacy); for the construction of unrestricted dividend payments, we use FINREP 02.00 and 46.00 (on profit and loss and changes in equity, respectively).

The sample includes 119 banks, starts in 2014 and ends in 2020. The analysed observations include 670 bank-year points, 294 observations of management buffers (for these banks and periods where the dividend payouts appear *unrestricted*).

The left-hand side variables in the regression of management buffers are sourced from FINREP 01.01 (on balance sheet's asset side), FINREP 01.02 and 08.01a for the composition and breakdown of liabilities, FINREP 12.01a for changes in credit loss allowances, and FINREP 18.00a for information on non-performing exposures. We focus on year-end observation only which matches the frequency of the management buffer proxy.

Results

Table 52 presents the results of the estimation. Management buffers are generally lower for large banks. A larger share of lending to sovereigns, central banks NCB and to the non-financial private sector $NFPS$ reduces the management buffer compared to reference banks with a relatively

[141] A weakness of this approach is that the only guiding motive for the setting of dividends is meeting an internal capital target, which in reality is not always the case. For example, a firm might want to smooth out dividend payments over the years.

[142] The calculation excludes custodian and state-owned banks. The capitalisation of these banks is often far above regulatory requirements and buffers. The guiding motive behind these surpluses is likely not a specific management buffer, but an idiosyncratic, internally (or externally) mandated balance sheet structure that leads to large risk-weighted capital ratios.

Variables	Observations	Mean	Median	Standard deviation
$ManBuf$	653	0.0752	0.0505	0.1045
$\frac{VolAssetTotal^{NCB}}{VolAssetTotal}$	666	0.0811	0.0691	0.0712
$\frac{VolAssetTotal^{NFPS}}{VolAssetTotal}$	666	0.5183	0.5779	0.2589
$\frac{VolLiabTotal^{WHSL}}{VolLiabTotal}$	666	0.2491	0.1784	0.2299
$(1-CovbonRatio)\frac{VolLiabTotal^{SECLT}}{VolLiabTotal}$	666	0.0047	0.0000	0.0131
$CovbonRatio\frac{VolLiabTotal^{SECLT}}{VolLiabTotal}$	666	0.0581	0.0169	0.1366
$netNPLR$	670	0.0445	0.0150	0.0779
$\frac{FCI}{TA}$	670	0.0115	0.0073	0.0399
$log(TA)$	670	10.9684	10.9806	1.5139

Table 51: Summary statistics: management buffer regressions

high share of lending to private financial institutions. Furthermore, a higher NPL ratio increases internal capital buffers.

On the liability side, a larger share of unsecured wholesale funding compared to retail funding increases the management buffer. Analogously, a larger share of covered bonds tends to increase the management buffers,[143] whereas a larger share of asset-backed securities tends to decrease it. Finally, a larger share of fee and commission income decreases the target capital buffers.

[143] It is possibly a consequence of double recourse against the collateral and the bank issuing the covered bond.

	log (ManBuf) (in %)
$\frac{VolAssetTotal_t^{NCB}}{VolAssetTotal_t}$	-1.386
	(0.192)
$\frac{VolAssetTotal_t^{NFPS}}{VolAssetTotal_t}$	-0.199
	(0.661)
$\frac{VolLiabTotal_t^{WHSL}}{VolLiabTotal_t}$	0.733^{+}
	(0.070)
$CovbonRatio\frac{VolLiabTotal_t^{SECLT}}{VolLiabTotal_t}$	0.404
	(0.811)
$(1-CovbonRatio)\frac{VolLiabTotal_t^{SECLT}}{VolLiabTotal_t}$	-6.468^{+}
	(0.092)
$netNPLR_t$	0.419
	(0.739)
$\frac{FCI_t}{TA_t}$	-22.82^{+}
	(0.079)
$log(TA_t)$	-0.247^{**}
	(0.000)
$const.$	0.0503
	(0.947)
Banks	119
Obs	294

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 52: Management buffer regressions: 2014 Q1 – 2020 Q4

D Empirical models of the pass-through of economic conditions into bank parameters

D.1 IFRS 9 risk parameters

The assessment of credit risk impairments depends on the projection of the transitions among the three stages of IFRS 9 impairment (see Section 4.1.3) and the calculation of the expected credit loss (ECL) (see Section 4.1.4). To achieve this, we estimate two sets of essential IFRS 9 credit risk parameters. The first set includes transition rates (TRs) (see Section D.1.1), while the second set involves loss-given default (LGD) and loss rate (LRs) parameters (see Appendix D.1.2).

D.1.1 Transition rates

The transition rate matrix is a stochastic matrix comprising nine elements that governs the flows of exposures among the individual impairment stages (S1, S2 and S3). However, due to the constraint that the sum of elements in each row of the matrix equals one, we only model the six transition rates that lie outside of the main diagonal. These are the transition rates of S1 to S2 $TR12$, from S1 to S3 $TR13$, from S2 to S1 $TR21$, from S2 to S3 $TR23$, from S3 to S1 $TR31$, and from S3 to S2 $TR32$.

Methodology

Transition rates are independently estimated for five sectors: non-financial corporations (NFC), households - house purchases ($HHHP$), households - consumer credit ($HHCC$), financial corporations (FIN), and sovereigns (SOV). The estimates of transition rate regressions are based on the banks' own projections of transition rates for stress test scenarios from the EBA/SSM stress test exercises in 2018 and 2021. This identification scheme follows the approach outlined by Niepmann and Stebunovs [2018] and allows circumventing the unavailability of longer time series data for variables under the IRFS9 standard, which only came into force in 2019. A potential limitation of this approach is that the projected transition rates may not fully represent the true sensitivity of their portfolio risks to actual macro-financial scenarios. However, the quality assurance process and the utilisation of data from the two subsequent EBA/SSM stress test exercises should have addressed any known systematic biases.

The four transition rates $\{TR12, TR13, TR21, TR23\}$ are jointly estimated as a system of equations following the logit-transformed weighted seemingly unrelated regression (SUR) approach with weighting of observations. This regression model implicitly acknowledges the potential correlation among the error terms of the four transition rates, providing a robust estimation for each sector's transition probabilities.[144] For $K \in \{12, 13, 21, 23\}$, the system of equations takes the following form:

[144] The estimation procedure is handled using the *sureg* function in Stata.

$$logit(TR12_{i,t}^{S,C}) = \beta_0^{12,S} + \sum_K \beta_1^{12,S,K} logit(TR[K]_{i,t-1}^{S,C}) + \beta_2^{12,S} ExpRel_{t-1}^{12,S,C}$$
$$+ \mathbf{X_t}\boldsymbol{\beta_X^{12,S}} + \boldsymbol{\Omega\beta_\Omega^{12,S}} + \varepsilon_{i,t}^{12,S,C}$$
$$logit(TR13_{i,t}^{S,C}) = \beta_0^{13,S} + \sum_K \beta_1^{13,S,K} logit(TR[K]_{i,t-1}^{S,C}) + \beta_2^{13,S} ExpRel_{t-1}^{13,S,C}$$
$$+ \mathbf{X_t}\boldsymbol{\beta_X^{13,S}} + \boldsymbol{\Omega\beta_\Omega^{13,S}} + \varepsilon_{i,t}^{13,S,C}$$
$$logit(TR21_{i,t}^{S,C}) = \beta_0^{21,S} + \sum_K \beta_1^{21,S,K} logit(TR[K]_{i,t-1}^{S,C}) + \beta_2^{21,S} ExpRel_{t-1}^{21,S,C}$$
$$+ \mathbf{X_t}\boldsymbol{\beta_X^{21,S}} + \boldsymbol{\Omega\beta_\Omega^{21,S}} + \varepsilon_{i,t}^{21,S,C}$$
$$logit(TR23_{i,t}^{S,C}) = \beta_0^{23,S} + \sum_K \beta_1^{23,S,K} logit(TR[K]_{i,t-1}^{S,C}) + \beta_2^{23,S} ExpRel_{t-1}^{23,S,C}$$
$$+ \mathbf{X_t}\boldsymbol{\beta_X^{23,S}} + \boldsymbol{\Omega\beta_\Omega^{23,S}} + \varepsilon_{i,t}^{23,S,C}$$

where transition rates are indexed by bank i, sector S and country C, and t refers to quarters. Variables ε represent the error terms, which are assumed to be independent between observations, but may exhibit cross-equation correlations for individual observations. The variables $ExpRel$ are defined as in equation (31). The model is estimated in logit space, ensuring that the projected transition rates remain bounded between 0 and 1. Moreover, the observations are weighted by the volume of non-defaulted exposures at the individual portfolio level to ensure the highest possible representativeness of the coefficient estimates.

Each transition rate is a function of the lagged values of (potentially) all transition rates and a set of lagged values of macrofinancial variables at the country level grouped in a vector $\mathbf{X_t}$. The selected macrofinancial variables include quarterly growth rates of real GDP ($YERgr$), imports of goods and services ($MTRgr$), residential property prices ($IHXgr$), HICP price level ($HICgr$), prices of exports of goods and services ($XTDgr$), and equity index ($ESXgr$), as well as variables in levels: unemployment rate (URX), long-term interest rate (LTN), short-term interest rate (STN), and spread between long- and short-term interest rates (SPR).

In particular, we get:

$$\mathbf{X_t}\boldsymbol{\beta^{K,S}} = \sum_p (\beta_{p,3}^{K,S} YERgr_{t-p}^C + \beta_{p,4}^{K,S} MTRgr_{t-p}^C + \beta_{p,5}^{K,S} IHXgr_{t-p}^C + \beta_{p,6}^{K,S} HICgr_{t-p}^C$$
$$+ \beta_{p,7}^{K,S} XTDgr_{t-p}^C + \beta_{p,8}^{K,S} ESXgr_{t-p}^C + \beta_{p,9}^{K,S} \Delta URX_{t-p}^C + \beta_{p,10}^{K,S} LTN_{t-p}^C$$
$$+ \beta_{p,11}^{K,S} STN_{t-p}^C + \beta_{p,12}^{K,S} SPR_{t-p}^C)$$

Suitable macrofinancial variables, along with their optimal lags, are carefully selected through a hybrid approach combining statistical learning model selection techniques, including the least absolute shrinkage and selection operator (lasso) and Bayesian Model Averaging (BMA), as well as expert judgement. The ultimately selected macrofinancial variables, as well as their optimal lags, can be observed in the tables provided within the results subsection of this chapter.[145]

Finally, we include a set of dummy variables $\boldsymbol{\Omega}$ that control for each:

- Vintage of the stress test data: 1 binary variable, taking value of 1 for the EBA/SSM stress test exercises in 2021 (and 0 for the EBA/SSM stress test exercise in 2018);

[145]The lasso technique aids in identifying the most relevant variables and their respective lags by applying regularisation, while BMA facilitates the evaluation and comparison of multiple potential models. Expert judgment complements the automated selection process by incorporating domain knowledge and insights. In practise, Stata is used for the statistical part, taking advantage of its *lasso* and *bma* functions.

- Scenario type: 1 binary variable, taking value of 1 for adverse scenarios (and 0 for baseline scenarios).

In particular, we get:

$$\mathbf{\Omega}\boldsymbol{\beta}_{\mathbf{\Omega}}^{\boldsymbol{K,S}} = \beta_{13}^{K,S}\omega^{vintage} + \beta_{14}^{K,S}\omega^{scenario} \tag{335}$$

Please note that the coefficient estimates for dummy variables are not included in the tables within the results subsection of this chapter.

The transition rates $\{TR31, TR32\}$ (i.e. cure rates) are estimated using separate SUR systems for each sector:

$$\begin{aligned} logit(TR31_{i,t}^{S,C}) &= \beta_0^{31,S} + \sum_K \beta_1^{31,S,K} logit(TR[K]_{i,t-1}^{S,C}) + \beta_2^{31,S} ExpRel_{t-1}^{31,S,C} \\ &+ \mathbf{X_t}\boldsymbol{\beta}_{\boldsymbol{X}}^{\mathbf{31,S}} + \mathbf{\Omega}\boldsymbol{\beta}_{\mathbf{\Omega}}^{\mathbf{31,S}} + \varepsilon_{i,t}^{31,S,C} \\ logit(TR32_{i,t}^{S,C}) &= \beta_0^{32,S} + \sum_K \beta_1^{32,S,K} logit(TR[K]_{i,t-1}^{S,C}) + \beta_2^{32,S} ExpRel_{t-1}^{32,S,C} \\ &+ \mathbf{X_t}\boldsymbol{\beta}_{\boldsymbol{X}}^{\mathbf{32,S}} + \mathbf{\Omega}\boldsymbol{\beta}_{\mathbf{\Omega}}^{\mathbf{32,S}} + \varepsilon_{i,t}^{32,S,C} \end{aligned} \tag{336}$$

for $K \in \{31, 32\}$.

The general specification of the model and the explanatory macrofinancial variables align with the approach to estimating {TR12, TR13, TR21, TR23} systems. This concerns the logit transformation, the relative amount of exposures $ExpRel$, as well as the dummy control variables from $\mathbf{\Omega}$. The observations are weighted by the volume of defaulted exposures at the individual portfolio level.

Data

The EBA/SSM stress test methodology requires banks to provide their annual projections of four transition rates {TR12, TR13, TR21, TR23} for both baseline and adverse stress test scenarios. Transition rates {TR31, TR32} are calculated based on the information reported by the banks for the purpose of the LGD calculation. This information provides the proportion of S3 exposures that cure through repayments with zero losses in all years until maturity. These bank-specific lifetime cure rates are then transformed into annual cure rates, accounting for the average maturity of the portfolio.[146] Subsequently, the annual projections of transition rates are converted into quarterly values, forming a transition probability matrix, assuming the constancy of the matrix across all four quarters of each year.

Similarly to the transition rates, the information on exposure volumes in the individual stages is sourced from the EBA/SSM stress test templates. For the purpose of estimation, the data for the baseline and adverse scenarios of the bank submissions in 2018 and 2021 are pooled together, separately for each economic sector and for {TR12, TR13, TR21, TR23} and {TR31, TR32} systems. The summary statistics for the transition rates are reported in Table 53.

Historical macroeconomic and financial data are sourced from the SDW. The macroeconomic and financial data for the projection periods of the 2018 and 2021 stress tests are obtained from the macrofinancial scenarios used in the respective stress testing exercises. Summary

[146] The maturity structure was cross-checked with the average maturity of defaulted exposures as reported in COREP. This cross-check aimed to rule out substantial differences in the maturity between performing and non-performing exposures for some banks.

statistics for both macrofinancial variables and the relative amount of exposures in individual stages are reported in Table 54.

