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Advancements in stress-testing methodologies for financial stability applications

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Abstract

This paper provides an overview of stress-testing methodologies in Europe, with a focus on the advancements made by the European Central Bank's Financial Stability Committee Working Group on Stress Testing (WGST). Over a four-year period, the WGST played a pivotal role in refining stress-testing practices, promoting collaboration among central banks and supervisory authorities and addressing challenges in the evolving financial landscape. The paper discusses the development and application of various stress-testing models, including top-down models, macro-micro models and system-wide models. It highlights the integration of new datasets and model validation efforts as well as the expanded use of stress-testing methodologies in risk and policy evaluation and in communication. The collaborative efforts of the WGST have demystified stress-testing methodologies and fostered trust among stakeholders. The paper concludes by outlining the future agenda for continued improvements in stress-testing practices.

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Executive summary

This paper provides a comprehensive overview of stress-testing methodologies in Europe with a focus on the advancements made by the European Central Bank's (ECB's) Financial Stability Committee Working Group on Stress Testing (WGST). From 2018 to 2022, the WGST played a pivotal role in advancing stress-testing practices, promoting collaboration among central banks and supervisory authorities, and addressing challenges related to the evolving financial landscape and emerging risks. The WGST successfully refined ECB stress-testing methodologies, ultimately enhancing various EU-wide stress-testing exercises.

First, the paper outlines the development and application of various stress-testing models, including top-down models, macro-micro models and system-wide models. The top-down models focus on credit risk, market risk and profitability, providing insights into default probabilities, revaluation losses and income sources. The macro-micro models examine the interactions between macroprudential policies, monetary policy changes and financial stability. The system-wide models capture interconnectedness among banks and non-banking financial institutions, addressing financial contagion and interdependencies.

The development of the models reflects evolving policy expectations, the emergence of opportunities such as new datasets and general efforts to enhance robustness and universality. The WGST identified 16 new models that were regularly used in policy processes, of which five replaced earlier models contained in the Stress Test Analytics for Macroprudential Purposes in the Euro Area tool (STAMP€) (Henry and Kok, 2013; Dees et al., 2017) and 11 covered areas not addressed by the ECB top-down toolkit before 2018. It improved and further developed five existing models, while two additional models were referred for testing at the end of 2022. On the back of model development, the WGST integrated 13 new datasets, which included transaction-level data, and started to use large datasets more broadly (in more applications). The model development was paired with efforts to improve stress test execution and non-model infrastructure, outlier detection and the analysis of new risks, including climate and cyber risks.

Validation efforts have been enhanced, with model performance being compared against banks' forecasts and back-testing against past exercises. The paper emphasises the importance of a comprehensive validation framework that combines ex ante and ex post elements, ensuring accuracy and reliability.

Second, the paper outlines the broadened use of stress-testing methodologies in the policy process. Stress-testing methods have expanded beyond their initial use in risk assessment, strengthening their role in policy evaluation and communication. Within the risk assessment area, the initial main application of the ECB benchmark models was to challenge the bottom-up submissions of banks in the European Union (EU)-wide supervisory stress test. Most recently, this application was supplemented using the same models in fully top-down (without bank participation) exercises, such as various scenario, vulnerability and sensitivity analyses for the banking sector. These applications inspired the development of models more capable of incorporating high sector-level detail, generating multiple scenarios, and of comprehensively assessing tail events and uncertainty.

Third, the WGST's collaborative efforts have demystified stress-testing methodologies and fostered trust among stakeholders. Through knowledge exchange and shared objectives, the WGST has played a significant role in advancing stress-testing practices in Europe, a legacy that will outlast the group itself.

Last, the paper provides insights into the state of stress-testing methodologies in Europe and outlines the future agenda for continued improvements in stress-testing practices.

1 Introduction

The global financial crisis highlighted to regulators, among others, the limits of a static assessment of bank solvency. The widespread belief that banks were sufficiently capitalised was falsified with new waves of financial market turmoil, unwinding second-round effects and finally economic recession. Stress testing had up to that point been part of financial institutions' internal risk management practices and shown promise in assessing bank solvency in a forward-looking manner and under realistic future crisis scenarios. It was this promise that convinced regulators to adopt it as part of their new toolbox.

The banking sector stress test in 2011, conducted by the European Banking Authority (EBA) in cooperation with the European Systemic Risk Board (ESRB) and the European Central Bank (ECB), marked the beginning of EU-wide stress testing in the current institutional set-up and facilitated the development of dedicated methodologies.¹ In 2011 the ECB established a comprehensive methodology for designing macro-financial scenarios for the EBA, which in later years was expanded to cover stress-testing exercises conducted by the European Securities and Markets Authority (ESMA) and the European Insurance and Occupational Pensions Authority (EIOPA). In tandem, the ECB also developed a rich set of models to scrutinise the results of the EU-wide banking sector stress test. Finally, to support the ESRB in its mission and to deliver on its own macroprudential oversight mandate within the framework of the Single Supervisory Mechanism (SSM), the ECB embarked on the development of its macro-financial stress-testing toolbox. These experiences were summarised first in Henry and Kok (2013), and then in a 2017 e-book on Stress Test Analytics for Macroprudential Purposes in the Euro Area (STAMP€) (Dees et al., 2017).

This paper provides a comprehensive overview of the top-down stress-testing methodologies developed between 2018 and 2022 by the Working Group on Stress Testing (WGST). The WGST was established in 2018 for an initial period of three years (later extended to four years) by the Financial Stability Committee and was tasked with advancing top-down stress test modelling that could support and complement the information in the bottom-up EU-wide stress-testing exercises. The group identified 16 new models that were regularly used in policy processes, of which five replaced earlier infrastructures (included in STAMP€) and 11 covered areas not addressed by the ECB top-down toolkit before 2018. It improved and further developed five existing models, while two additional models were referred for testing at the end of 2022. The new models include two comprehensive models for macroprudential stress testing of the banking sector, including banks and the real economy, and for system-wide stress testing, introducing interactions between banks and other financial institutions. On the back of model development, the WGST integrated 13 new datasets and started to use large datasets more broadly (in more applications). Lastly, the paper documents the efforts to introduce robust and regular model validation practices and takes stock of evolving expectations and policy applications of top-down stress-testing methods over the period 2018-22.

The paper targets a potentially broad readership of experts active in the field of stress testing and other users of stress-testing methods, including those who use stress test results for policy decisions and want to know more about how top-down stress tests are prepared. For stress-testing experts, it can serve as an overview of methodologies that can also be applied to their home institutions. Other users of stress-testing methods, or experts active in analysing banking and financial systems, can gain inspiration and a better intuition regarding the complementarities between stress testing and their fields. Finally, the broadest group of "passive" stress test users can not only see the inner workings and develop a better understanding of the possibilities and limitations of various methods, but also see multiple examples of stress test applications, hopefully demonstrating how such methods can be used to prevent and manage future financial stability problems.

¹ The first Europe-wide banking sector stress test took place two years earlier in 2009 and was coordinated by the Committee of European Banking Supervisors (CEBS). For this purpose, the ECB provided the macro-financial scenarios and credit risk benchmark parameters.

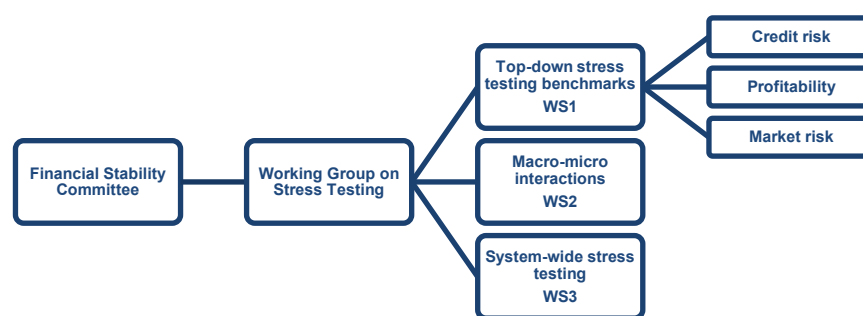
The mandate of the WGST was to develop operational tools based on stress-testing experience, academic research and the analytical frameworks already used by EU central banks and supervisory authorities. This included validating and developing further methodologies to support EU-wide stress-testing exercises as well as the new macroprudential policy mandates of designated or competent institutions. It spanned both risk analysis and counterfactual risk and policy impact assessments. The mandate served the aim of understanding macro-financial linkages and their effects when assessing the system-wide impact of risks, policy measures and regulations. Importantly, it called for specific and readily implementable tools, hinting at its hands-on policy-focused profile.

An important part of the WGST’s mandate was to foster cooperation between member institutions of the SSM and European System of Central Banks (ESCB). To this end, during its four-year existence, the WGST provided a forum for analytical exchange and policy discussion between experts from member institutions and a platform for regular and ad hoc data exchange.² As the first group with such a broad composition to specialise in the development of stress-testing models in the European sphere, it substantially strengthened networks of modellers working on methods for risk assessment. This latter aspect, which is difficult to quantify in this paper, is something that will outlast the WGST’s discontinuation in 2022.

The WGST was organised in three work streams, corresponding to the three development directions of stress-testing methods (Figure 1). The top-down stress-testing benchmarks work stream focused on modelling stress-testing parameters to support top-down stress testing with a constant balance sheet assumption. Its main ambition was to provide banks with benchmarks and support the quality assurance of bank submissions for bottom-up results provided in the context of EU-wide stress-testing exercises. It was further divided into three different sub-streams covering credit risk, market risk and profitability.³ The macro-micro interactions work stream focused on banking sector interactions with the real economy and worked toward the operationalisation of an effective macroprudential stress-testing framework for banks. It concentrated on releasing the constant balance sheet assumption and introducing the feedback loop between the banking sector and the real economy. The system-wide stress testing work stream was tasked with the development of a framework that extended beyond banks and included other sectors of the financial system. Its main aim was to improve the understanding of contagion and amplification mechanisms stemming from the interaction of banks with other non-banking financial institutions.

Figure 1

Organisational set-up for the top-down stress-testing benchmarks work stream



Source: ECB.

The top-down benchmarks work stream delivered a suite of new or revised models and a back-testing and validation framework, and continuously supported various constant balance sheet exercises. The models were enhanced based on more granular information and advanced modelling techniques, and their coverage of parameters increased. The benchmarks derived from these models were used by banks and by supervisors to scrutinise bottom-up bank submissions in the 2018, 2021 and 2023 EU-wide stress tests and comprehensive assessments, ensuring sufficient conservativeness and a

² This included, for example, regular so-called free-form data collection, where time series of default rate flows and transition rates are collected from national authorities. Since 2018, the ECB has carried out four of these data collections, which are used to calibrate the ECB top-down models before the launch of each EU-wide stress test.

³ The top-down stress testing benchmarks work stream’s organisational set-up consisted of approximately 40 colleagues, including ECB staff and experts from national authorities, as well as ECB Banking Supervision and the EBA who were acting as observers.

level playing field between participating banks.⁴ They have also become a core element of ECB/SSM vulnerability analyses, i.e., top-down (or desktop-based) stress-testing exercises closely following the methodology of the EU-wide stress tests (including the constant balance sheet assumption) but relying only on top-down model predictions.

The macro-micro interactions work stream assisted the finalisation of a comprehensive macroprudential stress-testing model and its transformation into a workhorse model used flexibly for the impact assessment of risks and banking sector-relevant policies and regulations. The core modelling framework advanced by the work stream was the ECB banking euro area stress test (BEAST) model (Budnik et al., 2023), although it continued supporting the development of other infrastructures at member institutions and discussing alternative modelling approaches. The model mechanisms were substantially expanded, allowing for banks' responses to macroeconomic conditions and policy changes by adapting their liability structure, voluntary capital buffers and dividend payouts, or defaulted asset write-off policies; all of which complemented the original dynamic balance sheet elements of loan pricing and volumes. The model ultimately accommodated more stress propagation channels, carefully modelling the dynamics of bank funding costs, the pass-through of standard and non-standard monetary policy instruments (including asset purchases and longer-term liquidity operations) and allowing for non-zero asset recovery rates, endogenous revaluation losses and regulatory risk charges. Finally, the model was expanded to accommodate more regulatory constraints on liquidity (liquidity coverage ratio, LCR), funding (net stable funding ratio, NSFR) and non-performing loan (NPL) coverage (SSM NPL coverage expectations), as well as pre-existing capital requirements and buffers, and factored in bail-in requirements (minimum requirement for own funds and eligible liabilities, MREL). The work stream oversaw the application of the model in the preparation of three ECB macroprudential stress-testing exercises, assessments of the macro-financial consequences of Basel III finalisation, NPL coverage expectations, coronavirus (COVID-19) bank-oriented policies (including public guarantees and moratoria), liquidity implications of the phase-in of central bank digital currencies and initial assessments of the interactions between monetary and prudential policies.

The system-wide stress testing work stream concluded with a dynamic, micro-structural tool for carrying out a joint stress test of banks and non-banks. The model considers the interactions between banks, investment funds and the insurance sector and features both direct and indirect contagion mechanisms. It can be applied to solvency and liquidity stress testing, and during the period of the WGST was successfully phased in for policy applications. From 2021 onwards it was also used to investigate the amplification of climate risks.

The analytical work of the WGST built on STAMP€ (Henry et al., 2013; Dees et al., 2017), a rich infrastructure of models and the framework for combining them to provide estimates of the macroeconomic feedback and contagion effects. STAMP€ was a stress-testing framework put together by ECB staff that featured models for the estimation of various bank parameters and supplementary macro-financial models for scenario design, supporting macroprudential and system-wide stress testing. The former model mapped macro-financial developments into credit risk, market risk and bank profitability. These models became the focus of the top-down benchmarks work stream and were further developed and tested within the WGST. The two other WGST work streams, macro-micro and system-wide stress testing, pushed further the agenda of macroprudential and system-wide stress testing respectively. The system-wide stress-testing model in particular leverages both the analytical question and solution (the hybrid model structure) of STAMP€. In parallel to the work of the WGST, STAMP€ continued to evolve into a comprehensive IT platform for stress testers (Henry and Januário, 2022) that allows for multiple-scenario stress tests and can be applied to reverse stress testing (Henry, 2021).

The report is structured as follows. Section 2 discusses the evolution of stress testing in the European Union since 2018 and places the work of the WGST in this context. Section 3 provides an overview of the ECB top-down models.⁵ Section 4 covers the work on macro-micro interactions and macroprudential stress testing. Section 5 describes the framework for system-wide stress testing, covering banks and non-banking financial institutions. The final section concludes and provides an outlook on future developments in stress-testing methods.

⁴ The predecessors of models maintained or initiated by the WGST had been used to scrutinise the results of the EU-wide stress test since 2011 (i.e., next to the dates mentioned in the main text, also in 2011, 2014 and 2016).

⁵ In comparison with work streams 2 and 3, the top-down models are described in more detail in this report. This is due to the availability of other related publications that provide a comprehensive overview of the applied modelling framework in these work streams.

2 Stress testing in Europe

Stress tests evaluate the robustness of financial institutions under adverse economic conditions.

Financial institutions are complex enterprises with balance sheets that are difficult for the wider public to read and understand. Stress tests estimate the solvency and/or liquidity of financial institutions under hypothetical unfavourable macro-financial conditions, such as a deep recession or financial market disturbances, providing a condensed and relatively easy way to interpret financial resilience.

Stress testing evolved from being part of financial institutions' internal risk management practices to becoming a standard regulatory tool in the wake of the global financial crisis.

As a crisis prevention instrument, stress tests act as an early warning mechanism, provide new information to supervisors and markets (Durrani et al., 2022; Durrani, Ongena and Ponte Marques, 2022) and can improve transparency and market discipline (Konietzschke et al., 2022b; Georgescu et al., 2017; Kok et al., 2022). They allow market participants to assess banks' ability to meet applicable minimum and additional capital requirements under adverse scenarios. As a crisis management instrument, they help to regain the public's trust in the financial system. Finally, stress test results contribute to ongoing supervisory dialogue in the context of the Supervisory Review and Evaluation Process (SREP). Qualitative outcomes are included in the risk governance part of the SREP, thereby influencing the determination of Pillar 2 requirements (P2R). Quantitative results are used as a key input for Pillar 2 guidance (P2G).

This section first reviews the evolving applications of stress testing in Europe in order to later place the deliverables of the WGST in this broader context.

ECB stress-testing methodologies have evolved jointly with the European regulatory landscape. In 2009 and 2010 the ECB contributed the macro-financial scenarios and so-called benchmark parameters for several variables reported by banks to the first EU-wide stress tests run by the Committee of European Banking Supervisors (CEBA). In 2010 CEBA's oversight responsibility for the banking sector was taken over by the EBA as part of the introduction of the European System of Financial Supervision. A dedicated new methodology of designing macro-financial scenarios was deployed in 2011, in the first EU-wide stress test run by the EBA. In subsequent years, the ECB also started to contribute similar macro-financial scenarios to the regular EIOPA and ESMA stress tests of the EU insurance sector and central counterparties respectively.

The progressive development of stress-testing models at the ECB has also been reflected in various top-down exercises.

The ECB continued to provide benchmark parameters for the 2011-14 EBA stress test and, later, the EBA/SSM EU-wide stress test. Additionally, from 2010 it employed its toolkit for benchmark parameters to prepare a top-down stress test of the largest European banks (initially 19 banks) for the two-year horizon. This top-down stress test featured regularly in the ECB Financial Stability Review. The vulnerability analysis, published for the first time in 2020, was conducted in the same tradition as earlier top-down stress test, namely by applying a constant balance sheet perspective and additional restrictions from the EBA/SSM exercises. However, vulnerability analyses were characterised by far higher granularity than the top-down stress test, close to the granularity of the EU-wide stress test.

Since 2016 the ECB has published a stand-alone macroprudential stress test taking account of second-round effects.

This was developed to support the ESRB and deliver on the ECB's own macroprudential oversight mandate within the European financial system. The advancement of stress-testing methods has facilitated their broader use in policy assessment and ECB communication.

2.1 Evolving uses of top-down stress testing

In recent years, the use of stress-testing methods in the prudential policy process has become increasingly frequent and versatile (Budnik, 2022).

Applications have included the measurement of risks in the financial system, i.e., the traditional remit of stress testing, and newer applications, such as the calibration of prudential instruments and communication with the industry, financial market participants and the public. These applications have served both microprudential and macroprudential purposes.

2.1.1 Risk measurement

The two main applications of the ECB top-down stress-testing models are to provide benchmarks for banks in otherwise bottom-up stress tests and subsequently to challenge banks' submissions.

The EBA/SSM (and earlier CEBA and EBA) EU-wide stress tests are conducted in a principally bottom-up fashion, while using consistent methodologies, scenarios and key assumptions developed in cooperation with the ESRB and the EBA. Their bottom-up design means that banks are asked to provide their own projections of balance sheet evolution under a baseline scenario and an adverse scenario. Thereby, banks that do not have an internal credit risk stress test model have the option to use the ECB top-down credit risk benchmarks. They can also use interest rate margins and dividend income benchmarks, and since 2023 EU-wide stress tests are obliged to apply the net fee and commission benchmark. These benchmark parameters are estimated by ECB staff and are discussed jointly with the EBA, EU competent authorities and national central banks.

For banks and risks not applying the ECB benchmarks, the latter make up an integral part of the bank submission quality assurance process.

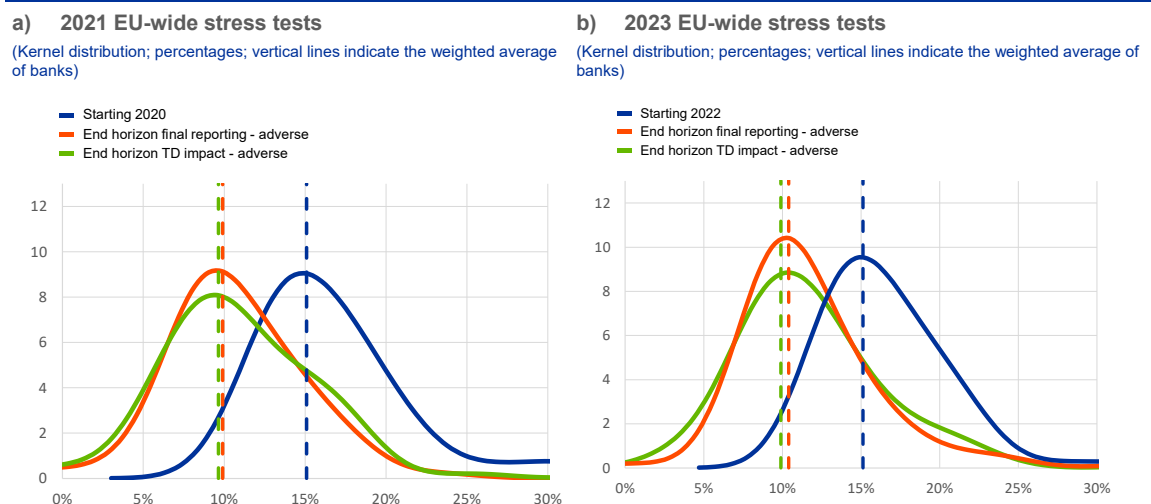
The banks results are subject to a comprehensive data quality check and are challenged and compared with earlier stress test results in several submission cycles. This process ensures maximum comparability and a level playing field between participating banks and minimises the incentives to “game” the process. It also guarantees that the overall exercise is sufficiently conservative. Within this quality assurance framework, banks' submissions are compared against the ECB benchmark parameters and, if need be, challenged by supervisors.

The intention to challenge bank submissions is illustrated in the outcomes of the 2021 and 2023 EU/SSM stress tests in Chart 1.

The chart contrasts the top-down outcome, integrating where possible the ECB benchmarks, with final bank submissions under an adverse scenario. The adverse scenario drives the elevated CET1 depletion (green versus other kernels). In each submission (other than green kernels), banks move closer to CET1 ratio depletion, as implied by the combination of top-down benchmarks and supervisory scrutiny based on peer benchmarking and bank-specific insights. The expected effect of challenging bank submissions is greater and more distributed capital depletion in the last submission.

Chart 1

Impact of quality assurance on CET1 ratio from initial to final submission in the 2021 and 2023 EU-wide stress tests - adverse scenario



Sources: Participating banks, ECB and ECB calculations.

Another form of ECB risk assessment is conducted fully in-house, without the involvement of banks. These exercises differ in terms of the risks they emphasise and the methodological assumptions they use. Table 1 summarises the different in-house stress tests, their policy role and the date they were published for the first time. Historically, the first such exercise was a top-down stress test that assessed risks to the EU banking system by applying the top-down benchmark model apparatus and the constant balance sheet perspective. Otherwise, it relied on a simplified representation of banks' balance sheets as compared with the biannual EU-wide EBA/SSM stress test. More recent constant balance sheet exercises that incorporate top-down benchmark models, such as vulnerability and sensitivity analyses, rely on a highly granular representation of banks' balance sheets, close to that of the EU-wide EBA/SSM stress tests, and the broadened top-down benchmark models infrastructure. Such top-down stress tests and vulnerability and sensitivity analyses have provided timely and tailored feedback on the impact of risks which "could not wait" until the next EU-wide stress-testing exercise.