Variables	Observations	Mean	Median	Standard deviation
$TR12\ NFC$	11358	0.0197	0.0130	0.0261
$TR12\ HHHP$	9668	0.0146	0.0091	0.0349
$TR12\ HHCC$	10046	0.0176	0.0132	0.0212
$TR12\ FIN$	4066	0.0106	0.0022	0.0314
$TR12\ SOV$	4010	0.0036	0.0006	0.0111
$TR13\ NFC$	11986	0.0026	0.0015	0.0032
$TR13\ HHHP$	9732	0.0023	0.0012	0.0034
$TR13\ HHCC$	10432	0.0038	0.0025	0.0053
$TR13\ FIN$	4454	0.0015	0.0005	0.0039
$TR13\ SOV$	4482	0.0003	0.0001	0.0006
$TR21\ NFC$	10832	0.0557	0.0351	0.0703
$TR21\ HHHP$	9110	0.0722	0.0605	0.0755
$TR21\ HHCC$	9692	0.0686	0.0548	0.0710
$TR21\ FIN$	3878	0.0411	0.0165	0.0638
$TR21\ SOV$	3756	0.0340	0.0121	0.0531
$TR23\ NFC$	11536	0.0158	0.0103	0.0210
$TR23\ HHHP$	9636	0.0241	0.0156	0.0302
$TR23\ HHCC$	10146	0.0281	0.0189	0.0358
$TR23\ FIN$	4080	0.0092	0.0031	0.0163
$TR23\ SOV$	4116	0.0065	0.0012	0.0161
$TR31\ NFC$	4770	0.0181	0.0089	0.0429
$TR31\ HHHP$	4862	0.0127	0.0045	0.0347
$TR31\ HHCC$	4634	0.0227	0.0062	0.0597
$TR31\ FIN$	1612	0.0415	0.0074	0.0745
$TR31\ SOV$	1638	0.0283	0.0018	0.1110
$TR32\ NFC$	4744	0.0176	0.0092	0.0297
$TR32\ HHHP$	4774	0.0130	0.0054	0.0283
$TR32\ HHCC$	4568	0.0255	0.0077	0.0641
$TR32\ FIN$	1568	0.0321	0.0052	0.0677
$TR32\ SOV$	1614	0.0115	0.0013	0.0381

Table 53: Summary statistics: Transition rates model - transition rates

Results

Tables 55 - 59 present the transition rates model estimation results for five sectors. In general, the autoregressive component is statistically significant and relatively high (above 0.85, but below 1) between sectors. However, explicit dependency among the individual transition rates is found to be significant only in a handful of cases.

Regarding macrofinancial variables, an increase in real GDP growth rates ($YERgr$), residential property prices ($IHXgr$), prices of exports of goods and services ($XTDgr$), and equity index ($ESXgr$) leads to a decrease in migrations to lower asset quality stages (i.e. TR12, TR13, and TR23) and an increase in migrations to higher asset quality stages (i.e. TR21, TR31, and

Variables	Observations	Mean	Median	Standard deviation
$YERgr$	69046	0.0015	0.0038	0.0308
$MTRgr$	69046	0.0037	0.0083	0.0558
$IHXgr$	69046	0.0015	0.0066	0.0208
$HICgr$	69046	0.0027	0.0030	0.0032
$XTDgr$	69046	0.0024	0.0031	0.0112
$ESXgr$	69046	0.0050	0.0108	0.0816
URX	72680	0.0857	0.0771	0.0434
LTN	72680	0.0079	0.0059	0.0128
STN	72680	-0.0027	-0.0033	0.0032
SPR	72680	0.0107	0.0089	0.0112
$NonDefExpS1Rel\ NFC$	18920	0.6145	0.7592	0.3520
$NonDefExpS1Rel\ HHHP$	15880	0.6436	0.8275	0.3646
$NonDefExpS1Rel\ HHCC$	16880	0.5871	0.7387	0.3565
$NonDefExpS1Rel\ FIN$	6960	0.7140	0.9310	0.3923
$NonDefExpS1Rel\ SOV$	6960	0.7510	0.9686	0.3941
$NonDefExpS2Rel\ NFC$	18920	0.1177	0.0840	0.1424
$NonDefExpS2Rel\ HHHP$	15880	0.0939	0.0616	0.1308
$NonDefExpS2Rel\ HHCC$	16880	0.1096	0.0694	0.1501
$NonDefExpS2Rel\ FIN$	6960	0.0684	0.0079	0.1474
$NonDefExpS2Rel\ SOV$	6960	0.0439	0.0048	0.1204
$DefExpRel\ NFC$	18920	0.0678	0.0264	0.1178
$DefExpRel\ HHHP$	15880	0.0625	0.0224	0.1255
$DefExpRel\ HHCC$	16880	0.1033	0.0512	0.2167
$DefExpRel\ FIN$	6960	0.0176	0.0015	0.0694
$DefExpRel\ SOV$	6960	0.0050	0.0006	0.0130

Table 54: Summary statistics: Transition rates model - explanatory variables

TR32). On the contrary, an increase in imports of goods and services ($MTRgr$), HICP inflation ($HICgr$), unemployment rate (URX), and interest rate spread (SPR) leads to an increase in migrations to lower stages and a decrease in migrations to higher stages.

The impact of the relative amount of exposures in a particular stage on the respective transition rates is generally more significant for the S2 and S3 exposures. The signs of the coefficients are typically negative for S2 (and also S1) exposures, but positive for S3 exposures. This means that when the relative amount of S2 exposures increases, a higher percentage of S2 exposures remains in S2. On the contrary, when the relative amount of S3 exposures increases, a higher percentage of S3 exposures tends to cure and move to S1 or S2.

D.1.2 LGD and LR Parameters

Loss given default (LGD) parameters refer to projected losses associated with possible default events (i.e. transition to S3). The model employs two LGD parameters and three loss rate (LR) parameters. Specifically, the two LGD parameters are as follows: the percentage loss associated with exposures that transition from S1 to S3 (LGD13) and the percentage loss associated with exposures that transition from S2 to S3 (LGD23).

Loss rate (LR) parameters refer to the expected credit losses due to default (S3) events expected over the lifetime of exposures. In total, we model three LR parameters: lifetime

	NFC					
	(1)	(2)	(3)	(4)	(5)	(6)
	TR12	TR13	TR21	TR23	TR31	TR32
$logit(TR12_{t-1})$	0.9099**		0.0655**			
	(0.000)		(0.000)			
$logit(TR13_{t-1})$		0.9483**				
		(0.000)				
$logit(TR21_{t-1})$	0.0388**		0.8959**	0.0054**		
	(0.000)		(0.000)	(0.000)		
$logit(TR23_{t-1})$				0.9203**		
				(0.000)		
$logit(TR31_{t-1})$					0.9735**	
					(0.000)	
$logit(TR32_{t-1})$						0.9723**
						(0.000)
$YERgr_{t-1}$	-1.0070^{+}	-0.7982**	5.3353**		16.9986**	15.9992**
	(0.081)	(0.000)	(0.000)		(0.000)	(0.000)
$HICgr_{t-1}$	10.6752**		-6.6612**	5.3642**		-5.9042**
	(0.000)		(0.000)	(0.000)		(0.000)
$ESXgr_{t-4}$		-0.4341**			0.1651**	
		(0.000)			(0.000)	
ΔURX_{t-2}	4.3143**	1.7812**	-3.8325**	2.3150**	-16.3984**	-15.6757**
	(0.003)	(0.002)	(0.009)	(0.000)	(0.000)	(0.000)
SPR_{t-1}		1.4867**		1.4497**		
		(0.000)		(0.000)		
$ExpRel_{t-1}$			-0.2240**	-0.3036**	0.0608^{+}	0.0482
			(0.003)	(0.000)	(0.090)	(0.202)
$const.$	-0.4030**	-0.3523**	-0.0551^{+}	-0.3596**	-0.3383**	-0.3186**
	(0.000)	(0.000)	(0.080)	(0.000)	(0.000)	(0.000)
Obs	9487	9487	9487	9487	4338	4338
Banks	89	89	89	89	89	89
R^2	0.8457	0.9315	0.8401	0.9332	0.9756	0.9736

p-values in parentheses; Δ stands for differences
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 55: Transition rates regressions for NFC: 2018 - 2021 stress test submissions

expected loss rate of the exposures that begin the quarter in S1 and end it in S2 (LR12), lifetime expected loss rate for all exposures that begin and end the quarter in S2, regardless of the stage they end up eventually during their lifetime (LR2X), and lifetime expected loss associated with all exposures that are in S3 at the beginning of each quarter (LR33).

Methodology

The methodology of estimating LGDs and LRs is akin to the methodology used for the transition rates, as introduced in Appendix D.1.1. The parameters are again estimated independently for five sectors: non-financial corporations (NFC), households - house purchase (HHHP), house-

	HHHP					
	(1) TR12	(2) TR13	(3) TR21	(4) TR23	(5) TR31	(6) TR32
$logit(TR12_{t-1})$	0.9321**		0.0886**			
	(0.000)		(0.000)			
$logit(TR13_{t-1})$		0.9269**				
		(0.000)				
$logit(TR21_{t-1})$	0.0576**		0.8842**	-0.0049*		
	(0.000)		(0.000)	(0.020)		
$logit(TR23_{t-1})$			-0.0536**	0.9256**		
			(0.000)	(0.000)		
$logit(TR31_{t-1})$					0.9521**	
					(0.000)	
$logit(TR32_{t-1})$						0.9510**
						(0.000)
$YERgr_{t-1}$	-0.6435	-2.9237**	4.1039**		0.6345*	0.6163*
	(0.183)	(0.000)	(0.000)		(0.015)	(0.019)
$HICgr_{t-1}$	7.4814**			5.4440**		
	(0.000)			(0.000)		
$ESXgr_{t-4}$		-0.4933**			0.1265+	0.1760*
		(0.000)			(0.088)	(0.019)
ΔURX_{t-2}		6.1125**	-1.8280	0.6947	-6.5560**	-6.4115**
		(0.000)	(0.117)	(0.186)	(0.000)	(0.000)
SPR_{t-1}		0.7717+		1.0080**		
		(0.082)		(0.000)		
$ExpRel_{t-1}$		-0.2437**	-1.1151**	-0.5388**	0.0990**	0.0821**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
$const.$	-0.2295**	-0.3131**	-0.0652+	-0.3285**	-0.4421**	-0.4459**
	(0.000)	(0.000)	(0.097)	(0.000)	(0.000)	(0.000)
Obs	7646	7646	7646	7646	4356	4356
Banks	89	89	89	89	89	89
R^2	0.8904	0.9210	0.8686	0.9056	0.9564	0.9569

p-values in parentheses; Δ stands for differences
$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$

Table 56: Transition rates regressions for $HHHP$: 2018 - 2021 stress test submissions

holds - consumer credit (HHCC), financial corporations (FIN) and sovereigns (SOV).[147]

The loss given default parameters and loss rates are estimated separately as two systems of equations following again the logit-transformed weighted seemingly unrelated regression (SUR) implemented in Stata.[148] This approach implicitly acknowledges that the error terms of

[147] Parameter estimates for the sovereign sector are utilized to project LGDs and LRs for the central banks (CB) sector. Additionally, the regression coefficients for LGDs and LRs in the rest of the world (ROW) sector are derived as a linear combination of NFC, HHHP and HHCC sector coefficients. This derivation is based on bank-specific weights, which map the share of these sectors to exposures in countries outside the euro area.

[148] In theory, a loss rate parameter can be expressed as a complex forward-looking function involving future transition rates, LGDs, exposure amounts and interest rates until the exposure's maturity. However, such forward-looking calculations are not supported by the construction of the BEAST model. Therefore, a reduced-form representation and modelling of the LRs are adopted.

	HHCC					
	(1) TR12	(2) TR13	(3) TR21	(4) TR23	(5) TR31	(6) TR32
$logit(TR12_{t-1})$	0.9247**		0.0466**			
	(0.000)		(0.000)			
$logit(TR13_{t-1})$		0.9196**				
		(0.000)				
$logit(TR21_{t-1})$	0.0435**		0.9110**	0.0126**		
	(0.000)		(0.000)	(0.000)		
$logit(TR23_{t-1})$				0.9370**		
				(0.000)		
$logit(TR31_{t-1})$					0.9854**	
					(0.000)	
$logit(TR32_{t-1})$						0.9813**
						(0.000)
$YERgr_{t-1}$	-0.7890*	-1.9064**	1.6837**			
	(0.036)	(0.000)	(0.000)			
$HICgr_{t-1}$	2.2002	3.3747**	-5.4073**	12.5982**		-3.4481**
	(0.235)	(0.002)	(0.000)	(0.000)		(0.000)
$ESXgr_{t-4}$		-0.2795**			0.0368+	0.0666**
		(0.000)			(0.093)	(0.000)
ΔURX_{t-2}		4.8455**	-1.7971+	2.1468**	-1.1908*	
		(0.000)	(0.074)	(0.000)	(0.010)	
SPR_{t-1}		2.1567**		1.0363**		
		(0.000)		(0.000)		
$ExpRel_{t-1}$			-0.6586**	-0.3461**	0.0910**	0.0334
			(0.000)	(0.000)	(0.000)	(0.202)
$const.$	-0.2478**	-0.5179**	0.0322	-0.2493**	-0.1561**	-0.1625**
	(0.000)	(0.000)	(0.126)	(0.000)	(0.000)	(0.000)
Obs	8428	8428	8428	8428	4166	4166
Banks	89	89	89	89	89	89
R^2	0.8861	0.9155	0.9051	0.9350	0.9850	0.9837

p-values in parentheses; Δ stands for differences
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 57: Transition rates regressions for $HHCC$: 2018 - 2021 stress test submissions

the variables within each system can be correlated. The two SUR systems are as follows:

$$\begin{aligned}
logit(LGD13^{S,C}_{i,t}) =& \beta_0^{13,S} + \sum_K \beta_1^{13,S,K}\, logit(LGD[K]^{S,C}_{i,t-1}) + \beta_2^{13,S}\, ExpRel^{13,S,C}_{t-1} \\
&+ \beta_3^{13,S}\, logit(CureRateLT^{S,C}_{i,t-1}) + \mathbf{X_t}\boldsymbol{\beta}^{\mathbf{13,S}}_{\boldsymbol{X}} + \boldsymbol{\Omega}\boldsymbol{\beta}^{\mathbf{13,S}}_{\boldsymbol{\Omega}} + \varepsilon^{13,S,C}_{i,t} \\
logit(LGD23^{S,C}_{i,t}) =& \beta_0^{23,S} + \sum_K \beta_1^{23,S,K}\, logit(LGD[K]^{S,C}_{i,t-1}) + \beta_2^{23,S}\, ExpRel^{23,S,C}_{t-1} \\
&+ \beta_3^{23,S}\, logit(CureRateLT^{S,C}_{i,t-1}) + \mathbf{X_t}\boldsymbol{\beta}^{\mathbf{23,S}}_{\boldsymbol{X}} + \boldsymbol{\Omega}\boldsymbol{\beta}^{\mathbf{23,S}}_{\boldsymbol{\Omega}} + \varepsilon^{23,S,C}_{i,t}
\end{aligned} \tag{337}$$

for $K \in \{13, 23\}$. And:

$$
\begin{aligned}
logit(LR12^{S,C}_{i,t}) =& \beta_0^{12,S} + \sum_K \beta_1^{12,S,K}\, logit(LR[K]^{S,C}_{i,t-1}) + \beta_2^{12,S}\, ExpRel^{12,S,C}_{t-1} \\
&+ \beta_3^{12,S}\, logit(LGDpit^{S,C}_{i,t-1}) + \sum_L \beta_4^{12,S,L}\, logit(TR[L]^{S,C}_{i,t-1}) \\
&+ \mathbf{X_t}\boldsymbol{\beta_X^{12,S}} + \boldsymbol{\Omega\beta_\Omega^{12,S}} + \varepsilon^{12,S,C}_{i,t} \\
logit(LR2X^{S,C}_{i,t}) =& \beta_0^{2X,S} + \sum_K \beta_1^{2X,S,K}\, logit(LR[K]^{S,C}_{i,t-1}) + \beta_2^{2X,S}\, ExpRel^{2X,S,C}_{t-1} \\
&+ \beta_3^{2X,S}\, logit(LGDpit^{S,C}_{i,t-1}) + \sum_L \beta_4^{2X,S,L}\, logit(TR[L]^{S,C}_{i,t-1}) \\
&+ \mathbf{X_t}\boldsymbol{\beta_X^{2X,S}}\boldsymbol{\Omega\beta_\Omega^{2X,S}} + \varepsilon^{2X,S,C}_{i,t} \\
logit(LR33^{S,C}_{i,t}) =& \beta_0^{33,S} + \sum_K \beta_1^{33,S,K}\, logit(LR[K]^{S,C}_{i,t-1}) + \beta_2^{33,S}\, ExpRel^{33,S,C}_{t-1} \\
&+ \beta_3^{33,S}\, logit(LGDpit^{S,C}_{i,t-1}) + \sum_L \beta_4^{33,S,L}\, logit(TR[L]^{S,C}_{i,t-1}) \\
&+ \mathbf{X_t}\boldsymbol{\beta_X^{33,S}}\boldsymbol{\Omega\beta_\Omega^{33,S}} + \varepsilon^{33,S,C}_{i,t}
\end{aligned}
\tag{338}
$$

for $K \in \{12, 2X, 33\}$ and $L \in \{12, 13, 21, 23, 31, 32\}$. $\{LGD13, LGD23\}$ are the projected loss given default parameters and $\{LR12, LR2X, LR33\}$ the projected loss rates parameters by bank i for sector S in country C and t refer to quarters. Each modelled risk parameter depends on the lags of (potentially) all other risk parameters in the system and a set of macrofinancial variables $\boldsymbol{X_t}$, which are identical to the transition rate regressions in Appendix D.1.1. The selection of suitable macrofinancial variables and their optimal lags is again determined by a combination of lasso, BMA and expert judgment.

In the LGD equations, we also consider lifetime cure rates $CureRateLT$, which represent the component of LGD corresponding to the estimated cumulative proportion of S3 exposures that cure through repayment with zero loss during a workout period (see equation (50)). In LR equations, we include transition rates (TR) and point-in-time LGDs ($LGDpit$) (see equation (51)). Transition rates and point-in-time LGDs are natural choices for loss rates regressors, as LRs represent the expected lifetime loss expressed as a percentage of current exposure. As such, LRs should be influenced by the information contained in the transition rates matrix (i.e., the likelihood of going up or down between the impairment stages) and by the loss rates associated with default (S3) events. Note that lifetime cure rates, transition rates, and point-in-time LGDs are logit-transformed before entering the regression.

As with the transition rate model, we also incorporate the relative amount of S1 exposures in the given sector of each bank $NonDefExpS1Rel$ in the LGD13 and LR12 equations, the relative amount of S2 exposures in the given sector of each bank $NonDefExpS2Rel$ in the LGD23 and LR2X equations, and the relative amount of S3 exposures in the given sector of each bank $DefExpRel$ for the LR33 equation (see equation (31)). Furthermore, we again control for the vintage and scenario of the stress test in each system by a set of dummies in Ω to account for possible variations in different scenarios and stress test exercises.

Data

Similarly to the transition rates, the estimation of the *LGD* and *LR* equations is based on the data submitted by the banks in the EBA stress test exercises conducted in 2018 and 2021. As part of the EBA stress test methodology, banks are required to provide their projections of two LGDs {LGD13, LGD23} and three LRs {LR12, LR2X, LR33} for each scenario. Bank projections are annual in nature, so they need to be subsequently transformed into quarterly values for the purpose of the model, assuming the constancy of the values in the four quarters of each year.

In addition, in this case, the data for both the baseline and the adverse scenarios are pooled together for each sector. Summary statistics for LGDs and LRs are reported in Table 60.

The historical macroeconomic and financial data are again sourced from the SDW, while the macroeconomic and financial data corresponding to the projection periods of 2018 and 2021 stress tests are obtained from the macrofinancial scenarios used in those respective stress testing exercises. Information on exposures and point-in-time cure rates and LGDs is sourced from the EBA stress test templates. The summary statistics for both macrofinancial variables and the relative amount of exposures in the individual stages are identical to those of the transition rates model and can be reviewed in Table 54.

Results

Tables 61 - 65 present the estimation results for the LGD and LR models in the corporate (NFC), households - house purchase ($HHHP$), households - consumer credit ($HHCC$), financial (FIN), and sovereign (SOV) sectors, respectively.

Regarding LGD estimations, the autoregressive component is statistically significant and relatively high (above 0.7, but below 1) among sectors. However, the explicit dependencies between LGDs within the systems are not significant. The LGD parameters also show a negative relationship with point-in-time cure rates, which is intuitive since an increase in S3 exposures that cure through repayments should lead to a decrease in the corresponding LGDs.

Regarding macrofinancial variables, an increase in real GDP growth rates ($YERgr$), residential property prices ($IHXgr$), export prices of goods and services ($XTDgr$), and the equity index ($ESXgr$) causes a decrease in LGD. On the other hand, an increase in HICP inflation ($HICgr$), unemployment rate (URX), and interest rate spread (SPR) causes an increase in LGDs.

The impact of the relative amount of exposures in a particular stage on the respective LGDs is significant only for the sector SOV. The sign of the coefficients is positive for S1 exposures and negative for S2 exposures.

Moving on to the LR estimations, we observe a pattern similar to the LGD estimations. The autoregressive component remains statistically significant and relatively high (above 0.7, but below 1) in all sectors. However, there are statistically significant explicit dependencies among the LRs within the systems in several cases. Additionally, the LR parameters demonstrate dependencies on transition rates and LGDs, which is also intuitive as discussed earlier in this section. An increase in the transition rates governing migrations to lower stages (i.e. TR12, TR13, and TR23) or an increase in the point-in-time LGDs results in an increase in the corresponding LRs. Conversely, an increase in transition rates governing migrations to higher stages (i.e. TR21, TR31 and TR32) leads to a decrease in the corresponding LRs.

Regarding macrofinancial variables, an increase in real GDP growth rates ($YERgr$), residential property prices ($IHXgr$), prices of exports of goods and services ($XTDgr$), and equity index ($ESXgr$) results in a decrease in LR. On the contrary, an increase in HICP inflation ($HICgr$), unemployment rate (URX), and interest rate spread (SPR) leads to an increase in LRs.

The impact of the relative amount of exposures in a particular stage on the respective LRs is significant in multiple equations. The coefficients typically exhibit a negative sign for S2 exposures and a positive sign for S1 and S3 exposures.

	FIN					
	(1)	(2)	(3)	(4)	(5)	(6)
	TR12	TR13	TR21	TR23	TR31	TR32
$logit(TR12_{t-1})$	0.8778**					
	(0.000)					
$logit(TR13_{t-1})$		0.9162**				
		(0.000)				
$logit(TR21_{t-1})$			0.8720**			
			(0.000)			
$logit(TR23_{t-1})$			0.0431**	0.9172**		
			(0.000)	(0.000)		
$logit(TR31_{t-1})$					0.9959**	
					(0.000)	
$logit(TR32_{t-1})$						0.9947**
						(0.000)
$YERgr_{t-1}$		-2.3692**		-3.5818**	8.2511**	9.1910**
		(0.000)		(0.000)	(0.000)	(0.000)
$IHXgr_{t-1}$		-1.5141**				
		(0.000)				
$HICgr_{t-1}$	12.0717*	4.6684+	-21.5972**			
	(0.021)	(0.050)	(0.000)			
$ESXgr_{t-4}$		-0.5956**				
		(0.000)				
ΔURX_{t-2}	6.1616			5.5034**	-5.0058**	-5.0044**
	(0.129)			(0.009)	(0.006)	(0.005)
SPR_{t-1}	7.2012**	8.9651**	-5.5323**	3.4626**		
	(0.000)	(0.000)	(0.008)	(0.002)		
$ExpRel_{t-1}$	-0.6666**			-0.1654*		
	(0.000)			(0.010)		
$const.$	-0.3695**	-0.7417**	-0.0801	-0.4789**	-0.1107**	-0.1280**
	(0.002)	(0.000)	(0.311)	(0.000)	(0.000)	(0.000)
Obs	3219	3219	3219	3219	1384	1384
Banks	89	89	89	89	89	89
R^2	0.8582	0.9019	0.8244	0.8719	0.9943	0.9940

p-values in parentheses; Δ stands for differences
$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$

Table 58: Transition rates regressions for FIN: 2018 - 2021 stress test submissions

			SOV			
	(1)	(2)	(3)	(4)	(5)	(6)
	TR12	TR13	TR21	TR23	TR31	TR32
$logit(TR12_{t-1})$	0.9438**					
	(0.000)					
$logit(TR13_{t-1})$		0.8462**				
		(0.000)				
$logit(TR21_{t-1})$			0.9847**			
			(0.000)			
$logit(TR23_{t-1})$				0.9167**		
				(0.000)		
$logit(TR31_{t-1})$					0.9546**	
					(0.000)	
$logit(TR32_{t-1})$						0.9459**
						(0.000)
$YERgr_{t-1}$			9.3490**		21.9710**	18.4586**
			(0.000)		(0.000)	(0.000)
$MTRgr_{t-1}$	1.0686**		-2.0082**	1.1277**	-4.4296**	-4.1786**
	(0.004)		(0.000)	(0.006)	(0.000)	(0.001)
$IHXgr_{t-1}$				-2.4643**		
				(0.000)		
$HICgr_{t-1}$	25.8994**					
	(0.000)					
$XTDgr_{t-1}$		-3.9326**		-1.3926	14.6783**	14.7214**
		(0.000)		(0.331)	(0.000)	(0.000)
$ESXgr_{t-4}$				-0.3501**		
				(0.002)		
ΔURX_{t-2}			-13.9672**		-23.2588**	-26.5668**
			(0.000)		(0.000)	(0.000)
SPR_{t-1}	1.4088	8.6894**		3.9969**		
	(0.175)	(0.000)		(0.000)		
$ExpRel_{t-1}$			-0.3157*	-0.6479*	0.1013	1.4261+
			(0.026)	(0.000)	(0.868)	(0.062)
$const.$	-0.6053**	-1.5078**	-0.1454	-0.7012**	-0.5442**	-0.6127**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs	3184	3184	3184	3184	1470	1470
Banks	89	89	89	89	89	89
R^2	0.9157	0.8824	0.9613	0.8900	0.9369	0.9226

p-values in parentheses; Δ stands for differences

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 59: Transition rates regressions for SOV: 2018 - 2021 stress test submissions

Variables	Observations	Mean	Median	Standard deviation
LGD13 NFC	12268	0.2958	0.2860	0.1367
LGD13 HHHP	10268	0.1521	0.1258	0.1268
LGD13 HHCC	10760	0.3491	0.3242	0.2052
LGD13 FIN	4600	0.3457	0.3625	0.1662
LGD13 SOV	4582	0.3376	0.3938	0.1147
LGD23 NFC	11544	0.2763	0.2680	0.1413
LGD23 HHHP	9792	0.1488	0.1233	0.1218
LGD23 HHCC	10302	0.3421	0.3210	0.1954
LGD23 FIN	4118	0.3406	0.3544	0.1741
LGD23 SOV	4092	0.3276	0.3914	0.1404
LR12 NFC	11545	0.0323	0.0207	0.0413
LR12 HHHP	9886	0.0296	0.0151	0.0409
LR12 HHCC	10252	0.0643	0.0339	0.0867
LR12 FIN	4076	0.0236	0.0079	0.0521
LR12 SOV	4073	0.0241	0.0083	0.0425
LR2X NFC	11566	0.0376	0.0240	0.0482
LR2X HHHP	9794	0.0315	0.0180	0.0408
LR2X HHCC	10262	0.0634	0.0400	0.0769
LR2X FIN	4087	0.0278	0.0090	0.0613
LR2X SOV	4070	0.0240	0.0078	0.0408
LR33 NFC	11966	0.4353	0.4420	0.2137
LR33 HHHP	9474	0.2435	0.2233	0.1706
LR33 HHCC	10554	0.5108	0.5380	0.2359
LR33 FIN	4406	0.3537	0.3750	0.2193
LR33 SOV	4532	0.3321	0.3864	0.1694
CureRateLT NFC	5138	0.1134	0.0702	0.1367
CureRateLT HHHP	5113	0.0909	0.0396	0.1404
CureRateLT HHCC	4880	0.1276	0.0559	0.1926
CureRateLT FIN	1754	0.1713	0.0461	0.2380
CureRateLT SOV	1754	0.0974	0.0150	0.1830
LGDpit NFC	12268	0.2931	0.2805	0.1332
LGDpit HHHP	10296	0.1557	0.1280	0.1246
LGDpit HHCC	10816	0.3467	0.3287	0.1973
LGDpit FIN	4620	0.3434	0.3613	0.1595
LGDpit SOV	4602	0.3375	0.3943	0.1159

Table 60: Summary statistics: LGDs and LR regressions

	NFC				
	(1)	(2)	(3)	(4)	(5)
	LGD13	LGD23	LR12	LR2X	LR33
$logit(LGD13_{t-1})$	0.9615**				
	(0.000)				
$logit(LGD23_{t-1})$		0.9648**			
		(0.000)			
$logit(LR12_{t-1})$			0.9167**		
			(0.000)		
$logit(LR2X_{t-1})$			0.0625**	0.9358**	
			(0.000)	(0.000)	
$logit(LR33_{t-1})$			0.0237**	0.0059*	0.9713**
			(0.001)	(0.049)	(0.000)
$logit(TR12_{t-1})$			0.0257**	0.0123**	
			(0.000)	(0.000)	
$logit(TR23_{t-1})$				0.0210**	
				(0.000)	
$logit(TR32_{t-1})$				-0.0041**	
				(0.000)	
$logit(CureRateLT_{t-1})$	-0.0010*	-0.0032**			
	(0.013)	(0.000)			
$logit(LGDpit_{t-1})$				0.0148**	0.0126**
				(0.000)	(0.000)
$YERgr_{t-1}$	-0.6777**	-0.4728*	-3.4074**	-1.1062**	-0.4537*
	(0.000)	(0.013)	(0.000)	(0.000)	(0.026)
$IHXgr_{t-1}$	-0.1777*	-0.2410**			
	(0.033)	(0.006)			
$ESXgr_{t-1}$	-0.1018**	-0.1206**	-0.1776**	-0.2198**	-0.1077**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
ΔURX_{t-2}		1.2472**			
		(0.000)			
SPR_{t-1}	1.0745**	0.5259**			
	(0.000)	(0.002)			
$RelExp_{t-1}$	0.0725**	-0.0881**		-0.1795**	0.0743**
	(0.000)	(0.000)		(0.000)	(0.000)
$const.$	-0.1044**	-0.0335**	0.0186	-0.0766**	-0.0065
	(0.000)	(0.000)	(0.512)	(0.000)	(0.224)
Obs	4705	4705	4122	4122	4122
Banks	89	89	89	89	89
R^2	0.9729	0.9726	0.9200	0.9765	0.9739

p-values in parentheses; Δ stands for differences
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 61: LGDs and LR regressions for NFC: 2018 - 2021 stress test submissions