Table 1
Overview of naming conventions for various ECB stress-testing exercises

Type	Role	Core assumptions	First use	Modelling framework
Supervisory (CEBS,⁶ EBA and finally EBA/SSM) stress test	Regular, biannual, three-year horizon EU-wide exercise	Constant balance sheet and other constraints, e.g., zero cure rates Macro-financial scenarios derived with the dedicated macro-financial framework (since 2011)	2009	Top-down benchmark analytics (developed under WGST work stream 1) versus bottom-up
Top-down stress test	Irregular, two-year horizon EU-wide exercise reflecting evolving financial stability risks with a reduced granularity and/or bank sample compared with the supervisory stress test (commonly reported in the Financial Stability Review)	Constant balance sheet and other constraints as in the EU-wide stress test, e.g., zero cure rates Macro-financial scenarios derived with the framework used in the EU-wide stress test	2010	Top-down benchmark analytics (developed under WGST work stream 1)
Macroprudential stress test	Biannual, three-year-horizon exercise complementing the EU-wide stress test and placing the emphasis on the adjustments of banks and macro-financial feedback loops	Dynamic balance sheet and releasing other constraints present in the EU-wide stress test Macro-financial scenarios shared with the EU-wide stress test	2016	Since 2018: BEAST model (developed under WGST work stream 2); previously: STAMPE framework
Vulnerability analysis	Three-year-horizon exercise substituting for the EU-wide stress test in cases of emergency and a substantial increase in financial stability risks (especially between the biannual rounds of the EU-wide stress test)	Constant balance sheet and other constraints as in the EU-wide stress test, e.g., zero cure rates Macro-financial scenarios derived with the framework used in the EU-wide stress test	2020	Top-down benchmark analytics (developed under WGST work stream 1)
Scenario analysis	A macroprudential stress test-type exercise with varying horizons (i) featuring in selected Financial Stability Reviews and focusing on the assessment of risks prevalent at the current juncture, or (ii) emphasising a group of topical risks, e.g., climate	Dynamic balance sheet and releasing other constraints present in the EU-wide stress test Macro-financial scenarios developed within the macroprudential stress test apparatus	2020	Since 2018: BEAST model (developed under WGST work stream 2); previously: STAMPE framework
Sensitivity analysis	Emphasising a selected risk factor	Constant or dynamic balance sheet and to a differing degree following the EU-wide constraints No or very reduced macro-financial scenarios	2022	Top-down benchmark analytics and/or BEAST model (developed under WGST work streams 1 and 2)
System-wide stress test	An exercise placing the emphasis on the interplay between different financial sectors and a group of topical risks, e.g., climate	Macro-financial scenarios derived with the framework used in the EU-wide stress test Allowing market prices to adjust and defaults to propagate through the system	2022	ISA model (developed under WGST work stream 3)

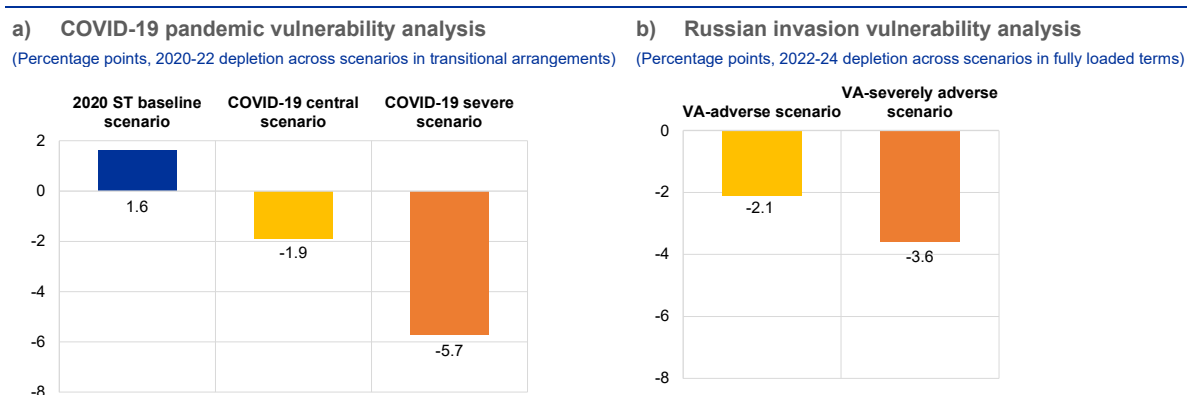
Source: Authors.

⁶ The Committee of European Banking Supervisors (CEBS) was an independent body in charge of advising on and coordinating banking regulation and supervision in the EU.

The two vulnerability exercises in 2020 and 2022 are an example of a fully top-down constant balance sheet stress-testing exercise. Both exercises provided a quantification of the bank solvency position in terms of CET1 depletion, conditional on severe scenarios triggered by the COVID-19 pandemic and the Russian invasion of Ukraine, respectively (Chart 2). The vulnerability analysis for the COVID-19 pandemic showed that, under the severe scenario, the overall bank capital shortfall would remain contained (CET1 ratio depletion of -5.7 percentage points in 2022).⁷ The subsequent vulnerability analysis for the Russia-Ukraine war concluded with a CET1 ratio depletion of 2.1 percentage points under the adverse scenario and 3.6 percentage points under the severely adverse scenario.⁸ Based on the unfolding risks, both vulnerability analyses showed that the banking sector was sufficiently capitalised to withstand the shocks. Additionally, the latter exercise revealed a substantial sectoral concentration of credit risk in sectors most exposed to changes in energy prices.

Chart 2

Vulnerability exercises for the COVID-19 pandemic (panel a) and Russian invasion (panel b): CET1 ratio depletion across scenarios



Sources: ECB Banking Supervision website and ECB (2022).

Note: The CET1 ratio for the vulnerability exercise in the COVID-19 pandemic is presented in transitional arrangements, as defined in Part Ten Title I Transitional Provisions of CRR, Article 473a of CRR.

A macroprudential stress test is another type of an in-house exercise that emphasises dynamic balance sheet aspects and the real economy-banking sector feedback loop. The ECB macroprudential stress test (earlier a macroprudential extension of the EU-wide stress test) has been published biannually since 2016 and elaborates on banks' behaviour under the baseline and adverse scenarios of the EU-wide stress test. It acknowledges that banks adjust their balance sheets in response to shocks and that these adjustments can feed back into the real economy. Furthermore, since 2018 it applies a broad interpretation of a dynamic balance sheet, including endogenous adjustments of asset and liability volumes, endogenous write-offs and non-zero recovery rates of defaulted assets. It also removes other caps and floors present in the EU-wide exercise.

The ECB macroprudential stress test complements the EBA/SSM EU-wide stress test results along three dimensions. First, it provides an alternative metric of bank solvency at any juncture. The dynamic balance sheet aspect, where banks adapt their balance sheets to prevailing macro-financial conditions, will generally result in an expansion of bank assets under benign (baseline) scenarios and their contraction under adverse scenarios. In panel a) of Chart 3, the deviation between the system-wide CET1 ratio results in the 2021 macroprudential versus EBA/SSM EU-wide stress test is broken down into the impact of core methodological differences between the exercises. Banks' asset adjustments are reflected in lower CET1 ratios under a baseline scenario, and higher ratios under an adverse scenario, than when applying the constant balance sheet assumption.⁹ The amplification effects present in the macroprudential assessment, including the real economy-banking sector and solvency-funding cost feedback loops, are expected to have the largest negative impact on the CET1 results in severe macro-financial conditions. Finally, the impact of policies that cannot always be factored in in the constant balance sheet exercises can lead to further, generally ambiguous changes in CET1 outcomes.

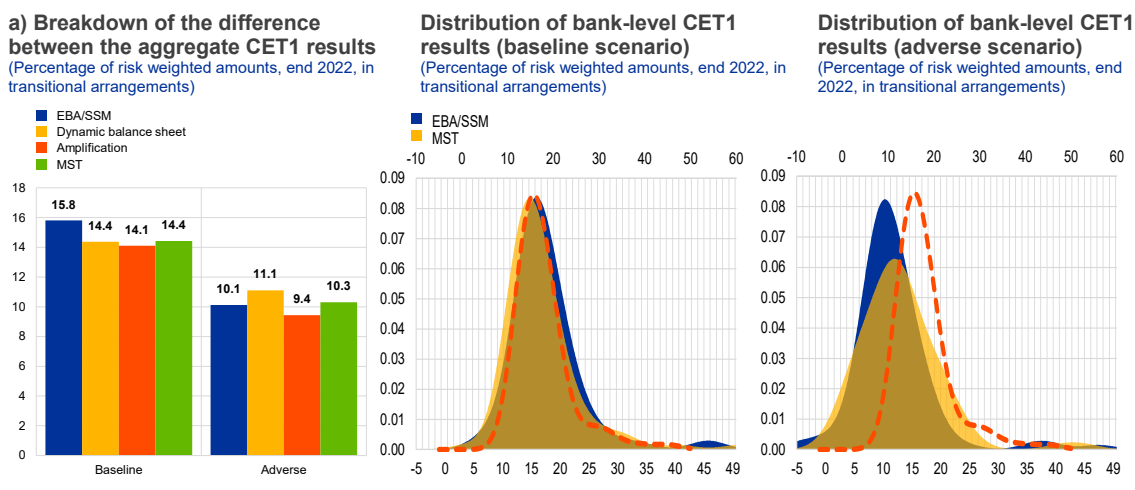
⁷ For more information, please consult: www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200728~7df9502348.en.htm.

⁸ Please consult: https://www.ecb.europa.eu/pub/financial-stability/fsr/focus/2022/html/ecb.fsrbox202205_06~9aaa17d9e8.en.html.

⁹ A dynamic balance sheet affects the solvency rate via two countervailing channels: (i) asset size (denominator effect), and (ii) profitability impact (numerator effect). In the case of both deleveraging and asset expansion, and provided that most bank loans have a longer maturity, i.e., asset changes fully feed into profitability with a certain lag, the former effect is likely to dominate in the short run.

Chart 3

Bank solvency in the 2021 macroprudential stress test compared with the EBA/SSM EU-wide stress test: CET1 ratio at the end of the three-year horizon



Source: Budnik et al. (2021a).

Notes: The empirical kernel density functions with a bandwidth equal to 3%. The red dashed line represents the CET1 ratio density at the end of 2020.

Greater flexibility of bank adjustments, and the presence of amplification mechanisms, generally lead to higher heterogeneity of bank-level results in the macroprudential compared with the EU-wide stress tests. The results of the two stress tests in baseline (Chart 3, panel b)) and adverse (Chart 3, panel c)) scenarios are generally positively correlated. However, especially under adverse scenarios, the distribution of bank-level CET1 ratio results can become significantly flatter in the macroprudential exercise, which can be attributed primarily to the dynamic balance sheet mechanisms. Interestingly, the initial bank-level CET1 ratios tend to be a better predictor of the end point of the stress test in the constant balance sheet compared with the macroprudential approach. In other words, macroprudential stress testing seems to “add” more information to the information already provided by measures of bank resilience at a given juncture.

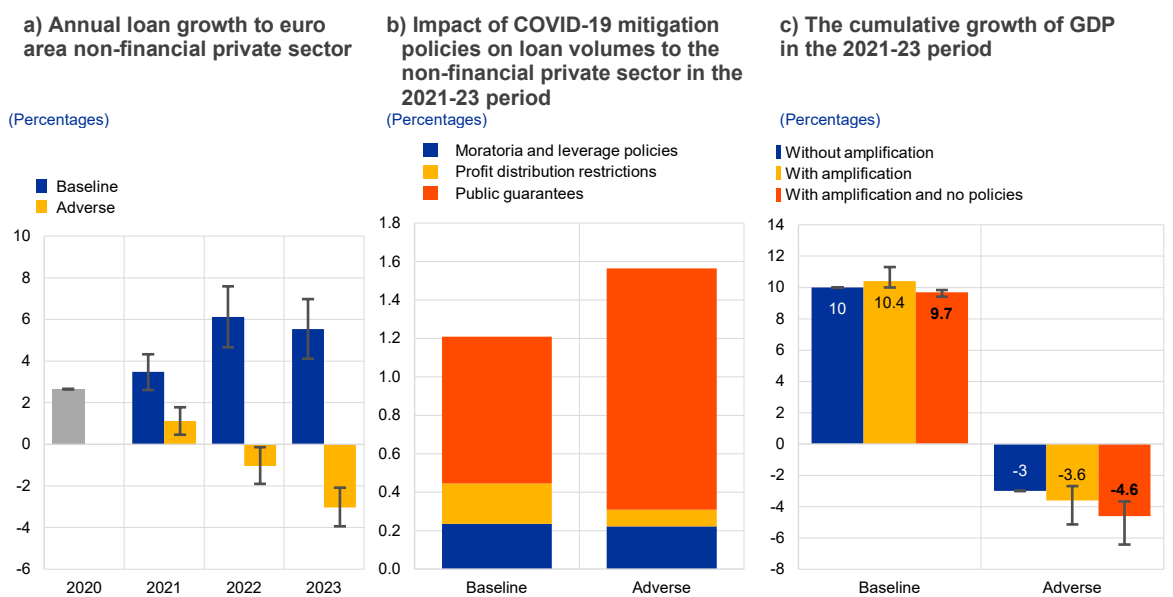
Second, the macroprudential stress test includes additional information relevant from the macro-financial perspective. The projections of bank lending provide information about banks' ability to provide lending to the real economy in normal conditions and with credit crunch risks under adverse scenarios (Chart 4, panel a)). The dynamic balance sheet approach captures changes in banks' behaviour related to policies that are due to be phased out or phased in over the stress test horizon. For instance, at the end of 2021, i.e., the starting point of both the EBA/SSM and the macroprudential stress tests in 2022, banks still held assets that were covered by either public guarantee or moratoria schemes deployed to contain the impact of the COVID-19 pandemic on bank lending (Chart 4, panel b)). The constant balance sheet perspective kept these exposures unchanged over the stress horizon, while the macroprudential stress test incorporated the expiration of these programs along with their country-specific duration, which meant that the corresponding maturing exposures were not replaced.

The ECB macroprudential stress test can provide estimates of uncertainty related to assumptions about banks' behaviours. This can be achieved by repetitively evaluating baseline and adverse scenarios with different plausible values of parameters entering estimated banks' reaction functions.¹⁰ Such uncertainty is illustrated for projected lending volumes in the panels a) and c) of Chart 4.

¹⁰ The supervisory exercise in 2023 (ECB, 2023) also provided an evaluation of uncertainty for the counterparty credit risk (CCR) (Box 4) and net interest income (NII) (Box 5) estimates. The difference between both approaches is the breadth of the exercise (the number of parameters evaluated) and the source of the information about parameter distributions (empirical estimates based on historical data in the macroprudential stress test versus reasonable expert-chosen ranges of parameters in the EBA/SSM stress test).

Chart 4

Additional information in the 2021 macroprudential stress test: loan growth, policy impact and second-round effects



Source: Budnik et al. (2021a).

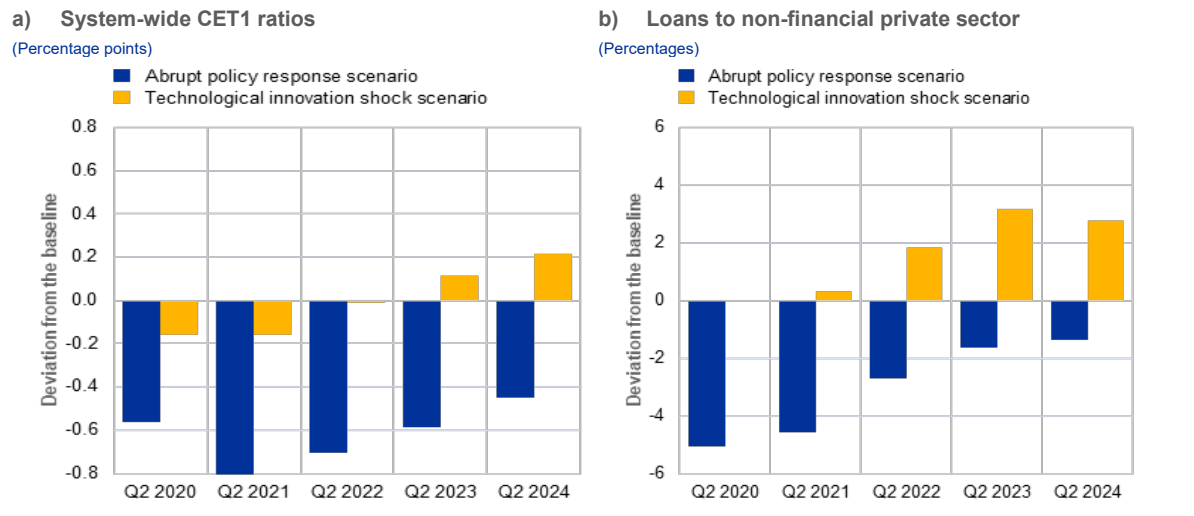
Notes: The whiskers depict 90% uncertainty bands around estimates. The cumulative GDP impact without amplification relies on the original macro-financial scenarios feeding into the 2021 EU-wide stress test exercise. The results with amplification include the impact of the real economy-banking sector feedback loop.

Third, by estimating second-round effects, the ECB macroprudential stress test illustrates the system-wide consequences of banks' most likely decisions. A macroprudential stress test emphasises the role of coordination failures, whereby individual banks take actions that are optimal from their own perspective, such as deleveraging to restore regulatory solvency rates, but can trigger adverse amplification mechanisms. The ultimate effect of these decisions on economic activity (Chart 4, panel c)) and bank capitalisation levels can thus turn out to be negative. The assessment of macro-financial vulnerabilities in macroprudential stress tests can support policy calibration and communication aimed at circumventing coordination failures.

The evolution of ECB stress testing is also reflected in its expansion beyond the assessment of "traditional" cyclical risk. An example is the application of ECB stress testing apparatus to the evaluation of climate-related risks. The earliest assessment of climate transition risks combined the ECB macroprudential stress test and elements of the 2018 climate stress test by De Nederlandsche Bank (Vermeulen et al., 2018). Chart 5 recalls the main conclusions of this pilot stress test in terms of deviations of system-wide levels of the CET1 ratio and lending to the non-financial private sector from their baseline levels in the event of a sharp increase in energy prices ("an abrupt policy response scenario") and the emergence of green technological innovation with a transitory negative impact on brown sectors of the economy ("technological innovation shock scenario"). Overall, the pilot climate stress test conveyed the reassuring message that even the most disruptive transition to a green economy should have a very contained and gradually diminishing negative impact on banking sector solvency and lending.

Chart 5

Effects of the abrupt policy response and asymmetric technological innovation shock scenarios on system-wide CET1 ratios (panel a) and loans to the non-financial private sector (panel b)

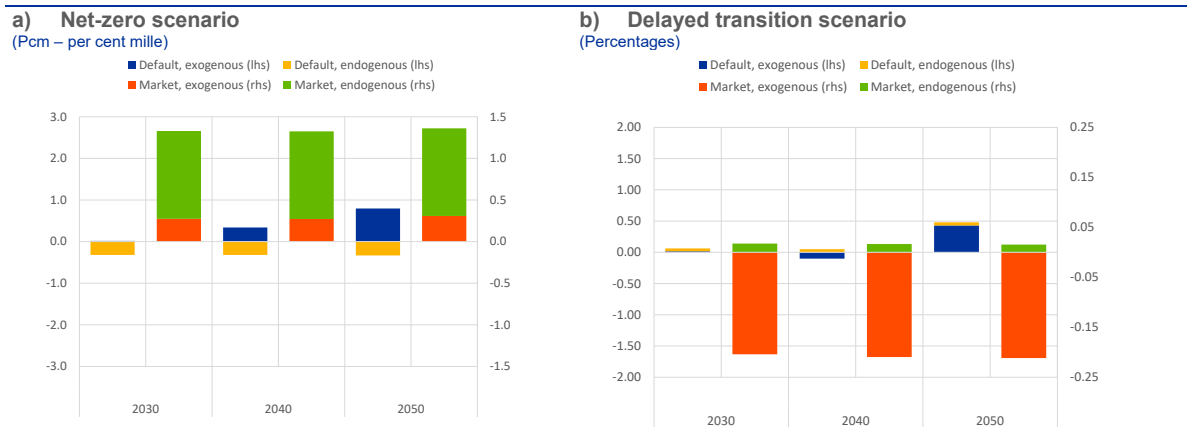


Source: ESRB (2020).

One of the later climate risk analyses highlighted the system-wide nature of climate risks. The exercise looked at the propagation of climate risk scenarios, with timely and orderly (“net zero”) and delayed (“delayed transition”) scenarios against the baseline scenario of no policy adjustment (“current policy scenario”) through the lenses of the ECB system-wide stress test. The stress test demonstrated that climate risks are likely to trigger pronounced amplification effects in a financial system with interconnected banks, insurance companies and investment funds. Chart 6 contrasts the exogenous (first-round) and endogenous (second-round) effects of the scenarios on financial system losses related to credit and market risk. The system-wide amplification of initial market risk shocks in the net zero 2050 compared with the current policy scenario multiplies the initial first-round reduction in relative revaluation losses by over five times.

Chart 6

System asset gains or losses in the net zero (panel a) and delayed transition (panel b) scenarios compared with the current policy scenario



Source: ECB/ESRB Project Team on climate risk monitoring (2022).

Notes: “Default, exogenous” refers to NFC defaults. “Market, exogenous” refers to exogenous market losses both due to the market scenario and due to the price drop of exogenously defaulting NFCs issuing securities. “Endogenous” losses are model-driven.

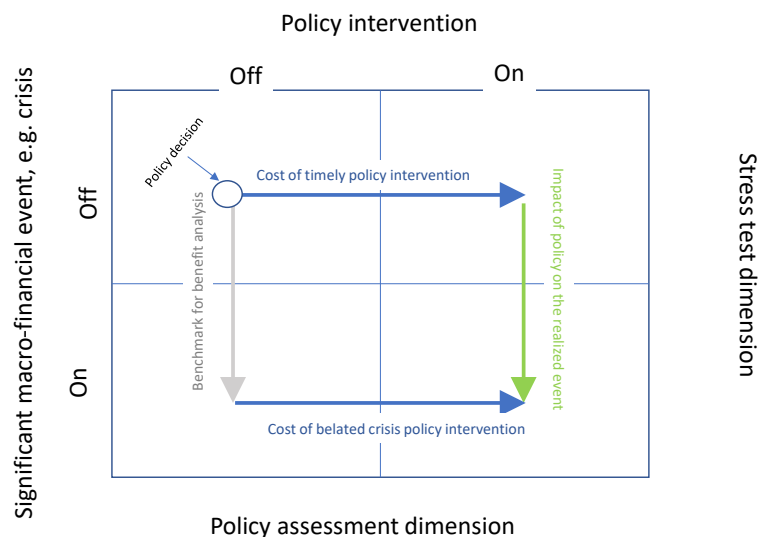
2.1.2 Policy assessment and calibration

The impact assessment of prudential policies deployed to “tame the cycle” is relatively straightforward. Similarly to monetary policies, their benefits are commensurate with the change in target variables over the impact horizon. A capital buffer that has been increased with a view to defueling house price growth, or interest rates that have been increased to undercut inflation, should be judged against the resulting actual or projected drop in house or general prices. Assessing the impact of such policies commonly involves studying the economy with and without a policy in the absence of extraordinary events.¹¹ In other words, such impact assessment boils down to comparing two sets of conditional simulations, with and without regulation.

The benefits of resilience-building policies are harder to assess, as they come to the surface only in rare adverse circumstances. Assessing the costs of resilience-enhancing policies commonly relies on tracking changes in lending or economic activity during their phase-in. However, their benefits call for examination of possible but negative future scenarios.

Stress testing adds an important dimension to the impact assessment of pre-emptive policies. Figure 2 illustrates the advantage of stress testing for resilience-building policy analysis. Traditional impact assessment approaches follow the upper horizontal arrow. Measuring the impact of a policy in normal macro-financial conditions (a significant macro-financial event is “off”) boils down to assessing the impact on variables of interest of a movement from no policy (policy intervention “off”) to policy (“policy intervention “on”). For resilience-building policies, it often corresponds to the costs of policy implementation, as such policies tend to be introduced in relatively good times. The value added of stress testing is that it can “generate” macro-financial states where pre-emptive policies matter. It is indicated by two arrows pointing downwards. The benefit of resilience-building policies is captured by the difference between the outcome along with the green arrow (from micro-financial event “off” to “on”) in the presence of a policy against a similar outcome along with the grey arrow in its absence. An additional dimension offered by stress testing is the bottom horizontal arrow. It can warn about high costs of policy phase-in in disadvantageous times (with a significant macro-financial event being a crisis scenario)¹² or more exactly measure the advantages of “taming the cycle” policies (with a significant macro-financial event being a boom or overheating scenario).

Figure 2
Stress testing in support of policy assessment



Source: ECB authors.