	HHHP				
	(1)	(2)	(3)	(4)	(5)
	LGD13	LGD23	LR12	LR2X	LR33
$logit(LGD13_{t-1})$	0.9931**				
	(0.000)				
$logit(LGD23_{t-1})$		0.9874**			
		(0.000)			
$logit(LR12_{t-1})$			0.9233**		
			(0.000)		
$logit(LR2X_{t-1})$			0.0333**	0.9491**	
			(0.000)	(0.000)	
$logit(LR33_{t-1})$			0.0149**		0.9629**
			(0.003)		(0.000)
$logit(TR12_{t-1})$			0.0158**	0.0152**	
			(0.000)	(0.000)	
$logit(TR21_{t-1})$				-0.0165**	
				(0.000)	
$logit(TR23_{t-1})$				0.0320**	
				(0.000)	
$logit(TR31_{t-1})$			-0.0075**	-0.0026**	
			(0.000)	(0.002)	
$logit(CureRateLT_{t-1})$	-0.0012**	-0.0012**			
	(0.000)	(0.000)			
$logit(LGDpit_{t-1})$					0.0135**
					(0.000)
$YERgr_{t-1}$	-0.6497**	-0.9753**		-1.0881**	-0.3202
	(0.000)	(0.000)		(0.000)	(0.139)
$IHXgr_{t-1}$		-0.1376*	-0.3523*	-0.2418+	-0.6066**
		(0.010)	(0.044)	(0.094)	(0.000)
$HICgr_{t-1}$	2.7773**	3.9676**	7.1189**	4.4239**	2.5550**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
$ESXgr_{t-1}$	-0.1629**	-0.1744**	-0.2826**	-0.2775**	-0.1422**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SPR_{t-1}			1.2008**		1.0689**
			(0.004)		(0.000)
$ExpRel_{t-1}$			0.0936**	-0.0763+	
			(0.002)	(0.065)	
$const.$	-0.0412**	-0.0514**	-0.2672**	-0.0948**	-0.0489**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs	4571	4571	3744	3744	3744
Banks	89	89	89	89	89
R^2	0.9879	0.9832	0.9616	0.9739	0.9790

p-values in parentheses; Δ stands for differences

$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$

Table 62: LGDs and LR model for $HHHP$ regressions: 2018 - 2021 stress test submissions

	HHCC				
	(1)	(2)	(3)	(4)	(5)
	LGD13	LGD23	LR12	LR2X	LR33
$logit(LGD13_{t-1})$	0.9889**				
	(0.000)				
$logit(LGD23_{t-1})$		0.9773**			
		(0.000)			
$logit(LR12_{t-1})$			0.9625**		
			(0.000)		
$logit(LR2X_{t-1})$			0.0225**	0.9944**	
			(0.000)	(0.000)	
$logit(LR33_{t-1})$			0.0215**	0.0120**	0.9857**
			(0.000)	(0.000)	(0.000)
$logit(TR12_{t-1})$				0.0205**	
				(0.000)	
$logit(TR23_{t-1})$			0.0197**		
			(0.000)		
$logit(TR32_{t-1})$			-0.0022**		
			(0.004)		
$logit(CureRateLT_{t-1})$	-0.0016**	-0.0015**			
	(0.000)	(0.000)			
$logit(LGDpit_{t-1})$				0.0079*	
				(0.015)	
$YERgr_{t-1}$	-0.7992**	-0.5315**	-1.1455**	-0.4133+	
	(0.000)	(0.006)	(0.000)	(0.067)	
$IHXgr_{t-1}$	-0.2282**	-0.4001**		-0.5045**	-0.8884**
	(0.000)	(0.000)		(0.000)	(0.000)
$HICgr_{t-1}$	1.0608*	2.4487**	6.6014**	6.0769**	1.8655**
	(0.032)	(0.000)	(0.000)	(0.000)	(0.008)
$ESXgr_{t-1}$	-0.1636**	-0.1178**	-0.2022**	-0.1793**	-0.1185**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ΔURX_{t-2}	4.5967**	3.8617**	1.5711**		
	(0.000)	(0.000)	(0.014)		
SPR_{t-1}		0.7390**			0.8966**
		(0.000)			(0.000)
$ExpRel_{t-1}$			0.0702**	-0.2407**	
			(0.000)	(0.000)	
$const.$	0.0053	-0.0157**	-0.0611**	0.0808**	-0.0061
	(0.110)	(0.001)	(0.007)	(0.000)	(0.172)
Obs	4314	4314	3968	3968	3968
Banks	89	89	89	89	89
R^2	0.9916	0.9822	0.9785	0.9804	0.9789

p-values in parentheses; Δ stands for differences

$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$

Table 63: LGDs and LR for $HHCC$ regressions: 2018 - 2021 stress test submissions

	FIN				
	(1)	(2)	(3)	(4)	(5)
	LGD13	LGD23	LR12	LR2X	LR33
$logit(LGD13_{t-1})$	0.7926**				
	(0.000)				
$logit(LGD23_{t-1})$		0.8462**			
		(0.000)			
$logit(LR12_{t-1})$			0.8847**		
			(0.000)		
$logit(LR2X_{t-1})$			0.0216*	0.9447**	
			(0.043)	(0.000)	
$logit(LR33_{t-1})$					0.7098**
					(0.000)
$logit(TR12_{t-1})$			0.0468**		
			(0.000)		
$logit(TR21_{t-1})$			-0.0334**		
			(0.000)		
$logit(TR23_{t-1})$				0.0301**	
				(0.001)	
$logit(TR32_{t-1})$				-0.0055+	-0.0423**
				(0.086)	(0.000)
$logit(CureRateLT_{t-1})$	-0.0067**				
	(0.000)				
$logit(LGDpit_{t-1})$					0.2456**
					(0.000)
$YERgr_{t-1}$		-0.4681		-3.3304**	
		(0.239)		(0.001)	
$ESXgr_{t-1}$	-0.0889**	-0.0910	-0.4618**	-0.3904**	-0.2778*
	(0.000)	(0.140)	(0.000)	(0.000)	(0.040)
ΔURX_{t-2}	1.4771	1.5657			
	(0.304)	(0.665)			
SPR_{t-1}	5.9176**		3.7516**		15.2530**
	(0.000)		(0.017)		(0.000)
$ExpRel_{t-1}$			0.5530**	-0.1470*	
			(0.000)	(0.038)	
$const.$	-0.3078	0.0867	-0.9892**	-0.0685	-0.5240**
	(0.000)	(0.000)	(0.000)	(0.113)	(0.000)
Obs	1586	1586	1236	1236	1236
Banks	89	89	89	89	89
R^2	0.9124	0.8987	0.9455	0.9597	0.9116

p-values in parentheses; Δ stands for differences

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 64: LGDs and LR for FIN regressions: 2018 - 2021 stress test submissions

	SOV				
	(1)	(2)	(3)	(4)	(5)
	LGD13	LGD23	LR12	LR2X	LR33
$logit(LGD13_{t-1})$	0.7374**				
	(0.000)				
$logit(LGD23_{t-1})$		0.7450**			
		(0.000)			
$logit(LR12_{t-1})$			0.9391**		
			(0.000)		
$logit(LR2X_{t-1})$				0.9519**	
				(0.000)	
$logit(LR33_{t-1})$					0.7966**
					(0.000)
$logit(TR12_{t-1})$			0.0253**		
			(0.000)		
$logit(TR23_{t-1})$			0.0451**	0.0380**	
			(0.000)	(0.000)	
$logit(TR32_{t-1})$					-0.0047
					(0.125)
$logit(CureRateLT_{t-1})$	-0.0058**	-0.0024*			
	(0.000)	(0.035)			
$logit(LGDpit_{t-1})$				0.0667**	0.0605**
				(0.002)	(0.008)
$YERgr_{t-1}$		-0.7436	-2.9937*		-1.8048
		(0.179)	(0.015)		(0.120)
$HICgr_{t-1}$				10.3433*	
				(0.021)	
$XTDgr_{t-1}$			-5.3179**	-8.1593**	
			(0.000)	(0.000)	
ΔURX_{t-2}	1.7935*	5.5560**		3.9826+	9.0420**
	(0.049)	(0.000)		(0.080)	(0.001)
SPR_{t-1}				2.1074*	
				(0.024)	
$ExpRel_{t-1}$	0.1918**	-0.1742*	-0.4757**		2.2807**
	(0.000)	(0.029)	(0.001)		(0.004)
const.	-0.3890**	-0.1669**	0.6352**	-0.0363	-0.0449
	(0.000)	(0.000)	(0.000)	(0.525)	(0.252)
Obs	1602	1602	1387	1387	1387
Banks	89	89	89	89	89
R^2	0.8765	0.8369	0.9349	0.9598	0.9070

p-values in parentheses; Δ stands for differences

$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$

Table 65: LGDs and LR for *SOV* regressions: 2018 - 2021 stress test submissions

D.2 Models for credit risk capital charges

This section delves into the modelling of credit risk weights for exposures measured using both internal ratings-based (IRB) and standardised (STA) approaches. In the industry, there is a wide range of practises regarding the estimation of parameters for credit risk weights. However, most banks use internal granular datasets, which include information at the obligor level, including borrower characteristics, individual loan sizes, breakdown of exposures between secured and unsecured portions, collateral amounts, potential recoveries, paid and unpaid fees, expected discount rates, and more. In our case, however, the modelling decisions are predominantly driven by limited data availability, necessitating a heavy reliance on conditional projections of regulatory risk parameters from the previous EU-wide stress test exercises, as provided by the participating banks.

D.2.1 Regulatory PD (*PDreg*)

The regulatory parameters for PD and LGD are stipulated by the CRR and are used to calculate the risk weights, as demonstrated in equation (125). Unlike PD and LGD for credit risk impairments, which capture prevailing trends in the business cycle, regulatory parameters encompass a conservative long-term average concept that also accounts for potential "downturn" conditions. These parameters are designed to be less responsive to economic fluctuations, thus helping to mitigate unwarranted cyclicality in capital requirements.[149]

Methodology

In our approach, we operate under the simple assumption that regulatory PDs would move in tandem with projected point-in-time PDs $PDpit$. Consequently, we employ a standard linear model where we regress the changes in $PDreg$ against its lagged values and the changes in $PDpit$. The model incorporates additional variables to control for factors such as bank $\beta_{0,i}$, country β_0^C, year $\beta_{0,t}$, scenario, and vintage of the stress test in $\mathbf{\Omega}$. The regressions are estimated separately for five exposure sectors $S \in \{HHCC, HHHP, NFC, FIN, SOV\}$.

$$\Delta PDreg_{i,t}^{S,C} = \beta_{0,i}^{S} + \beta_0^{S,C} + \beta_{0,t}^{S} + \beta_1^{S,C}\Delta PDreg_{i,t-1}^{S,C} + \beta_2^{S,C}\Delta PDpit_t^{S,C} + \mathbf{\Omega}\boldsymbol{\beta}_{\mathbf{\Omega}}^{\boldsymbol{S}} + \varepsilon_{i,t}^{S,C}$$

where ε is the error term and $\mathbf{\Omega}$ consists of:

- Vintage of the stress test data: 2 binary variables, taking value of 1 for the EBA/SSM stress test exercises in 2021 (and 0 otherwise) and taking value of 1 for the EBA/SSM stress test exercises in 2018 (and zero otherwise);
- Scenario type: 1 binary variable, taking value of 1 for adverse scenarios and and 0 for baseline scenarios

.

Data

We use annual data provided by banks through the EBA stress test exercises in 2016, 2018 and 2021. The values for $PDreg$ are directly extracted from the bank submissions, while the values for $PDpit$ are calculated as described in equation (32) (i.e., essentially a weighted average of

[149] See EBA Stress Test Methodological Note, par 85, (EBA [2021b]).

$TR13$ and $TR23$, which are also sourced from the EBA stress test templates; for summary statistics, see Appendix D.1.1). The data for all three vintages (2016, 2018 and 2021) and both scenarios (baseline and adverse) are pooled together for each sector. The summary statistics for $PDreg$ and $PDpit$ can be found in Table 66.

Variables	Observations	Mean	Median	Standard Deviation
$PDreg\ HHCC$	2144	0.0251	0.0194	0.0243
$PDreg\ HHHP$	2136	0.0155	0.0108	0.0172
$PDreg\ NFC$	2680	0.0146	0.0099	0.0187
$PDreg\ FIN$	4564	0.0039	0.0016	0.0119
$PDreg\ SOV$	2172	0.0016	0.0003	0.0131
$PDpit\ HHCC$	2142	0.0210	0.0162	0.0211
$PDpit\ HHHP$	2110	0.0131	0.0094	0.0158
$PDpit\ NFC$	2680	0.0128	0.0095	0.0126
$PDpit\ FIN$	4546	0.0035	0.0013	0.0089
$PDpit\ SOV$	2172	0.0011	0.0002	0.0024
$\Delta PDpit$ (all sectors)	10770	0.0006	0.0000	0.0078
$\Delta PDreg$ (all sectors)	10806	0.0002	0.0000	0.0027

Table 66: Summary statistics: point-in-time PD and regulatory PD

Results

Estimation results are presented in Table 67. The coefficient β_1, which can be interpreted as inertia, exceeds β_2, denoting the impact originating from observed variations in risk that are proxied by the increase or decrease in $PDpit$. Since $PDreg$ is expected to remain relatively stable throughout the projected horizons. A point-in-time default probability shift from 0 to 1 in the $HHCC$ sector would lead to an increase in the corresponding regulatory probability of approximately $\beta_2(1+\beta_1) = 0.22 \times (1+0.29) = 28\%$. In our simulations, changes in $PDreg$ seldom surpass about 1% within projection spans of 2-3 years, which is generally aligned with available data.

	(1) HHCC	(2) HHHP	(3) NFC	(4) FIN	(5) SOV
$\Delta PDreg_{t-1}$	0.2921**	0.1689**	0.2689**	0.2719**	0.0374**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta PDpit_t$	0.2194**	0.1130**	0.0478**	0.0208**	0.0092
	(0.000)	(0.000)	(0.000)	(0.000)	(0.486)
Obs	1068	1056	1340	2,268	1,485
Banks	49	53	58	50	36
$R^2(adj.)$	0.4959	0.3893	0.2583	0.4924	0.4350

p-values in parentheses; Δ stands for differences

$^{+}\ p<0.10$, $^{*}\ p<0.05$, $^{**}\ p<0.01$

Table 67: Regulatory PD regressions: 2018 - 2021 stress test templates

D.2.2 Regulatory LGD for non-defaulted exposures (*LGDreg_ND*)

Regulatory parameters for the endogenous calculation of risk weights are estimated independently for the two categories of exposures: non-defaulted and defaulted. The coefficients derived for *LGDreg_ND*, as described below, are applied in equation (129).