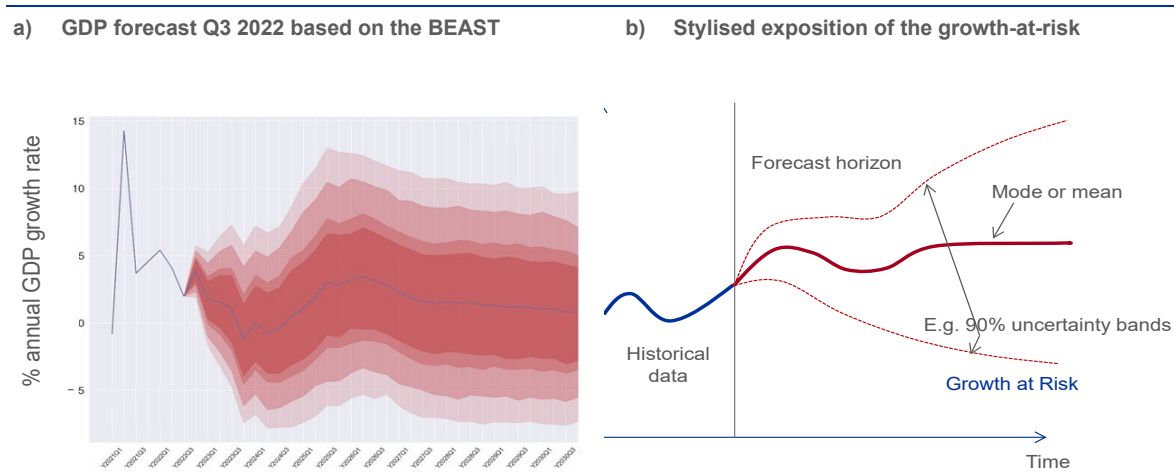
¹¹ In fact, most empirical and theory-based (e.g., dynamic stochastic general equilibrium model based) impact assessments of policies operate under a silent assumption that the economy remains in its normal state (e.g., around its steady state).

¹² For instance, in the Basel III finalisation impact assessment, this dimension was used to illustrate the disadvantage of phasing in Basel III in a crisis and contrast the relatively low costs of its phase-in following the fading of the COVID-19 pandemic.

Another property of most stress-testing methods is that they can be applied to multiple scenarios that follow different economic narratives. In the ECB vulnerability analysis for the COVID-19 pandemic, there were three scenarios (Chart 4): (i) the baseline scenario, which was defined before the coronavirus outbreak and provided a benchmark to assess the impact of the pandemic on banks; (ii) the COVID-19 central scenario, which reflected the most likely scenario to materialise according to the June 2020 Eurosystem staff macroeconomic projection; and (iii) the COVID-19 severe scenario, which assumed a deep recession and slow economic recovery.

The ability to generate multiple scenarios links to the growth-at-risk perspective. With a sufficient number of plausible future macro-financial scenarios, it is possible to describe a full distribution of macroeconomic or financial outcomes. Fan charts, such as in the left-hand panel of Figure 3, can illustrate the level of economic activity with surrounding uncertainty. Moreover, the lower percentiles of the derived distributions directly link to growth at risk. Such stress test analyses can describe tail risks or events without taking a stance on the most relevant economic narratives.

Figure 3
Fan charts based on semi-structural models and growth-at-risk measures

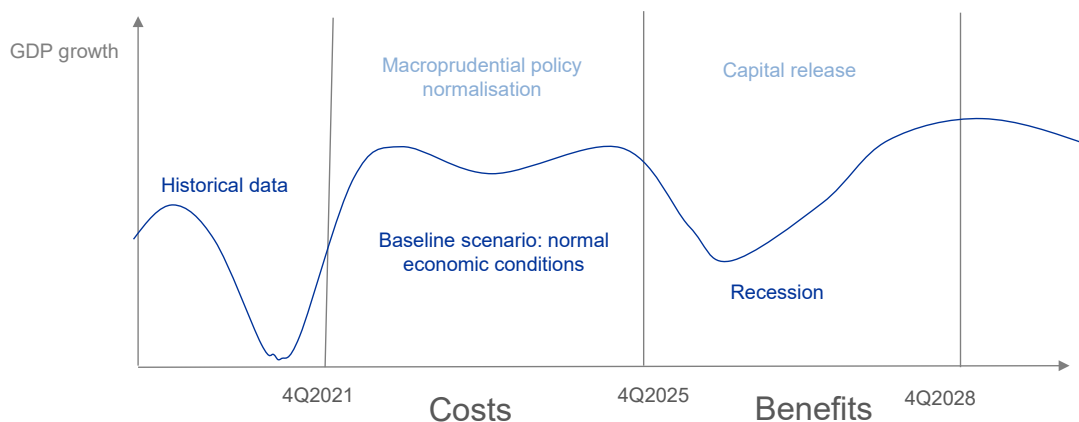


Source: ECB authors.

2.1.2.1 Releasable capital buffers

The approach to balancing the costs and benefits of a countercyclical capital buffer (CCyB) or a releasable sectoral systemic risk buffer (sSyRB) is summarised in Figure 4. The assessment shown here was conducted upon exiting the COVID-19 recession by applying the ECB macroprudential stress test. The phase-in of a releasable buffer was considered in the context of the conditions described in available economic forecasts, which for the assessment run in early 2022 was the December 2021 ECB staff macroeconomic projections. In Figure 4, this part of the assessment is represented by the stylised evolution of euro area GDP growth between the end of 2021 and 2025 in “Baseline scenario: normal economic conditions”. The impact of the buffer phase-in on bank lending amounts to policy costs.

Figure 4
Buffer build-up and release under stylised economic conditions



Source: ECB authors.

Buffer release is considered at the onset of a hypothetical country-specific recession starting at a future point in time. The release of the buffers at the onset of a recession (here at the beginning of 2026) would ideally stabilise lending to the real economy. This additional lending amounts to benefits from the buffer policy.¹³

The phase-in of German policies announced in January 2022, namely a CCyB of 0.75% and an sSyRB of 2%, were estimated to have a very limited impact on bank lending. The phase-in of buffers under forecasted economic conditions translated into an increase in the actual CET1 ratio of 0.3 percentage points (green bar for the end of 2025 in Chart 7), while imposing practically no credit supply constraints. The buffer policy was estimated to lead to only a very minor cumulative reduction of 0.3% in lending to the non-financial private sector by the end of 2025 (blue bar for the end of 2025 in Chart 7).

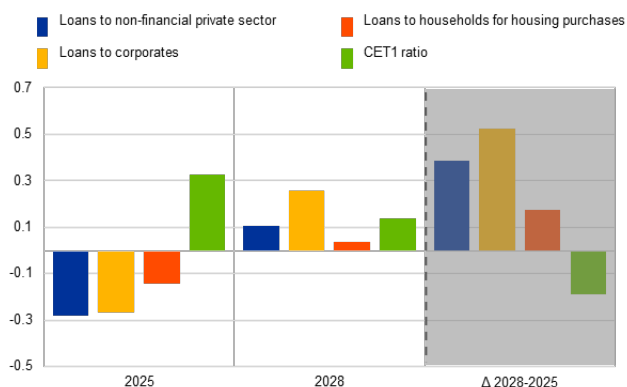
The release of capital buffers at the onset of a subsequent recession was found to support lending without compromising the actual solvency of banks. A joint release of the CCyB and sSyRB was estimated to lessen the reduction in lending to the non-financial private sector by 0.4 percentage points. Cumulative lending to the non-financial private sector at the end of 2028 was found to be 0.1 percentage point higher than in the absence of any buffer policies over the entire period (blue bar for the end of 2028 in Chart 7) and 0.4 percentage points higher than at the end of 2025 (blue bar to the right of Chart 7). The analogous boost to lending for corporates during the recession amounted to 0.5 percentage points (yellow bar to the right of Chart 7). At the end of the recession, the average CET1 ratio in Germany was estimated to be 0.14 percentage points higher than if the buffers had not been built up earlier.

¹³ In the quoted application, country-specific recessions are designed to be triggered by negative aggregate demand shocks and coupled with a general recession in the euro area. The economic crises selected have, on average, a peak decline in annual real GDP growth of around 2.5-3.0%.

Chart 7

Impact of the phase-in and release of the 0.75% CCyB and 2% sSyRB in Germany

Deviation from the baseline with 0% CCyB and sSRB at the end of 2025 and 2028 and difference between the cumulative deviations from the baseline in 2028 versus 2025.
(Percentage points)



Source: Budnik et al. (2022a).

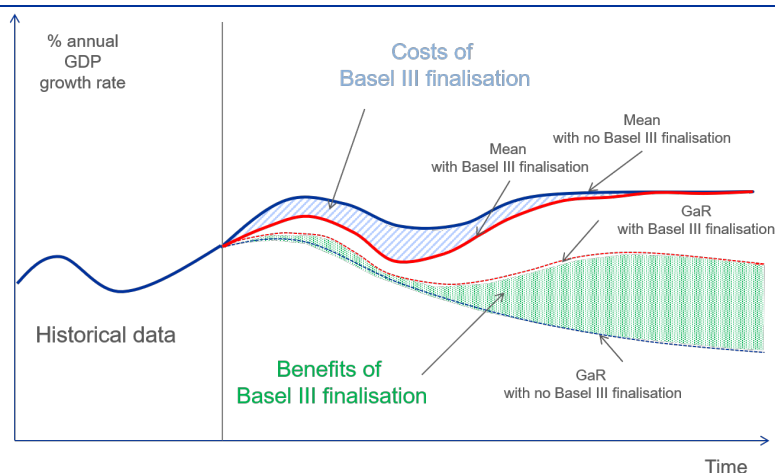
Notes: The left-hand and middle bars show the cumulative deviation from the baseline at the end of 2025 and 2028 respectively. Δ 2028-2025 corresponds to the differences between the cumulative deviations from the baseline at the end of 2028 versus 2025, i.e., the difference between two earlier bars of the same colour. It captures the benefits deriving from the implementation of higher buffers in preceding years and their release during a recession. The benchmark corresponds to a CCyB and an sSRB of 0% over the entire period of analysis.

2.1.2.2 Non-releasable capital instruments and automatic stabilisers

Non-releasable capital instruments and regulatory limits are expected to contribute to financial system resilience even in the absence of their situation-specific adjustment. Over-the-cycle capital buffers as well as requirements, caps and floors on certain activities or parameters modify banks' and other financial institutions' incentives to take on risks. They can become more binding in certain circumstances, acting as automatic stabilisers. Though the impact assessment of such instruments can follow the same format as that of releasable buffers, their constancy over time reduces the need to specify the moment and type of their adjustment.

The benefits of capital regulation can be assessed by looking at the shifts in the tails of distributions of variables such as lending or output. The assessment calls for two conditional simulations (with and without policies), each of which should cover the full distribution of plausible or specific eventualities, such as scenarios portraying economic booms or recessions. The means of the two simulations provide information about the expected effect of the regulation. A negative difference between the means of economic output, as illustrated by the blue-shaded area in Figure 5, would indicate the economic costs. Tails, or lower percentiles such as the 10th percentile of the distribution, provide information about the effects of the package in adverse economic conditions. A positive difference between the tails of the distributions, represented by the green area in Figure 5, would show the benefits of the regulation which stem from improved financial intermediation when the economy is hit by a crisis.

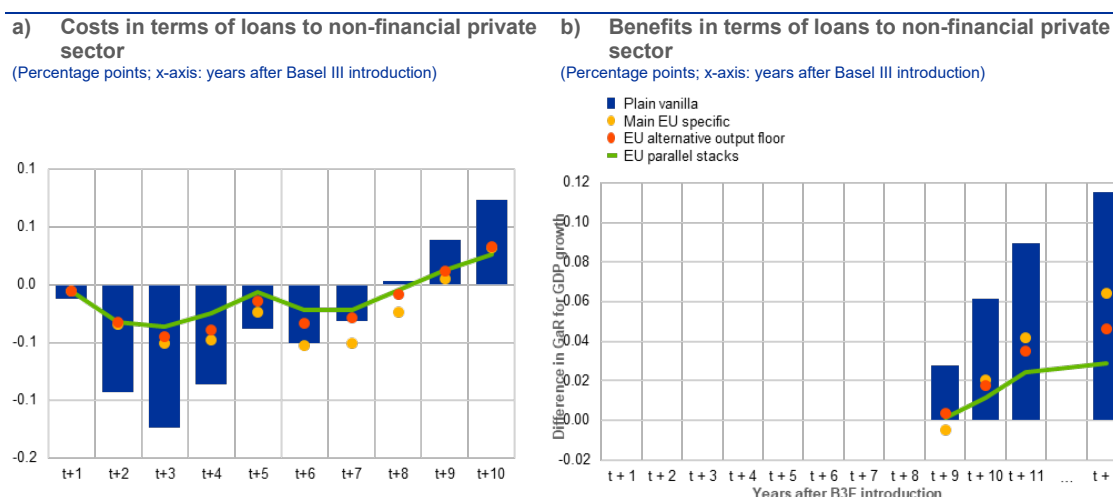
Figure 5
Stylised representation of a growth at risk-based cost-benefit assessment



Source: ECB authors.

The growth-at-risk approach of measuring the benefits of regulation leverages the ability of stress-testing tools to analyse multiple macro-financial scenarios conditional on policies. This approach was successfully implemented within the macroprudential stress test model to analyse the impact of Basel III finalisation, or the SSM NPL coverage expectations phased in in 2018. In both instances, the regulation was a complex solution set, such as multiple adjustments to risk weights, the introduction of an output floor and additional leverage buffers for the Basel III finalisation, and various and time-varying provisioning coefficients for NPLs depending on their time in arrears. This brought to the fore yet another advantage of stress-testing methods in the service of policy assessment: their ability to accommodate highly complex regulatory solutions thanks to their detailed treatment and comprehensive illustration of banks' balance sheets. Chart 8 presents the results of the most recent impact assessment of Basel III finalisation with its costs measured as losses in expected euro area GDP (panel a)) and benefits as gains in the 10th percentile of growth distributions (panel b)).

Chart 8
GDP costs and long-term growth-at-risk benefits of the plain vanilla versus three EU approaches to the Basel III implementation based on the pre-COVID-19 scenario



Source: Budnik et al. (2021c).

Notes: Impact is measured relative to the regime without Basel III finalisation. In the right-hand panel, the difference is shown between annual euro area GDP growth with and without Basel III finalisation in the corresponding 10th percentile of the output distributions. The plain vanilla reform corresponds to the original Basel III finalisation package and excludes any EU specificities. The main EU-specific approach considers three additional features: the application of the SME supporting factor on top of the Basel SME preferential risk weight treatment, the continuation of existing exemptions regarding the calculation of capital requirements for CVA risk, and the exclusion of the bank-specific historical loss component from the calculation of the capital for operational risk (ILM=1). The output floor is implemented as it is under the plain vanilla approach. The alternative EU-specific approach builds on the main EU-specific approach but modifies the implementation of the output floor. This option assumes that Pillar 2 requirements and the systemic risk buffer (SyRB) apply to unfloored RWAs and not to floored RWAs (as is the case in the plain vanilla and main EU-specific approach). The EU parallel stacks approach builds on the main EU-specific approach but implements the output floor such that bank capital requirements are defined as the higher of the floored requirements excluding Pillar 2 and SRB and the unfloored requirements including Pillar 2 and the SyRB.

2.1.2.3 Temporary policies in times of high uncertainty

The possibility of designing various macro-financial scenarios can help to assess prudential policies taken to weather a crisis. The onset of any crisis or recession introduces high levels of uncertainty about how the economy will evolve and how deep and long the adverse event will be. At the same time, the impact of policies is likely to depend on the nature of the event. The ex ante effectiveness and sufficiency of policies in highly uncertain conditions can be reasonably addressed by analysing policy effects under several alternative scenarios.

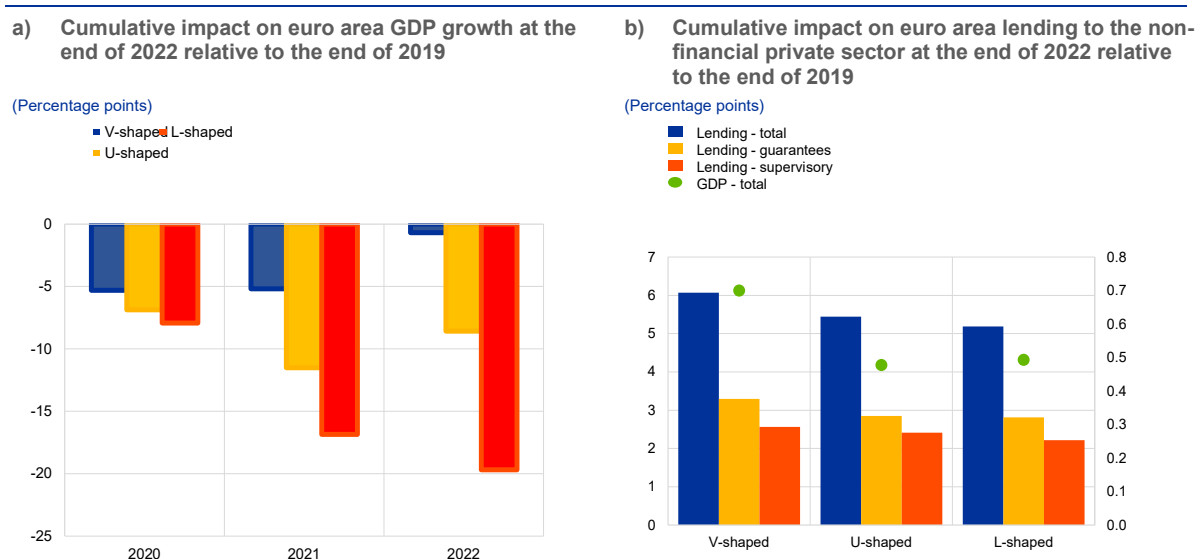
The ECB's macroprudential stress testing was used to address prodigious economic uncertainty and assess the effectiveness of policies taken during the COVID-19 pandemic (Budnik et al., 2022a). Three families of scenarios were selected to address the uncertainty about the duration and depth of the COVID-19 pandemic. The three narratives expressed an increasing degree of pessimism about economic activity in 2020-22. The first family of scenarios, dubbed a V-shaped recession, predicted a sharp contraction in economic activity and a relatively quick recovery (starting as early as the second half of 2020). The second family, a U-shaped recession, predicted a slower recovery potentially interrupted by a second wave of the COVID-19 pandemic in the second half of 2020. The third family, an L-shaped recession, envisaged a prolonged period of lockdown causing severe economic contraction.

In response to the severe economic shocks triggered by the outbreak of the pandemic, supervisory and macroprudential authorities in Europe promptly introduced capital relief measures. This capital release package complemented targeted government policies. Generous public guarantee policies were put in place across almost all euro area countries to lessen the credit supply constraints for corporates, given that losses from guaranteed loans were largely covered by the government. In addition, public moratoria were introduced for both the corporate and household sectors, enabling them to postpone debt repayments for a certain period.

The scenario-sensitive impact assessment of the COVID-19 prudential and public guarantee mitigation policies revealed that the policies were best tailored to a relatively short-lasting recession. Under the V-shaped scenario, the cumulative impact of public guarantees was estimated to add around 3.3% to lending to the non-financial private sector in the euro area by the end of 2022. Under the L-shaped scenario, this was 2.8% (panel b) of Chart 9). The capital release package introduced by supervisory and macroprudential authorities, jointly with profit distribution restrictions and policies supporting public moratoria, complemented targeted government policies. This added 2.6% to lending to the non-financial private sector in the case of a short-lasting (V-shaped) recession and 2.2% in a deep and long-lasting (L-shaped) recession. Jointly, the policies were found to stabilise economic activity measured in GDP terms by 0.7% for the least severe scenario and by more than 0.5% for the more severe scenario (panel a) of Chart 9). The impact of supervisory and government policies that primarily sought to prevent credit supply shortages was found to decrease with the recession severity due to the progressively weaker credit demand outlook.

Chart 9

Alternative COVID-19 scenarios and cumulative lending impact of mitigation measures



Source: Budnik et al. (2021b).

Notes: The V-shaped recession assumed a sharp contraction in economic activity and a relatively quick recovery (starting as early as the second half of 2020). The U-shaped recession predicted a slower recovery potentially interrupted by a second wave of the COVID-19 pandemic in the second half of 2020. The L-shaped recession envisaged a prolonged period of lockdown causing severe economic contraction. Blue bar in panel b): cumulative impact of all policies jointly. Red bar in panel b): supervisory policies. Yellow bar in panel b): national guarantee policies. The green dots in panel b) illustrate the total cumulative impact of all policies on GDP (right-hand scale).

2.1.3

Communication

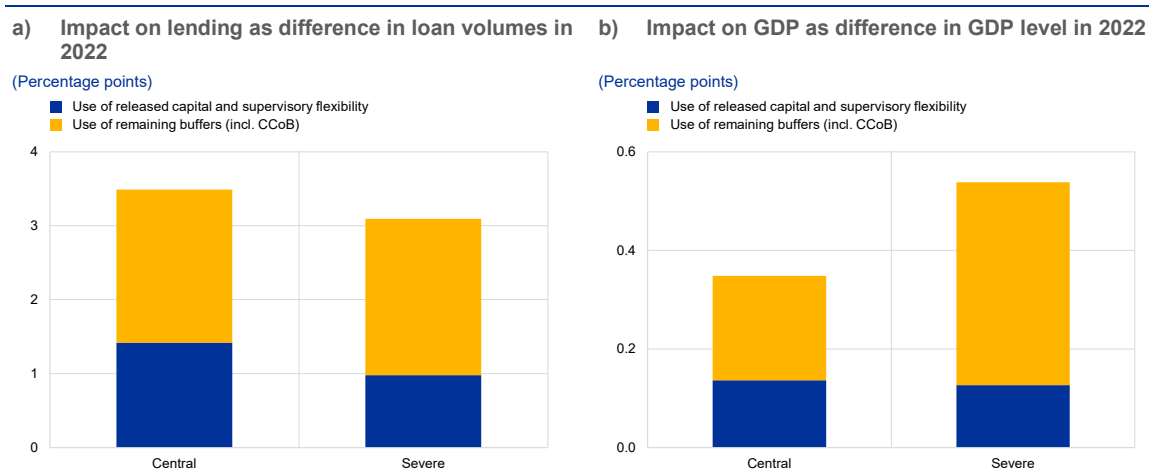
Stress testing can support authorities' communication with the industry and markets by providing a timely assessment of the quality of banks' assets or their vulnerabilities. The publication of stress test results allows market participants to assess banks' ability to meet applicable minimum and additional capital requirements. Thus, the disclosure of bank-level results provides new information to market participants (Durrani et al., 2022; Durrani, Ongena and Ponte Marques, 2022), therefore promoting market discipline and transparency (Konietschke et al., 2022b; Georgescu et al., 2017; Kok et al., 2022). This suggests that stress tests play an important role in improving financial stability and restoring confidence in the banking system by mitigating bank opaqueness among market participants and, at the same time, building up confidence in the banking system.

The potential of stress testing to serve as a communication tool does not end there. For instance, macroprudential stress testing can be used to help financial institutions take the best decisions from a system-wide perspective.

During the COVID-19 pandemic, the ECB used macroprudential stress testing in its communication to support banks' use of capital buffers. Model simulations were used to illustrate that when banks refrain from dipping into their non-releasable but usable capital buffers, they are more likely to amplify credit supply shortages and intensify the downturn. Non-use of capital buffers is a form of coordination failure, whereby an individual bank that seeks to maintain solvency above regulatory targets prevents the optimal sector-wide use of buffers by all banks in the system.

The model results provided timely reassurance that banks' use of capital buffers would lead to better economic outcomes without negatively affecting their resilience. The analysis depicted in Chart 10 determined that using capital buffers to absorb losses and continue lending would lead to an increase in cumulative lending to the real economy of between 2% and 3%, and in GDP by more than 0.5%, over the two-year horizon of the pandemic-induced recession. The resulting positive impact on economic activity was estimated to reduce credit losses and protect banks' profitability. The CET1 ratios were projected to remain essentially unaffected due to dividend restrictions on banks.