Methodology

We employ a fractional logistic regression model[150] to ensure that the dependent variable remains within the interval $[0,1]$. This choice of specifications enables us to account for varying elasticities at different levels of *LGDreg*. The coefficients are estimated within a panel setting, individually for each of five sectors $S \in \{HHCC, HHHP, NFC, FIN, SOV\}$, using the bank sector country portfolios as the cross-sectional dimension (retaining the country dimension also for the FIN and SOV sectors).

The estimated model takes the following form:

$$\begin{aligned} logit(LGDreg\_ND^{AIRB,S,C}_{i,t}) = & \beta^S_0 + \beta^{S,C}_0 + \beta^S_1 LGDreg\_ND^{AIRB,S,C}_{i,t-1} + \beta^S_2 LGDpit^{S,C}_{i,t-1} \\ & + \beta^S_3 YERgr^C_{t-1} + \beta^S_4 IHXgr^C_{t-1} + \beta^S_5 URX^C_{t-1} \\ & + \beta^S_6 LTN^C_{t-1} + \beta^S_7 (LTN^2)^C_{t-1} + \boldsymbol{\Omega\beta^S_\Omega} + \varepsilon^{S,C}_{i,t} \end{aligned}$$

Data

We utilise template data provided by banks for EU-wide stress test exercises conducted in 2016, 2018 and 2021. The value of *LGDpit* is calculated as the weighted average of *LGD*_13 and *LGD*_23 (see equation (51)) from the CSV_CR_SCEN template. On the other hand, the parameters *LGDreg* are extracted from the CSV_CR_REA template. To accommodate differences in reporting standards between template submissions in different stress test years, including the adoption of IFRS 9, we make necessary adjustments. For the 2021 stress test data, we specifically adjusted all variables related to the corporate sector by excluding exposures covered by public guarantees, which we model separately.

Each of the three EU-wide stress test vintages has four time points (historical starting point and annual projections for three years) for both the baseline and adverse scenario. Thus, the framework allows us to capture the considerable variability of *LGDreg_ND*, *LGDreg_D*, and *ELBE* under different economic conditions. The summary statistics for the relevant risk parameters are reported in Table 68.

Results

In all sectors, there exists a positive relationship between *LGDreg_ND* and the levels of unemployment and the yields of government bonds. On the contrary, there is a negative relationship with the growth rates of GDP and house prices. The autoregressive coefficient consistently maintains a positive and highly statistically significant value in nearly all the specifications tested. The only exception is the regression for the corporate sector, where it keeps the expected positive sign, but lacks statistical significance. Detailed estimates of sector-specific regression parameters can be found in Table 69.

[150] Using a fractional probit model yields very similar results.

Variables	Observations	Mean	Median	Standard Deviation
LGDreg_ND HHCC	2280	0.3455	0.3493	0.1844
LGDreg_ND HHHP	2514	0.1478	0.1381	0.0975
LGDreg_ND NFC	2626	0.2240	0.2625	0.1706
LGDreg_ND FIN	3696	0.2100	0.2065	0.1702
LGDreg_ND SOV	2488	0.1723	0.1000	0.1827
LGDpit HHCC	2142	0.3378	0.3298	0.1900
LGDpit HHHP	2110	0.1349	0.1122	0.1044
LGDpit NFC	2608	0.2768	0.2700	0.1178
LGDpit FIN	3662	0.2973	0.2893	0.1662
LGDpit SOV	2300	0.3195	0.4000	0.1450
$\Delta LGDreg\_ND$ (all sectors)	10194	0.0019	0.0000	0.0226
$\Delta LGDpit$ (all sectors)	9612	0.0155	0.0000	0.0821

Table 68: Summary statistics: Regulatory LGD and ELBE

	(1) HHCC	(2) HHHP	(3) NFC	(4) FIN	(5) SOV
$LGDreg\_ND_{t-1}$	0.4312^{+}	0.8040**		0.3001*	0.1327
	(0.081)	(0.006)		(0.045)	(0.103)
$LGDpit_{t-1}$	0.1141**	0.0941	0.1905**	0.0829	0.0972*
	(0.000)	(0.296)	(0.000)	(0.141)	(0.036)
$YERgr_{t-1}$	-0.0759^{+}		-0.1147**	-0.0718**	
	(0.061)		(0.004)	(0.000)	
$IHXgr_{t-1}$		-0.1303**			
		(0.000)			
URX_{t-1}		0.8007**	0.9813**		1.2225**
		(0.000)	(0.000)		(0.000)
LTN_{t-1}					-5.7912*
					(0.028)
LTN^2_{t-1}					154.0511**
					(0.002)
$const.$	-0.8608**	-1.8625**	-0.9637**	-1.1829**	-2.0799**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bnk-Ctr-Sec-Scen Control	YES	YES	YES	YES	YES
Obs	1590	1568	1844	1688	304
Pseudo-R^2	0.0967	0.0456	0.0448	0.0834	0.2120

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 69: Regulatory loss given default for non-defaulted exposures: 2018 - 2021 stress test templates

D.2.3 Regulatory LGD for defaulted exposures (*LGDreg_D*) and Expected Loss Best Estimate (*ELBE*)

Methodology

The coefficients estimated for *LGDreg_D* and *ELBE* are used in equations (136) and (138), respectively. The regression specifications for *LGDreg_D* and *ELBE* - regulatory parameters governing the computation of risk weights for defaulted exposures - follow a slightly distinct yet interrelated approach compared to that for non-defaulted exposures.

First, both *LGDreg_D* and *ELBE* are jointly estimated within a seemingly unrelated OLS regression (SUR) framework. This approach can accommodate contemporaneous correlations of error terms, as we anticipate that both parameters will be similarly influenced by macroeconomic conditions.

Then, in the equation for *LGDreg_D*, we incorporate *LGDreg_ND* to acknowledge the expectation that the risk weights for bank exposures, whether in default or not, would exhibit coherent movements. On the contrary, *ELBE* is regressed directly on $LGDpit$.

The equations are estimated separately for the five distinct sectors $S \in \{HHCC, HHHP, NFC, FIN, SOV\}$ is considered separately and we transform the main variable of interest in each equation with the logit function.

$$\begin{aligned}
logit(LGDreg_D_{i,t}^{AIRB,S,C}) = \beta_0^{LGD,S} + \beta_0^{LGD,S,C} \beta_1^{LGD,S} logit(LGDreg_D_{i,t-1}^{AIRB,S,C}) \\
+ \beta_2^{LGD,S} LGDreg_ND_{i,t-1}^{AIRB,S,C} \\
+ \beta_3^{LGD,S} YERgr_{t-1}^{C} + \beta_4^{LGD,S} IHXgr_{t-1}^{C} \\
+ \beta_5^{LGD,S} URX_{t-1}^{C} + \beta_6^{LGD,S} SPR_{t-1}^{C} \\
+ \boldsymbol{\Omega\beta_{\Omega}^{S,LGD}} + \varepsilon_{i,t}^{LGD,S,C}
\end{aligned}$$

$$\begin{aligned}
logit(ELBE_{i,t}^{AIRB,S,C}) = \beta_0^{ELBE,S} + \beta_0^{ELBE,S,C} + \beta_1^{S} logit(ELBE_{i,t-1}^{AIRB,S,C}) \\
+ \beta_2^{ELBE,S} LGDpit_{i,t-1}^{S,C} \\
+ \beta_3^{ELBE,S} YERgr_{t-1}^{C} + \beta_4^{ELBE,S} IHXgr_{t-1}^{C} \\
+ \beta_5^{ELBE,S} URX_{t-1}^{C} + \beta_6^{ELBE,S} \Delta URX_{t-1}^{C} + \beta_7^{ELBE,S} SPR_{t-1}^{C} \\
+ \boldsymbol{\Omega\beta_{\Omega}^{S,ELBE}} + \varepsilon_{i,t}^{ELBE,S,C}
\end{aligned}$$

Data

The data collection process for *LGDreg_D* follows the same procedure as outlined for *LGDreg_ND* (see Appendix D.2.2 above). The parameters for *LGDreg* and *ELBE* are extracted from the CSV_CR_REA template. The summary statistics for the relevant risk parameters are reported in Table 68 and Table 70 jointly.

Results

The estimated sector-specific regression parameters for $LGDreg_D$ and *ELBE* are presented in Table 71 and Table 72, respectively. The notably high R^2 values can be attributed to the incorporation of the autoregressive term.

Variables	Observations	Mean	Median	Standard Deviation
LGDreg_D HHCC	2278	0.4860	0.5012	0.2450
LGDreg_D HHHP	2512	0.2187	0.1972	0.1742
LGDreg_D NFC	2578	0.2850	0.3038	0.2395
LGDreg_D FIN	3238	0.2401	0.2143	0.2379
LGDreg_D SOV	2170	0.1670	0.0708	0.2006
ELBE HHCC	2240	0.4674	0.4852	0.2459
ELBE HHHP	2480	0.1942	0.1673	0.1653
ELBE NFC	2564	0.2719	0.2901	0.2350
ELBE FIN	2110	0.1891	0.0842	0.2334
ELBE SOV	1401	0.1627	0.0016	0.2149

Table 70: Summary statistics: Regulatory LGD for defaulted exposures and ELBE

In general, adverse economic conditions such as negative GDP growth, a decrease in house prices, an increase in unemployment, or a steepening of the yield curve are associated with an increase in *LGDreg*. In most cases, the signs of the estimated coefficients are as anticipated and exhibit high statistical significance. A notable exception is the counterintuitive coefficient for house prices that positively affect *ELBE* in the *HHCC* sector. This anomaly could be attributed to the notably strong positive correlation (0.7155) between GDP and house prices in the estimation sample data.

	(1) HHCC	(2) HHHP	(3) NFC	(4) FIN	(5) SOV
$logit(LGDreg\_D_{t-1})$	0.1393**	0.1477**	0.0455**	0.2467**	0.5568**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$LGDreg\_ND_{t-1}$	2.2395**	1.8839**	3.5760**	0.7838	6.0467**
	(0.000)	(0.000)	(0.000)	(0.284)	(0.000)
$YERgr_{t-1}$	-0.9632*	-0.1408			-4.3421*
	(0.039)	(0.757)			(0.019)
$IHXgr_{t-1}$	-0.4083*	-0.2185	-0.3169*		
	(0.024)	(0.293)	(0.046)		
URX_{t-1}					5.6019*
					(0.032)
SPR_{t-1}			11.8986+	5.6355	27.5837**
			(0.053)	(0.613)	(0.005)
$const.$	-0.6239**	-0.7116**	-1.9396**	-1.6514**	-1.9003**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bnk-Ctr-Sec-Scen Control	YES	YES	YES	YES	YES
Obs	1680	1554	1892	1492	1019
R^2	0.9965	0.9756	0.9987	0.9976	0.9918
RMSE	0.1560	0.1658	0.1453	0.2019	0.3703

p-values in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 71: Regulatory loss given default for defaulted exposures regressions: 2018 - 2021 stress test templates

	(1) HHCC	(2) HHHP	(3) NFC	(4) FIN	(5) SOV
$logit(ELBE_{t-1})$	0.0198^{+}	0.0997**	0.0322**	0.0847**	0.7156**
	(0.079)	(0.000)	(0.000)	(0.000)	(0.000)
$LGDpit_{t-1}$		0.3597	0.4525**	0.4906*	2.1165**
		(0.247)	(0.000)	(0.025)	(0.000)
$YERgr_{t-1}$	-1.7210**				-4.8713
	(0.000)				(0.162)
$IHXgr_{t-1}$	0.8130**	-0.2052	-0.3944**		
	(0.001)	(0.461)	(0.002)		
URX_{t-1}				0.6637	
				(0.604)	
ΔURX_{t-1}		1.6297^{+}			2.0463
		(0.083)			(0.659)
$const.$	-0.3258	-0.7152**	-1.6026**	-2.1208**	-0.6079**
	(0.121)	(0.000)	(0.000)	(0.000)	(0.000)
Bnk-Ctr-Sec-Scen Control	YES	YES	YES	YES	YES
Obs	1680	1554	1892	1492	1019
R^2	0.9919	0.9705	0.9991	0.9952	0.9729
RMSE	0.2460	0.2221	0.1170	0.2849	0.7043

p-values in parentheses; Δ stands for differences

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 72: Expected loss best estimate (ELBE) regressions: 2018 - 2021 stress test templates

D.2.4 Wedge in risk weight calculation (*RWWedge*)

The risk weight wedge within the model serves the purpose of mitigating potential discrepancies resulting from aggregation of individually risk-weighted exposures (see Section 4.1.7.2). This correction term for the effective risk weight is derived by regressing the difference between the implied effective risk weight using the IRB formula with the aggregated value of $PDreg$ and the actual portfolio risk weight projected by the banks in their stress test submissions. This regression uses the curvature of the risk weight function $F'(PDreg)$ as an explanatory variable and determines a constant add-on per sector, denoted as $RWAddon^{S,C}$.

Methodology

To estimate the coefficient $\beta_1^{S,C}$ in equation (132), we employ a weighted least squares regression for each combination sector-country. The natural logarithm of the non-defaulted exposures in the corresponding portfolio subject to IRB treatment $NonDefExp\_REA_{i,t}^{S,C}$ serves as analytic weights, being inversely proportional to the variance of the observations. The constant term is omitted from the regression.

$$RWWedge_{i,t}^{S,C} = \beta_1^{S,C} F'(PDreg_{i,t}^{S,C}) + \varepsilon_{i,t}^{S,C}$$

To further reduce the discrepancy between the estimated and reported risk weights at the beginning of the simulations, we calculate a constant additive parameter $RWAddon$. This add-on is calculated after the estimation of β_1 and for the starting time point $t = 0$ of the last available EU-wide stress test.

$$RWAddon_i^{S,C} = \beta_1^{S,C} F'(PDreg_{i,0}^{S,C}) - RWWedge_{i,0}^{S,C} \tag{339}$$

Data

The $RWWedge$ is estimated using data from EU-wide stress test templates in 2018 and 2021. In instances when the wedge seems to be positive, it has been adjusted to zero. The summary statistics are reported in Table 73.

Variables	Observations	Mean	Median	Standard Deviation
$RWWedge$	7021	-0.0441	-0.0374	0.0377
$F'(PDreg)$	7021	9.7639	5.7029	13.2517

Table 73: Summary statistics: risk weight wedge

D.2.5 Risk weights for exposures under the Standardised Approach (STA)

Standardised risk weights are estimated for two sectors: FIN and NFC. Within the sector NFC we further split exposures into two subtypes: small and medium enterprises SME and other non-financial corporate entities $NSME$ (see equation (113)).

Methodology

The standardised risk weights for the two subsegments of sector NFC entering equation (113) are estimated using a fractional probit model for transformed risk weights $\widehat{CRRW\_ND}^{B,STA,NFC}$ defined as in equation (114). The transformed risk weight equations are estimated separately for the subsectors SME and $NSME$:

$$\begin{aligned}\widehat{CRRW\_ND}_{i,t}^{B,STA,NFC,C} = probit\Big(&\beta_0^B + \beta_1^B \widehat{CRRW\_ND}_{i,t-1}^{B,STA,NFC,C} \\ &+ \beta_2^B YERgr_{t-1}^C + \beta_3^B IHXgr_{t-1}^C \\ &+ \beta_4^B SPR_{t-1}^C + \beta_5^B \Delta STN_{t-1}^C \\ &+ \beta_6^B PDpit_{i,t}^{NFC,C} + \beta_7^B log(TA_{i,t}) \\ &+ \beta_8^B f\widehat{CRRW\_ND}_{i,0}^{B,STA,NFC,C} + \varepsilon_{i,t}^{B,STA,NFC,C}\Big)\end{aligned} \tag{340}$$

The term $f\widehat{CRRW\_ND}_{i,0}^{B,STA,NFC,C}$ accounts for the starting point conditions. It is derived after the estimation of equation (340) with β_1^B and β_9^B set to zero and estimated separately in cross-sectional regressions for years 2015, 2017 and 2020. These estimates are then used to build predicted values which are inserted into the final regressions so that the predictions built on the 2015 data are used co-jointly with the observations based on 2016 EBA/SSM stress test data, and the following predictions with 2018 and 2021 EBA/SSM stress test data, respectively.

The estimation of standardised risk weights for the FIN sector is based on logit transformed risk weights $\widehat{CRRW\_ND}^{STA,FIN}$ (see equation (117)) with OLS estimator. To control for time trends, dummies are included for each year, scenario, and stress test vintage. The equation takes the following form:

$$\begin{aligned}logit(\widehat{CRRW\_ND}_{i,t}^{STA,FIN}) = \beta_0 &+ \beta_1 logit(\widehat{CRRW\_ND}_{i,t-1}^{STA,FIN}) \\ &+ \beta_2 YERgr_{t-1}^C + \beta_3 IHXgr_{t-1}^C \\ &+ \beta_4 SPR_{t-1}^C + \beta \Delta STN_{t-1}^C \\ &+ \beta_6 \Delta PDpit_{i,t}^{FIN} + \beta_7 ProvCovNonDefR_{i,t}^{FIN} \\ &+ \beta_8 log(TA_{i,t}) \\ &+ \boldsymbol{\Omega\beta}_\Omega + \varepsilon_{i,t}\end{aligned}$$

Data

The estimation employs annual data collected from EU-wide EBA / SSM stress test templates from 2016, 2018 and 2021 using the same approach as for $LGDreg\_ND$ (see Appendix D.2.2). Descriptive statistics can be found in Table 74 where standardised risk weights are expressed as before multiplication by 12.5.

Results

The estimates of sector-specific regression parameters for $CRRW\_ND^{STA}$ are presented in Table 75. Overall, standardised risk weights are expected to increase if GDP growth slows down, if house prices decrease, if probabilities of default rise, if the coverage of exposures with loan-loss

Variables	Observations	Mean	Median	Standard Deviation
$CRRW\_ND\ NFC\ SME$	2633	0.0709	0.0711	0.0110
$CRRW\_ND\ NFC\ NSME$	3614	0.0756	0.0790	0.0215
$CRRW\_ND\ FIN$	6243	0.0255	0.0192	0.0202

Table 74: Summary statistics: standardised risk weights

provisions is thin, or if short-term interest rates go up. The total assets of the bank TA have a negative coefficient sign.

	(1) (frac. probit) NFC SME	(2) (frac. probit) NFC NSME	(3) (OLS) FIN
$\widehat{CRRW\_ND}$	2.6455**	2.9253**	
	(0.000)	(0.000)	
$logit(\widehat{CRRW\_ND})$			7.3454**
			(0.000)
$log(TA_t)$	0.0036**	-0.0054**	-0.0129
	(0.001)	(0.000)	(0.214)
$ProvRatio_t$			-2.8242**
			(0.007)
$PDpit_t$		0.2180+	
		(0.059)	
$\Delta PDpit_t$			6.6818**
			(0.000)
$YERgr_{t-1}$	-0.0484	-0.3062+	
	(0.748)	(0.099)	
$IHXgr_{t-1}$	-0.0668	-0.0389	-0.7750
	(0.218)	(0.530)	(0.137)
SPR_{t-1}	-0.4442*		5.0856**
	(0.022)		(0.006)
ΔSTN_{t-1}		3.2356+	
		(0.051)	
$f\widehat{CRRW\_ND}_0$	0.1178**	-0.1828**	
	(0.009)	(0.000)	
$const.$	-1.3730**	-1.3843**	-3.1200**
	(0.000)	(0.000)	(0.000)
Year-Scen-ST Control	NO	NO	YES
Obs	1950	2631	2392
$R^2(adj.)$	0.0284	0.0576	0.6993
RMSE			0.7633

p-values in parentheses; Δ stands for differences

$^{+}\ p < 0.10$, $^{*}\ p < 0.05$, $^{**}\ p < 0.01$

Table 75: Standardised risk weights regressions: 2016 – 2018 stress test templates

D.3 Net fee and commission income

Methodology

The empirical specification of net fee and commission income (NFCI) employs NFCI divided by the overall size of the bank's assets. The use of NFC to asset ratio accounts for the large heterogeneity across banks in non-interest income size, which to a degree relates to bank size. The methodology follows closely Kok et al. [2019].

$$\frac{NFCI_{i,t}}{TA_{i,t}} = \beta_{0,1} + \beta_1 \frac{NFCI_{i,t-1}}{TA_{i,t-1}} + \beta_2 \Delta YERgr_{i,t}^{C_i} + \beta_3 \Delta LTN_{i,t}^{C_i} + \beta_4 \Delta STN_{i,t}^{C_i} + \beta_5 ESXgr_{i,t}^{C_i} + \beta_6 \frac{NII_{i,t-1}}{TA_{i,t-1}} + \varepsilon_{i,t}$$

NFCI is related to changes in the market environment, especially the prices of equity $ESXgr$ and fixed income assets LTN. Additionally, the NFCI to asset ratio is regressed on its autoregressive component, real GDP growth $YERgr$, the change in short-term rates STN and the unemployment rate URX. For macroeconomic variables, the model takes the domestic country C_i of the bank i approximating the macroeconomic conditions underlying most of the customer activity of banks. The specification additionally includes banks' net interest income over total assets NII/TA that captures potential substitution effects present in a low interest rate environment from NII towards a more fee- and commission-based business model.

The model is estimated using fixed bank effects and applying the Arellano-Bond dynamic panel estimator (Arellano and Bond [1991]).

Data

The regression employs annual data on banks from Bloomberg and SNL, in order to ensure that time series cover a long time span. The macroeconomic variables are sourced from SDW. The unbalanced sample covers 59 large euro area banks and their income flows over 17 years starting in 2003. The summary statistic for the variables included in the estimation can be found in Table 76.

Variables	Observations	Mean	Median	Standard deviation
$NFCI/TA$	713	0.0060	0.0054	0.0055
$YERgr$	713	0.0065	0.0135	0.0321
$ESXgr$	713	-0.0001	0.0632	0.2415
ΔSTN	713	-0.0019	-0.0009	0.0099
ΔLTN	713	-0.0028	-0.0026	0.0209
URX	713	0.0975	0.0820	0.0581
NII/TA	713	0.0149	0.0133	0.0079

Table 76: Summary statistics: NFCI regression

Figure 49 illustrates the individual ratios $NFCI/TA$ and NII/TA in the median, mean, and interquartile range for individual banks in the historical sample, highlighting the dynamics and its importance over time.

Figure 49: NFCI and NII over total assets across banks

Results

The estimation results are summarised in Table 77. The autoregressive coefficient is positive, relatively high (approximately 80%) and statistically significant. The NFCI ratio is positively related to GDP $YERgr$, stock market growth $ESXgr$ and increases in short-term rates ΔSTN. The interest income to asset ratio enters the regression with a negative sign, validating the hypothesis that banks substitute between (low) NII toward (higher) net fee- and commission income.

	(1) NFCI/TA
$NFCI_{t-1}/TA_{t-1}$	0.794^{***}
	(0.000)
$YERgr_t$	0.0038^{**}
	(0.024)
$ESXgr_t$	0.0005^{**}
	(0.014)
ΔSTN_t	0.0117^{**}
	(0.022)
ΔLTN_t	0.0021
	(0.343)
URX_t	-0.0013
	(0.369)
NII_{t-1}/TA_{t-1}	-0.0469^{***}
	(0.008)
Obs	713
Banks	59
R^2	0.949

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 77: NFCI regression: 2003 - 2020

D.4 Client revenues

Methodology

Bank client revenues (see Section 4.4.1) to the total asset ratios are assumed to depend on the conditions in the stock market and follow the following simplified dynamics:

$$\begin{aligned}\frac{ClientRev_{i,t}}{TA_{i,t}} &= \beta_1 \frac{ClientRev_{i,t-1}}{TA_{i,t-1}} + \beta_2 \Delta ESXgr^{C_i}_{t-1} \\ &+ \beta_3 \Delta (BLR^{C_i}_t - STN^{EA}_t)) + \varepsilon_{i,t}\end{aligned}$$

The equation is estimated using a generalised least squares (GLS) estimator with a panel-specific AR1 autocorrelation structure.

Data

Data on bank client revenues from 2013Q1 until 2019Q4 are sourced from dedicated bank submissions during the EU-wide stress test in 2018. In the latter context, banks were requested to submit their historical client revenue incomes on a quarterly frequency over the last 4 years. The total asset figures are sourced from public data sources (Bloomberg), while the information on macrofinancial variables such as stock market growth and bank lending rate spread is sourced from balance sheet items (BSI) statistics available on SDW. The sample includes 31 euro area banks.

Variables	Observations	Mean	Median	Standard deviation
$ClientRev/TA$	406	0.0002	0.0002	0.0002
$ESXgr$	406	52.3779	32.2778	64.1340
$BLR-STN$	406	-0.0006	-0.0006	0.0009

Table 78: Summary statistics: client revenue regression

Results

The estimated coefficients of the bank client revenue equations are provided in Table 79. An autoregressive term with a coefficient of more than 0.9 indicates a high inertia for bank client revenues over total assets. The growth of the stock market ($ESXgr$) in the domestic country C of a bank and the bank lending spreads have a significant and positive impact on the revenues of the banks' clients.

D.5 Operating expenses

Methodology

The annual growth of bank i' operating expenses (see Section 4.4.2) is modelled along with the specification:

$$\begin{aligned}\Delta_4 log(OpExpense_{i,t}) &= \beta_{0,i} + \beta_1 \Delta_4 log(OpExpense_{i,t-1}) + \beta_2 \Delta_4 log(TA_{i,t-1}) \\ &+ \beta_3 \Delta_4 log(YER^{C_i}_{t-1} \times HIC^{C_i}_{t-1}) + \beta_4 RelCostEfficiency_{i,t-1} + \varepsilon_{i,t}\end{aligned}$$

	(1)
	ClientRev
$ClientRev/TA_{t-1}$	0.923^{**}
	(0.000)
$ESXgr_{t-1}$	0.0000^{**}
	(0.001)
$BLR_{t-1} - STN_{t-1}$	0.0041
	(0.274)
Banks	31
Obs	406
R2	0.899

p-values in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 79: Client revenue regression: 2013 Q1 –2019 Q4

It depends on its past values (autoregressive term), total asset growth TA, nominal GDP growth $YER \times HIC$ in the domestic country C_i of bank i and bank cost efficiency compared to its peers $RelCostEfficiency$ which is defined as:

$$RelCostEfficiency_{i,t} = \frac{OpExpense_{i,t}}{TA_{i,t}} - \frac{\sum_i OpExpense_{i,t}}{\sum_i TA_{i,t}}$$

By not imposing additional restrictions on regression coefficients, the specification allows for a degree of economies-of-scale model rather than a constant cost efficiency per asset unit. Regression is estimated using bank fixed effects $\beta_{0,i}$ and applying the Arellano-Bond dynamic panel estimator (Arellano and Bond [1991]).

Data

The underlying data for the operating expense model are sourced from quarterly supervisory information, precisely the FINREP templates F01.01 and F02.00. The macroeconomic time series are sourced from the SDW. The estimation sample covers 88 banks and quarterly observations between 2016Q1 and 2020Q4 for which the summary statistics is provided in Table 80.

Variables	Observations	Mean	Median	Standard deviation
$\Delta_4 log(OpExpense)$	1,407	-0.0361	0.0020	0.1929
$\Delta_4 log(TA)$	1,407	0.0172	0.0208	0.0845
$\Delta_4 log(YER \times HIC)$	1,407	0.0177	0.0314	0.0492
$RelCostEfficiency$	1407	0.0004	0.0003	0.0018

Table 80: Summary statistics: operating expenses regression

Results

The results of the estimation are summarised in Table 81. Expectantly, total asset growth leads to higher operating expenses. There is also a substantial degree of inertia in operating expenses with the autoregressive coefficient estimated at 0.56. Banks's operating costs evolve along with the business cycle, which can be at least partially attributed to procyclical salary adjustments. The error correction term that captures the difference between bank *i* cost efficiency and market average cost efficiency enters negatively and statistically significantly.

	(1)
	(OpExpense)
$\Delta_4 log(OpExpense_{t-1})$	0.561***
	(0.000)
$\Delta_4 log(TA_{t-1})$	0.241***
	(0.004)
$log(YER_{t-1} \times HIC_{t-1})$	0.187**
	(0.049)
$RelCostEfficiency_{t-1}$	-29.08*
	(0.085)
Banks	88
Obs	1407
R^2	0.279
Model	(AB)

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 81: Operating expenses regressions: 2016 Q1 - 2020 Q4

E Scenario selection: algorithm and examples

E.1 Algorithm to rank and select simulations

To illustrate the scenario selection algorithm, we consider in detail the example described in Section 6.5. For illustration purposes, we choose only two simple criteria – one to impose a condition on the path of GDP, and one to impose a condition on the path of inflation – in order to create a scenario that resembles a short period of stagflation.

Step 1: Generate the distribution of plausible outcomes

The examples are based on a large set of 90,000 stochastic simulations, using parametric sampling of macroeconomic shocks without imposing any conditional values.

Step 2: Define the sorting criteria

The mapping of a desired narrative to quantitative criteria can be illustrated in Table 82. Each criterion c (a single row in the table) is equivalent to mapping some identified risk (or narrative interpretation) into a specific function F_c that can be applied to the values of a variable at given time points. It requires specifying: a variable to consider, time periods of interest, a function to be applied, a quantile to aim for, a distance measure[151] and a weight for the relative importance assigned to the criterion.

In this example, we look at the cumulative growth in GDP and inflation from the current moment (2021 Q1) until 8 quarters later (2023 Q4) and aim for the largest drop in both GDP and inflation.

#	Variable	Time point(s)	Function F	Quantile Q	Distance measure	Weight W
1	Euro area GDP YER	[1, 8]	$\Delta(log(x))$	0 (min)	manhattan	1
2	Euro area HICP HIC	[1, 8]	$\Delta(log(x))$	0 (min)	manhattan	1

Table 82: Mapping of narrative criteria into sorting Functions

Step 3: Sorting simulations along with the criteria

Sorting of numerous stochastic simulations along with different variables and their transformations and at different time points poses the challenge of comparing items with different magnitudes. To avoid it, we use ordinal sorting.