Chart 10
Buffer use in support of lending and economic activity



Source: Enria (2020).
Notes: Estimates use the central and severe scenarios from the ECB's 2020 vulnerability analysis. "Use of released capital and supervisory flexibility" includes use of P2G, CET1 capital released with the front loading of P2R changes and released macroprudential buffers. "Use of remaining buffers (incl. CCoB)" comprises the use of all capital above P1R and P2R, with MDA restrictions still binding. The analysis takes account of non-buffer elements of the supervisory support packages of 12 and 27 March 2020, national moratoria and guarantee schemes.

2.2 An overview of WGST deliverables and achievements

The WGST delivered on its mandate of operationalising state-of-the-art methodologies. The work stream on top-down benchmarks continued improving and expanding the models used to produce benchmarks in the EU-wide stress test exercises. It strengthened the validation of these models and swiftly adapted especially credit risk models to new challenges introduced by the COVID-19 pandemic, such as the need for sector-level analysis. The work stream on macro-micro interactions finalised the development of the core semi-structural BEAST model and supplied new evidence on banks' lending behaviour, benefiting dynamic balance sheet stress testing in more general terms. Finally, the system-wide stress testing work stream delivered on its promise to provide a multi-sector financial system model for system-wide stress testing.

The cooperation and discussions within the working group helped to facilitate its achievements, surpassing initial expectations. Table 2 breaks down the activities of each work stream into deliverables, i.e., items inherently present in the initial working group mandate, and achievements, i.e., additional items that pushed the ECB stress testing beyond initial expectations. The latter included the use of ECB top-down models to perform stand-alone top-down vulnerability analyses, the intense use of the BEAST model for policy analysis (and communication) and initial policy applications of the system-wide stress-testing platform.

Table 2
Overview of main deliverables and achievements of the WGST

	Top-down benchmarks	Macro-micro interactions	System-wide stress test
Deliverables	<ul style="list-style-type: none"> Improvement and expansion of benchmark models for credit, market risk and profitability employing new techniques Implementation of a comprehensive validation framework Fostering of data exchange and incorporation of new datasets, e.g., EMIR, Anacredit Provision of benchmarks for EU-wide stress tests Timely response to new challenges, such as the need for sector-level analysis (climate risks, COVID-19) 	<ul style="list-style-type: none"> Further development of a macro-financial semi-structural model for macroprudential stress tests Introduction of multiple-scenario analysis and growth-at-risk approaches within the model Validation of estimates of main behavioural equations in macroprudential stress tests Expanded use of dedicated datasets, e.g., NPL coverage expectations 	<ul style="list-style-type: none"> Development of a three-sector model for banks, insurance companies and investment funds with an emphasis on direct and indirect contagion

	Top-down benchmarks	Macro-micro interactions	System-wide stress test
Achievements	<ul style="list-style-type: none"> • Top-down vulnerability analysis in 2020 and later analyses in 2022, including interest rate sensitivity and impact of Russia-Ukraine war • Core position in the EBA centralised approach that aims to increase the top-down component of the EU-wide stress test 	<ul style="list-style-type: none"> • Regular macroprudential stress tests • Assessment of Basel III finalisation • Tailored assessments of prudential (and other) policy measures • Macroprudential risk assessments, including for climate risks and interest rate sensitivity 	<ul style="list-style-type: none"> • System-wide climate stress test in 2022 • Support for the implementation of the model by other institutions

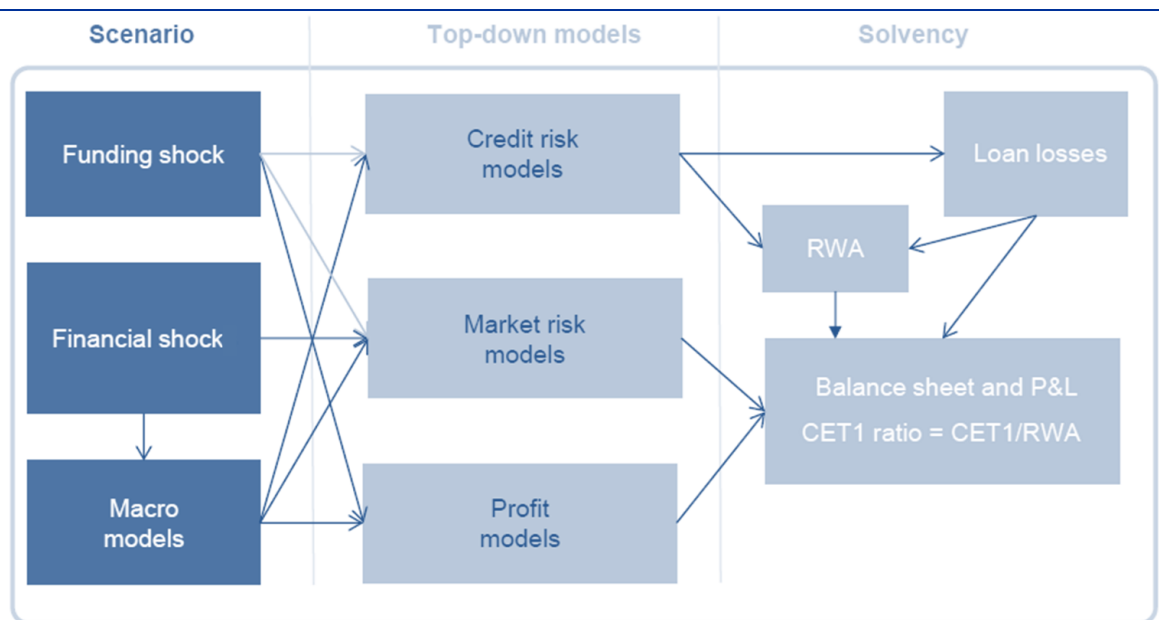
Source: ECB authors.

3 Top-down models

3.1 Overview of top-down models

The ECB offers a suite of analytical tools for top-down risk benchmarks developed by ECB staff over the past ten years. The ECB top-down modelling framework is essential to assessing banking system vulnerabilities and gauging risks to financial stability (Figure 6). The top-down credit risk modelling suite concerns the risk of borrower default and includes both loan-loss provisioning and risk-weighted asset components, for which banks need to hold capital. The market risk modelling suite is mainly focused on the revaluation of losses and affects mostly larger global systemically important institutions given their sizeable trading books. On the profitability side, the suite of models looks at different income sources, including net interest income (NII), net fee and commission income (NFCI) and dividend income. Overall, the focus of the modelling framework is on the variation of banks' profits and losses and, consequently, solvency positions.

Figure 6
Top-down modelling framework



Source: Adapted from Henry and Kok (2013).

The top-down models translate macro-financial scenarios into projected profits and losses and capital charges. In the EU-wide stress tests, these projections are primarily used as a benchmark of banks' estimates, while in stand-alone vulnerability exercises, they underlie a comprehensive assessment of bank solvency. Table 3 provides a full overview of top-down model applications.

Table 3
Top-down model applications

	Topic	Main outlets	Description
Assessment of multiple risks to capital	EU-wide stress-testing exercises (CEBS, EBA and finally EBA/SSM)	2009-23 EU-wide stress-testing exercises	Assessment of the resilience of financial institutions to adverse market developments as well as contribution to overall assessment of systemic risk in the EU financial system. The top-down models, as the primary challenger, are considered the main contributor in such exercises.
	Comprehensive assessment stress-testing exercises	Comprehensive assessment stress-testing exercises (since 2014)	Assessment of the resilience of banks' balance sheets entering the Single Supervisory Mechanism. Top-down models are used as the main challenger against banks' projections.
	Vulnerability analysis exercises	COVID-19 vulnerability analysis, Russia/Ukraine vulnerability analysis (2020, 2022)	Analysis of the impact on the banking sector based on hypothetical scenarios targeting emerging vulnerabilities that could be seen as a threat to financial stability, e.g., COVID pandemic , Russia/Ukraine conflict .
	Interest rate risk sensitivity analysis	VoxEU article on interest rate risk sensitivity analysis (2022)	Assessment of the interest rate risks affecting banks' balance sheets. In particular, assessment of how a parallel shift in the euro area yield curve, or its steepening, might affect banking sector profitability and solvency (Budnik et al. 2022b).
	Scenario impact assessment	Impact assessment for scenarios (different ECB outlets, since 2010)	Assessment of the impact on specific risk areas or solvency positions under various scenarios. Typical outlets include the Financial Stability Review (ECB, 2022).
Selection of topical assessments and publications ¹⁴	Sector-level corporate probability of default	VoxEU article on the impact of the Russian invasion on firm default probabilities (2022)	Assessment of the heterogeneous impact of the war on firms in Europe via the application of country-specific macroeconomic shocks with heterogeneous sectoral characteristics under two tail scenarios to project probabilities of default over a three-year horizon (Konietschke et al., 2022a).
	Stress testing of net trading income	ECB Working Paper Series (2021)	Introduction of a two-step econometric approach to quantify the downside risk of financial shocks to banks' trading revenues (Cappelletti et al., 2021).
	CoVaR approach to asset commonality and its application to SSM banks	ECB Working Paper Series (2022)	Introduction of a new methodology for identifying and assessing banking sector systemic risk stemming from asset commonality in the spirit of CoVaR (Cappelletti et al., 2022).

Source: ECB authors.

The top-down benchmark models are complemented by a family of tools and infrastructures summarised in Table 4. Appendix 8.2 discusses these tools in more detail.

¹⁴ An internal financial stability report on top-down model development and enhancements was also distributed to SSM and ESCB members. This was the first interim report on ECB top-down model development across risk areas.

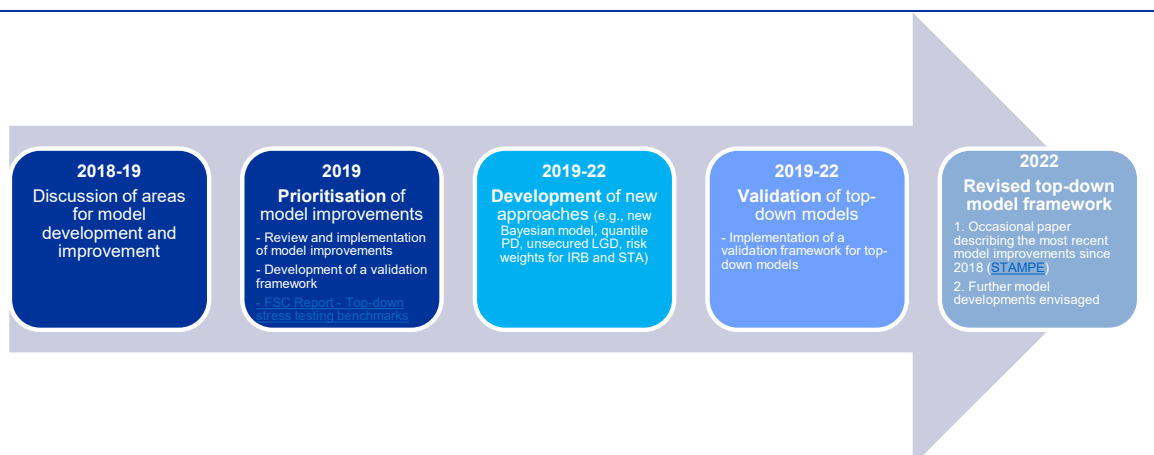
Table 4
Top-down model tools and infrastructure

Topic	ECB internal infrastructure	Shared with banks	Other
Credit risk	IFRS9er: a tool quantifying credit risk losses relying on benchmark parameters conditional on a macro-financial scenario.	Path Generator: an ECB Excel-based tool that replicates the methodology of the top-down credit risk models and provides the ECB credit risk benchmarks to banks.	Model assessment questionnaires: provided by banks and including supplementary technical information on banks' models. The main purpose is to elucidate modelling options and explain the differences in banks' projections relative to top-down projections.
Profitability	NlIer: a tool providing projections for net interest income relying on benchmark parameters conditional on a macro-financial scenario.		
Market risk	SHS-G: a tool building upon the database of Securities Holding Statistics by Reporting Banking Group (SHS-G) and computing the impact of a scenario on bank holdings of equities, fund shares and bonds. EMIR pricing (EPIC): a tool building upon the EMIR derivatives database and repricing items in derivative portfolios or providing their sensitivities to selected risk factors.		