The steps of the scenario sorting algorithm are as follows:

1. For each criterion c (row in the criteria table):

   1.1. For each individual simulation $Y_t = \mathscr{M}(\mathscr{P}, \mathscr{X})$ from the full simulation set, apply the function F to the values of the selected variable at the designated time point(s). The outcome can be denoted as $V_c = F_c(Y_t)$.

   1.2. Calculate the selected quantile of the functional value(s) $Target_c = Q_c(V_c)$.

[151] For instance, a manhattan distance measure refers simply to the sum of absolute deviations to the selected quantile. A Euclidean distance would be equal to the sum of squared deviations.

1.3. For each separate simulation, apply the distance measure from the value in the selected quantile $Dist_c = D(V_c - Target_c)$.[152]

1.4. Sort all scenarios by the resulting value in order to obtain their rank $UnweightedRank_c = sort(Dist_c)$.

1.5. Multiply the rank by the weight of the specified criterion $Rank_c = UnweightedRank_c \times W_c$.

2. Repeat for all criteria.

3. Sum up the ranks of each simulation for all criteria $Rank = \sum_c Rank_c$.

4. Sort all scenarios by $Rank$ to obtain the ordering $O = sort(Rank)$.

To demonstrate the sorting algorithm, we go over the same process with three examples. First, in Example 1, we use only a criterion for GDP from Table 82. Afterwards, in Example 2, we consider only inflation. Finally, in Example 3, we consider both variables together, noting that the correlation for the projected values of these two variables in the simulations is relatively low (see Table 83).

		YER	URX	TotalLoans	HIC
Gross domestic product, level, chained	YER				
Unemployment rate	URX	-0.4679			
Loans to NFCs, outstanding amounts	TotalLoans	0.5517	0.0732		
HICP index	HIC	-0.1898	0.2532	0.2965	

Table 83: Pairwise linear (Pearson) correlations for select variables

Taking a look at the same quantity (total cumulative change in GDP and inflation until 2023 Q4), in Figure 50, each column corresponds to Examples 1-3 from above. When simulations are sorted by only one variable, as in columns one and two, the values of the other variable do not exhibit monotonicity. When sorted by both criteria, the simulations in the final sorting order do exhibit a general trend for GDP and inflation, as see in column 3.

Step 4: Selecting and/or aggregating "best performing" scenarios

The steps of the scenario selection algorithm are as follows:
For each quantile (from 0 to 100):

1. Get the index of the ranked simulations, corresponding to the given quantile[153]
   Each simulation now corresponds to index s in ordering O, i.e. O_s

2. Select a certain number N of individual simulations (the number of simulations to consider together, which we call a "band" or a "family" of simulations)

[152] If V_c is a vector, i.e. for each simulation we have only a single values, the application of the distance measure does not matter because that would be equivalent to just sorting by the value itself.

[153] Note that this is different from the target quantile for the values of each criterion. Also note that the scenario designer may consider all quantiles, or alternatively focus on only one quantile corresponding to some tail measure; in this way, one can add a measure of severity/adversity without imposing exact values a priori.

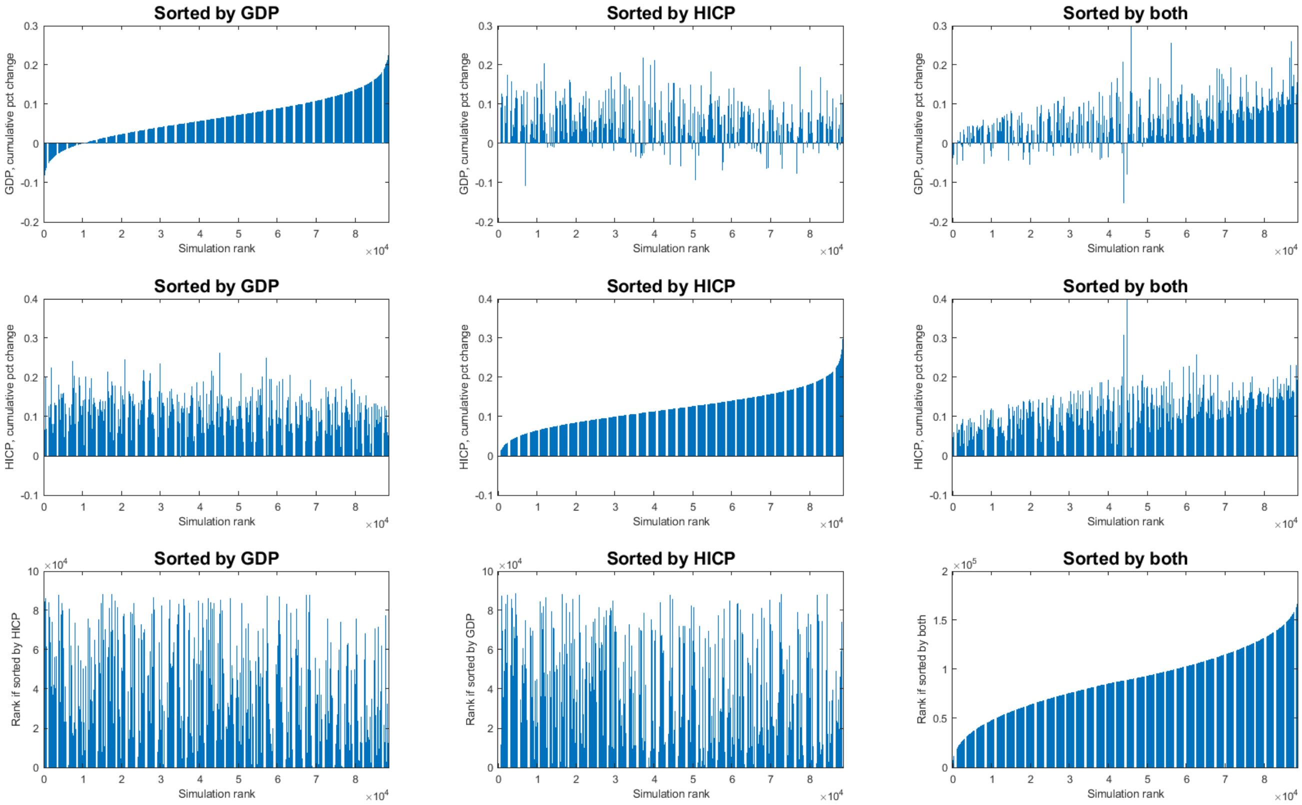


Figure 50: Simulation outcomes after sorting by both GDP and HICP

3. Take the $N/2$ simulations ranked higher and lower around the given quantile (a simulation can belong to more than one bands, i.e. bands can overlap), i.e. simulations $O_s - N/2 ... O_s + N/2$

4. Use a Local Outlier Factor algorithm (see Annex E.2) to check for outliers within these N simulations

5. Take the mean (or median) of the remaining simulations with each band $M = mean(O_{s-N/2}, ..., O_{s+N/2})$, which we call a "path".

The general distribution of simulations can now be classified by “sorted quantile paths”.

In each of the three examples, we show three possible scenario paths – those corresponding to the lowest 1^{st} percentile, 5^{th} percentile, and 10^{th} percentile, after the final sorting.

In Example 1, the scenarios corresponding to the 1^{th}, 5^{th} and 10^{th} percentile after sorting are plotted as green lines, superimposed on the fan chart of all unconditional projections in Figure 52. It can be seen that on average, as part of the scenario, large drops in GDP are associated with reduced domestic bank loans to non-financial corporations and higher unemployment rates.

In Example 2, simulations with the highest deflation do not necessarily occur with the highest decrease or increase in GDP in Figure 53. Therefore, in Example 3, we consider both criteria together to generate a scenario that fits a narrative for stagflation. Consequently, in Figure 18, there is some trade-off in the sorting order, in the sense that the final outcome will contain some drop in both GDP and inflation, but not as large as when the criteria were used independently.

The final scenarios correspond to the mean of a strip of simulations in sorting order. Individual simulations are generally more varied. To show this, the individual members that make up the quantile scenario 1^{th} (lowest green line) are plotted in blue in Figure 54.

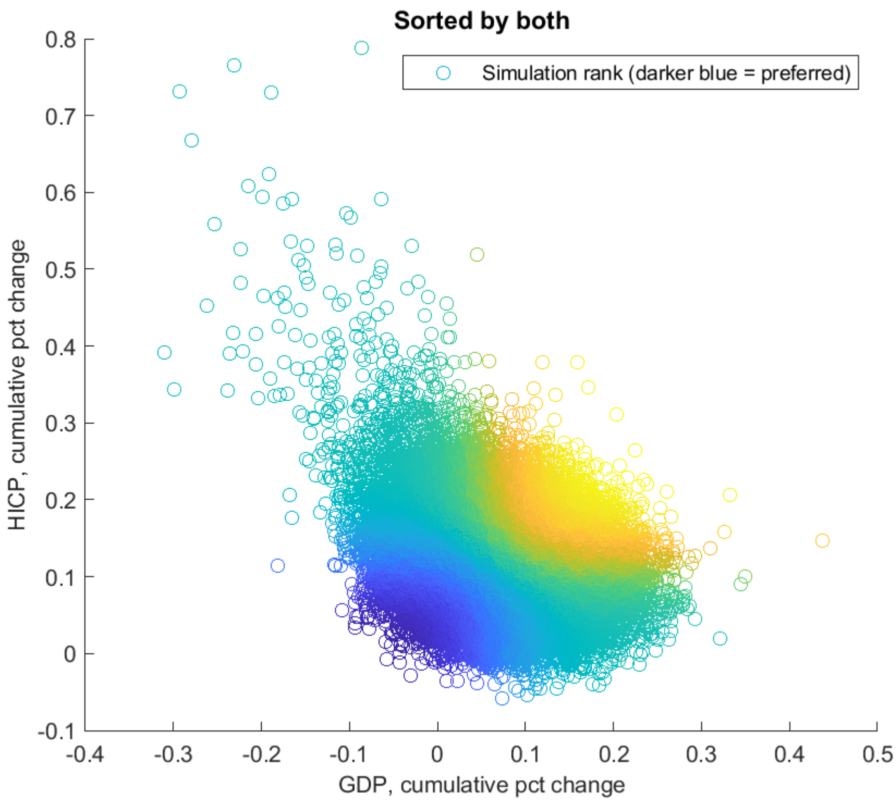


Figure 51: Example 3: Simulation outcomes after sorting by both GDP and HICP

E.2 Algorithm to compute the Local Outlier Factors

The local outlier factor (LOF) Breunig et al. [2000] is based on the concept of local density. The algorithm follows the following steps:

1. Specify the subset of V variables from simulations which will be compared.
2. For each variable x_v from the subset $x_1,\ldots,x_{|V|}$:

   2.1. Calculate the euclidean distance,

   $$d_v(x^{(i)},x^{(j)}) = \sqrt{\sum_t (x_v^{(i)} - x_v^{(j)})_t^2}.$$

   for each pair of simulations i and j.

   2.2. For each simulation i,

   2.2.1. Define k nearest neighbours (k closest paths) for variable v. The set of nearest neighbours will be denoted as $N_v(i)$. The number of nearest neighbours $k = |N_v(i)|$ is calibrated according to Breunig et al. [2000], between 10 and 20.

   2.2.2. Compute the maximum distance between simulation i and its neighbours (for variable v) i.e.,

   $$D_v(i) = max_{j \in N_v(i)}(d_v(x^{(i)},x^{(j)})),$$

   to obtain its local density measure. Define the local reachability density of a path as:

   $$lrd_v(i) = \frac{1}{\sum_{j \in N_v(i)} D_v(j)/|N_v(i)|}.$$

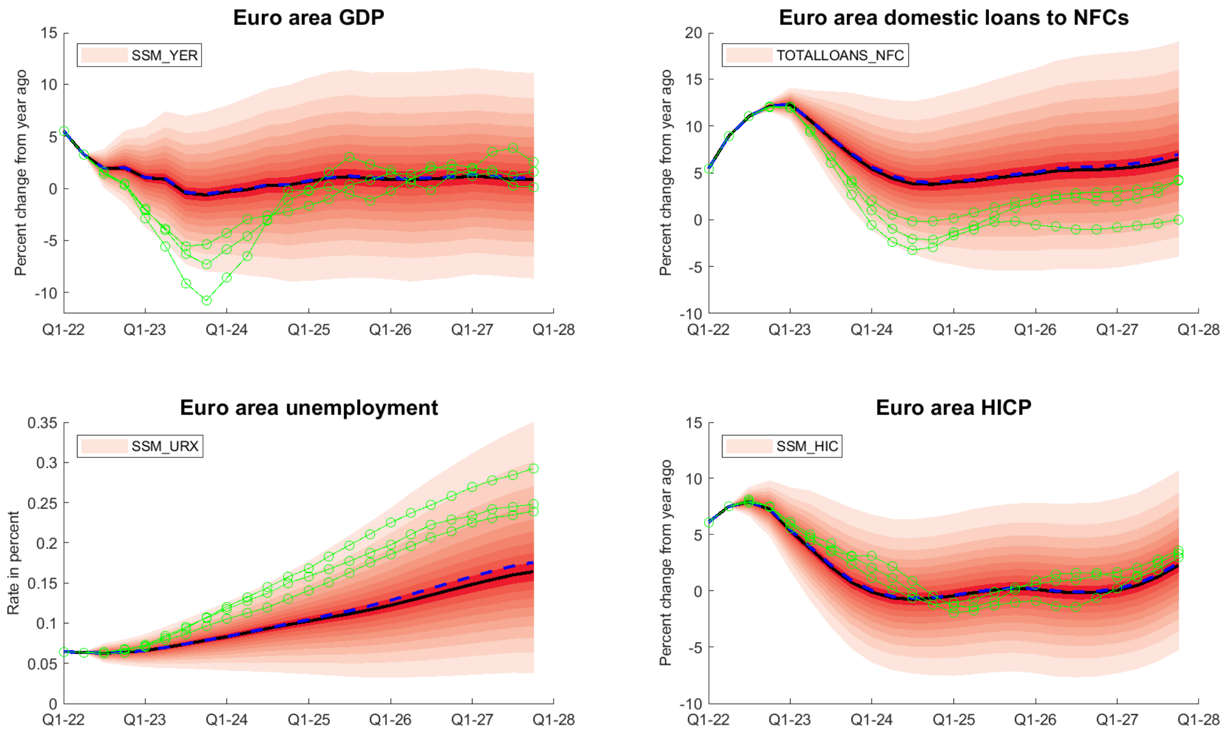


Figure 52: Example 1: Simulation results after sorting by GDP

2.2.3. Calculate the LOF score:

$$LOF_v(i) = \frac{\sum_{j \in N_v(i)} lrd_v(j)}{|N_v(i)| lrd_v(i)}.$$

3. Evaluate LOF scores for all variables x_v and paths i (from the matrix of LOF scores of size $variables \times simulations$). A LOF score around 1 indicates a region of similar density, the path is similar to its neighbours, i.e. not an outlier. A LOF score larger than 1 value indicates a lower density than its neighbours, i.e.:

   - LOF $< 1 \Rightarrow$ Inlier
   - LOF $= 1 \Rightarrow$ Average density
   - LOF $> 1 \Rightarrow$ Outlier

4. Discard simulation i if at least one variable path is an strong outlier i.e. LOF $> T$ where T is an additional threshold.

The algorithm ensures removal of any paths that violate the threshold value for any of the variables. The choice of threshold value depends on the data and the objectives. $T = 5$ has been applied in most of our scenario selection applications.

The algorithm has a quadratic algorithmic complexity (high), making it computationally demanding to apply it to large simulations ($> 10^5$ paths). We improve the execution speed by using an expectation maximisation algorithm as in Goldstein [2012], where the local outlier factor is computed incrementally and thus faster. The algorithm first divides the data into random samples. Then, the k-nearest-neighbour search is performed only for a sub-sample of the data.

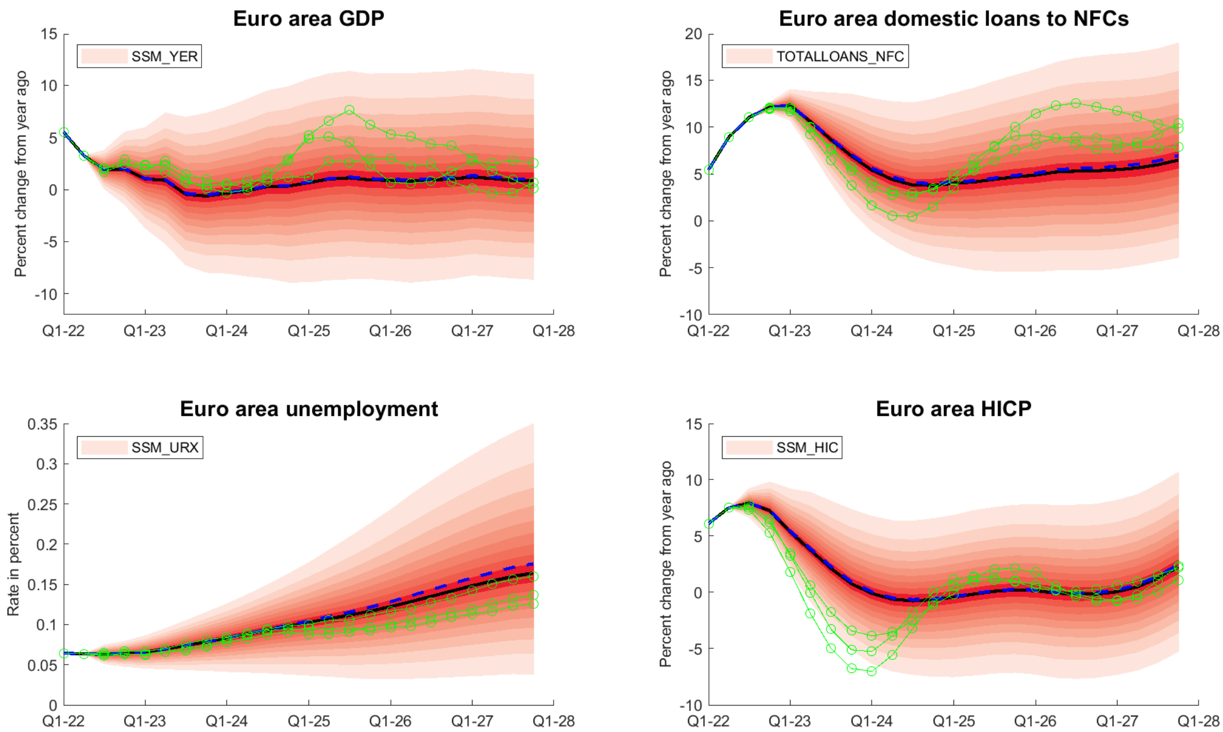


Figure 53: Example 2: Simulation outcomes after sorting by HICP

The LOF values calculated on this sub-sample of data are used to determine which data points have LOF higher than 1 and only these will be evaluated further within in a larger sample to find more accurate neighbours.

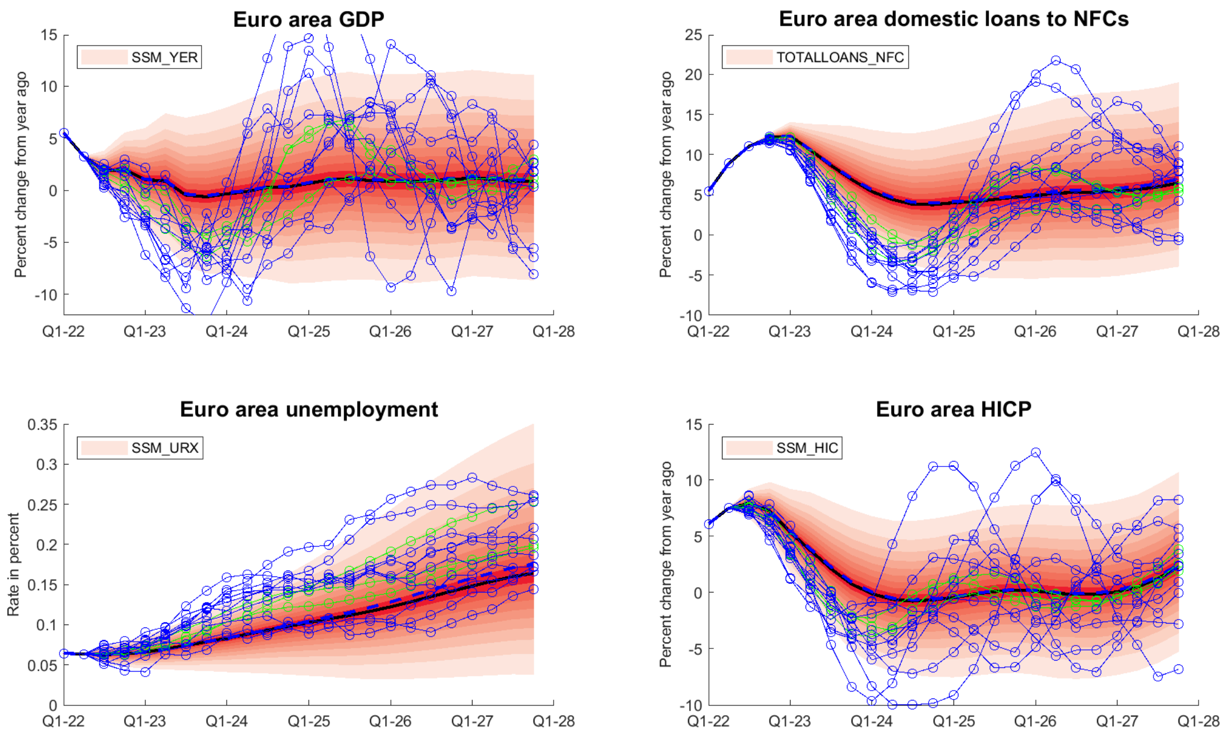


Figure 54: Simulation outcomes after sorting by both GDP and HICP

F Forecast assessment

The annex documents additional forecast quality statistics for the annual GDP growth rate of the euro area and the HICP inflation rate along with the description in Section 7.4.

F.1 Point forecast metrics

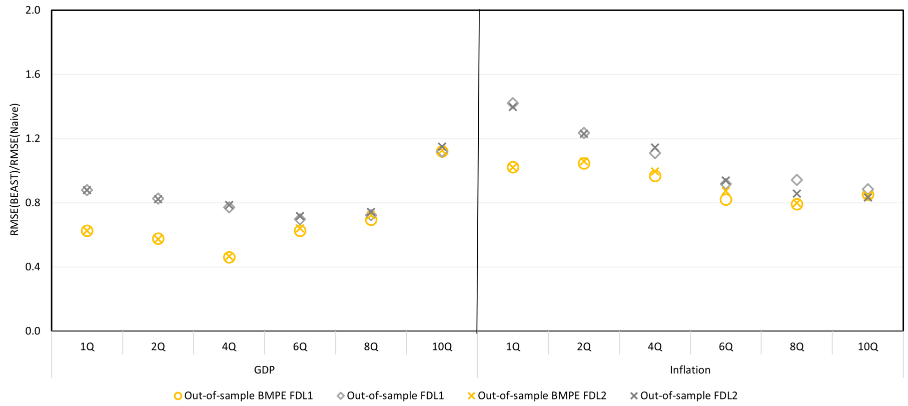


Figure 55: Root mean squared error of BEAST projection and naive forecast: macroeconomic variables

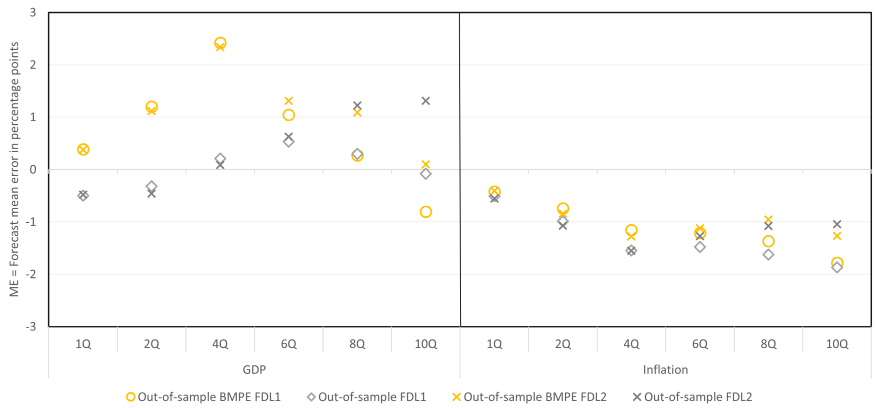


Figure 56: Mean forecast error of BEAST projections: macroeconomic variables

F.2 Interval forecast metrics

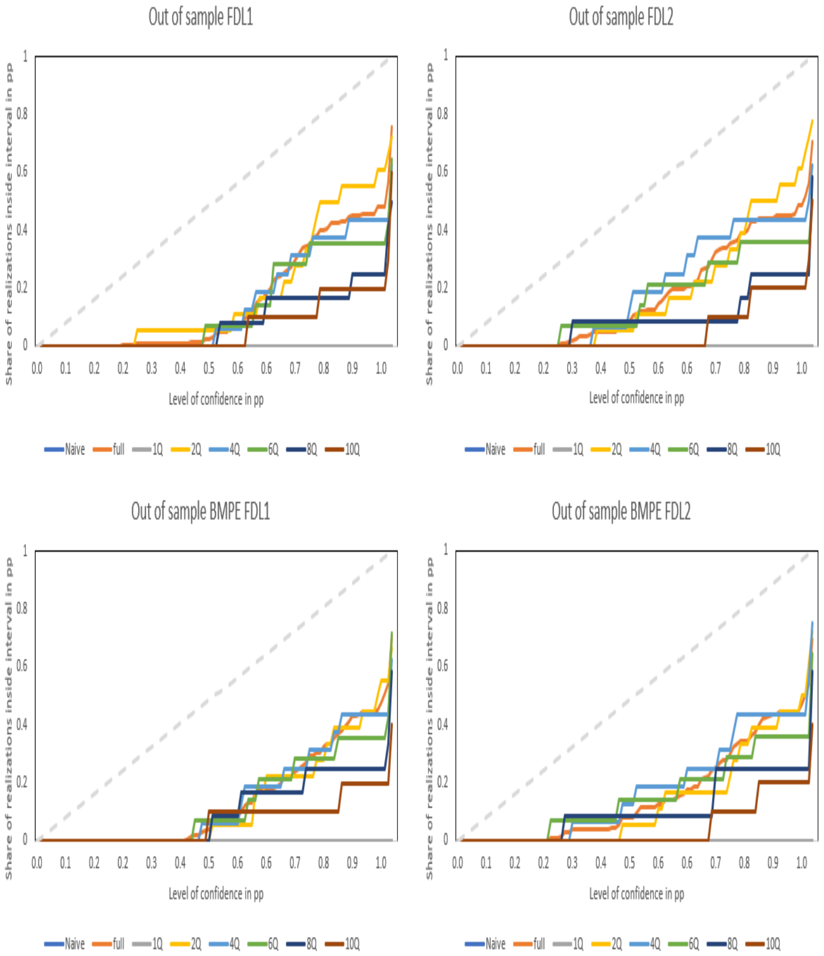


Figure 57: Two-sided interval forecast assessment: euro area GDP growth

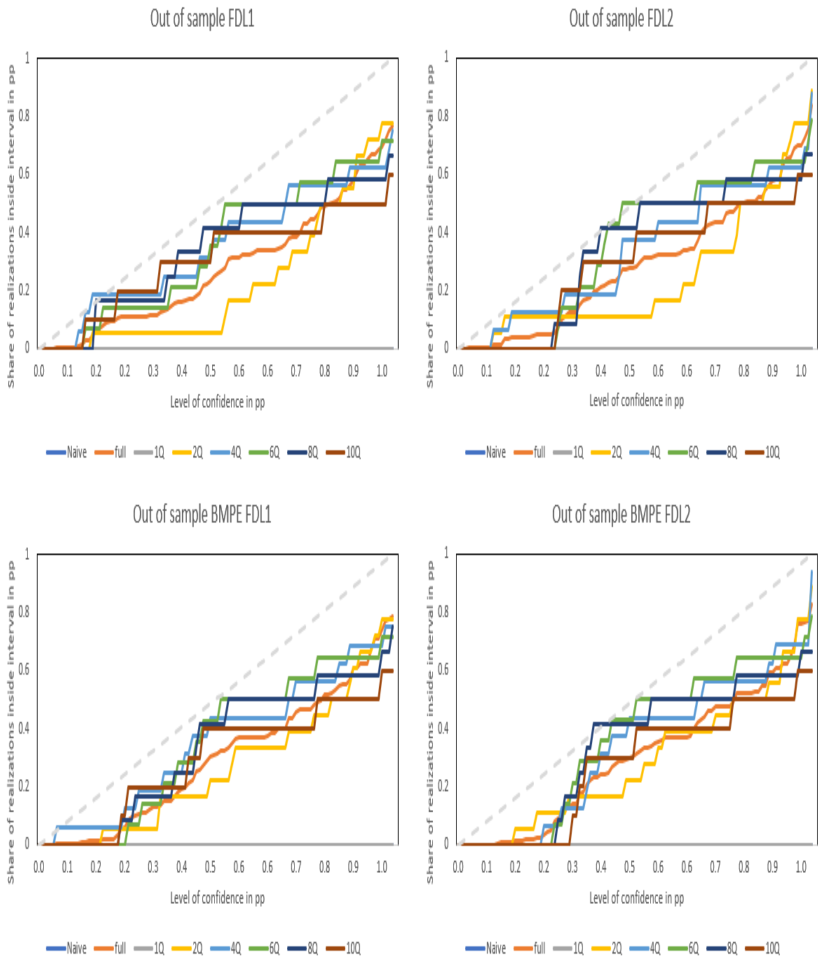


Figure 58: Two-sided interval forecast assessment: euro area HICP inflation

Acknowledgements

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