Source: ECB authors.

The work of the top-down benchmark work stream pursued the medium-term goal of developing a robust and consistent modelling framework in the three risk areas. Figure 7 provides an overview of the work stream's activities, which started with technical discussions on areas for model development and improvement, based on the lessons learned from earlier EU-wide stress tests and validations of the top-down models performed by an academic evaluator. This was followed by a prioritisation of model improvements. From 2019 onwards, the group focused on the development of both new approaches and a model validation framework, with the latter including back-testing and additional in-sample and out-of-sample validation tests.

Figure 7
Top-down model development timeline



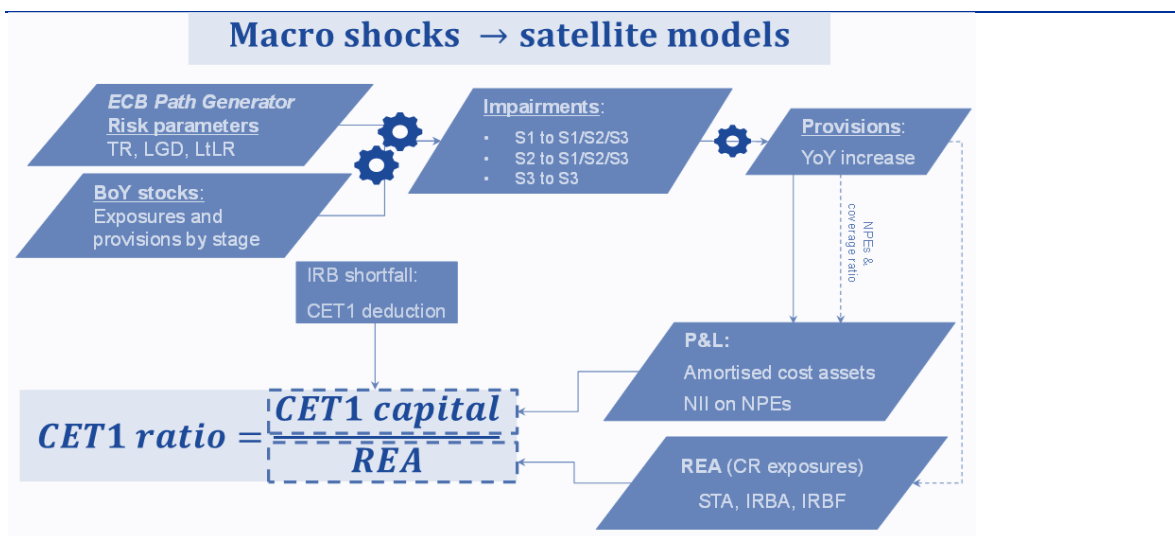
Source: ECB.

The remainder of this section is structured as follows. Subsections 3.2 to 3.4 describe the credit risk top-down models, while subsections 3.5 and 3.6 detail the top-down models for profitability and market risk, respectively.

3.2 Credit risk: overview

The credit risk models encompass the top-down models of IFRS 9 risk parameters (loan losses) and of risk exposure amount parameters (Figure 8).¹⁵ The IFRS 9 parameters are used to calculate impairments (that enter profit and loss) and affect the numerator of the bank capital adequacy ratio.¹⁶ The regulatory parameters, as prescribed in the Capital Requirements Regulation (CRR)¹⁷, are used to compute the risk exposure amounts and affect the denominator of the bank capital adequacy ratio.¹⁸ Jointly, they provide the quantification of credit risk losses conditional on a macro-financial scenario.

Figure 8
High-level overview of top-down credit risk computation



Source: ECB authors.

The main changes to the credit risk methodology introduced by the WGST are compiled in Table 5.

Table 5
Top-down credit risk model developments

1. Top-down IFRS 9 credit risk parameter-related projections:	2. Top-down risk exposure amount credit risk parameter-related projections
<ul style="list-style-type: none"> Adaptation of top-down approaches to the IFRS 9 standard, which outlines a “three-stage” framework for impairments based on changes in credit quality; Adoption of an alternative Bayesian variable selection approach to estimate expected default rates at country and portfolio level for EU geographies: the Stochastic Search Variable Selection (SVSS) model; Implementation of a non-linear panel quantile regression model to estimate expected default rates at country and sectoral level for non-financial corporations; Improvement of the framework based on bridge equations to estimate expected default rates for non-EU geographies; Development of an analytical framework to project loss given default parameters for loans not collateralised by real estate; Improvement of the framework to account for loss given default projections for loans collateralised by real estate, which includes the distribution of the “sales ratio” and the respective relation with bank starting points; Improvement of the lifetime loss rate projection model by including the transition rate from stage 2 to stage 1 (TR²⁻¹) path; 	<ul style="list-style-type: none"> Development of an econometric top-down set-up for portfolios using the standardised approach; Improvement of top-down models for portfolios under the internal ratings-based approach for both regulatory probabilities of default and loss given default parameters.

Source: ECB.

¹⁵ These two categories of credit risk are reported separately in the EBA templates (CSV_CR_SCEN and CSV_CR_REA).

¹⁶ On 24 July 2014, the International Accounting Standards Board (IASB) issued IFRS 9 incorporating a new expected loss impairment model, which was effective from 1 January 2018. It introduced a new methodology for incurred losses, which was replaced with a more forward-looking expected loss method. Impairments are also considered in the denominator of the bank solvency ratio via deductions to the exposure at default amounts (for loans under the standardised approach).

¹⁷ See <https://eur-lex.europa.eu/legal-content/en/TXT/?uri=celex%3A32013R0575>.

¹⁸ This is partly considered in the numerator of bank capital adequacy when computing the IRB shortfall.

3.3 Credit risk: IFRS 9 parameters

The ECB benchmarks are estimated using a suite of econometric models and are conditioned on the baseline and the adverse macro-financial scenario in stress-testing exercises. The models employed combine time series and panel data econometric techniques to capture the relationship between macroeconomic variables projected in the scenario and credit risk parameters, including quantile panel approaches that account for their non-linear behaviour in the tails. The historical data for default rates (or proxies thereof) and IFRS 9 transition probabilities used to calibrate the ECB models are reported by national authorities. This ensures that the parameter projections are based on a long time series that effectively captures the default dynamics of each country participating in the stress tests.

The projections of IFRS 9 parameters for bank portfolios are defined at country and market segment level. The scenario-conditional forward paths for IFRS 9 are derived for all countries covered by a macro-financial scenario¹⁹ and for the following market segments: real estate-collateralised portfolios (mortgages, non-financial corporates), non-real estate-related exposures (consumer credit, non-financial corporates, financials) and sovereigns. They account for expected default rates (subsection 3.3.1), transition probabilities (3.3.2), loss given default (3.3.3) and lifetime loss rates (3.3.4).

3.3.1 Expected default rates (or point-in-time probabilities of default)

A top-down stress test involves estimating scenario-conditional projections, where expected default rates (or point-in-time probabilities of default) follow a path under a baseline and a severe but plausible scenario for loans located in both EU and non-EU countries (from EU banks with cross-border activity). The scenario-conditional shift in the path of the top-down point-in-time probability of default is applied in a distance-to-default space to ensure the bank's starting-point dependency²⁰ (detailed in Appendix 8.1). The distance to default is implemented to ensure the application of top-down parameters, provided at country and portfolio levels, to bank-specific starting points. The quantification of distance to default can be empirically ascertained through the application of a power equation derived from probabilities of default. For example, Moody's KMV maps distance to default to probability of default. For a detailed explanation, refer to the work of Crosbie and Bohn (2003).²¹

The selected modelling options to estimate scenario-conditional forward paths for expected default rates are presented in the following subsections. The first subsection details the baseline specification, while the next subsection introduces a novel model tailored to firms at both country and sectoral levels. This model was developed with a focus on sectoral vulnerabilities, given recent events such as COVID-19 and the Russian invasion of Ukraine. The last subsection details the model used for non-EU geographies.

3.3.1.1 Bayesian stochastic approach (baseline specification)

The Bayesian stochastic framework delivers scenario-conditional forward paths for expected default rates for 27 EU countries. The framework can efficiently consider a large set of variables (reflecting different scenario features) while preserving a parsimonious model specification (in terms of number of parameters) that can be robustly estimated with the data at hand (i.e., accounting for overparameterisation). The framework relies on country-level historical default rate series from: (i) national authorities across EU countries, (ii) the Moody's Kealhofer, McQuown and Vasicek (KMV) model of default rates for financial corporations, and (iii) Kamakura-based indicators of expected default rates for sovereigns.

¹⁹ As published by the ESRB: Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, United Kingdom, Norway, United States, Japan, Canada, Switzerland, Australia & New Zealand, Turkey, Russia, Emerging Asia, China, India, Latin America, Brazil, Mexico, Chile, Rest of the World.

²⁰ To derive bank-specific point-in-time probabilities of default, top-down parameter paths are attached to bank starting points with a locational perspective in a distance-to-default space. Instead of the chosen transformation, alternative options such as a logit, a probit or an inverse normal could have been employed. The top-down benchmarks, sourced from a data collection which aggregates information on the banking system at a country level, are strategically applied in a distance-to-default space. This approach ensures that the starting points of individual banks are duly considered from a country perspective.

²¹ Some additional references provide insightful explanations on the concept of the distance-to-default measure and its relation to the probability of default, such as Kealhofer (2003), Sun et al. (2012) and Ferry et al. (2012).

The new framework for modelling default rates, known as stochastic search variable selection (SSVS) as presented in George et al. (2008), operationalises a Bayesian stochastic approach to select variables of Figueres and Sarychev (2024). It replaced the earlier Bayesian Model Averaging (BMA) model originally proposed by Sala-i-Martin et al. (2004) and known as Bayesian Averaging of Classical Estimates (BACE).^{22,23} The BMA approach estimates a pool of equations for a dependent variable and all possible combinations of candidate predictors (e.g., real GDP, unemployment, inflation, house prices, interest rates and other macroeconomic variables). Then, the posterior model equation is computed as the weighted average of the individual equations with weights reflecting in-sample predictive performance.

Both the phased-out BMA/BACE and new Bayesian models have the ability to account for model uncertainty (i.e., variable selection). However, the BMA/BACE framework does not account for issues related to data persistency, which means the corresponding projections may lack scenario sensitivity. Moreover, in cases where historical data is available only for short samples, the BMA/BACE approach, which features flat priors, may fail to provide stable estimates, thus creating a need for “cross-filling” (i.e., for countries/portfolios where robust estimates are infeasible, the median coefficients from other countries/portfolios are used).

The SSVS framework improves the scenario sensitivity of expected default rate projections and facilitates the estimation of models over rather short samples (often the case for historical default rates). It features informative priors, allowing to obtain the entire posterior distribution of the estimated model and validates whether restrictions on model parameters are supported by the data. Its specification reads as follows:

$$Y_t = c + \sum_{i=1}^p \Phi_{y,i} Y_{t-i} + \sum_{i=0}^q \Phi_{x,i} X_{t-i} + \epsilon_t \quad (1)$$

$$\epsilon_t \sim N(0, \sigma^2) \quad (2)$$

where Y_t is the endogenous variable, i.e., country- and portfolio-specific expected default rate, and X_t is the vector of exogenous variables containing the macro-financial indicators, c is the constant term and ϵ_t is the residual with zero mean and σ^2 variance.

Hierarchical priors for the parameters $\{c, \Phi_{y,i}, \Phi_{x,i}, \sigma^2\}$ governing the dynamics of the model reflect a belief in the statistical relevance of each macro-financial factor for the endogenous variable. They reflect a prior belief in the non-zero value of individual elements ϕ_i of $\{\Phi_{y,i}, \Phi_{x,i}\}$ and the significance of the corresponding variables i.e., $\phi_i = 0$, thus avoiding imposing “preselected restrictions” and considering models that are supported by the data. The prior belief ρ_i that an element ϕ_i of $\{\Phi_{y,i}, \Phi_{x,i}\}$ should be included in the model is:

$$\gamma_i \sim \text{i. Bernoulli}(\rho_i) \quad (3)$$

where γ_i denotes a 0-1 independent Bernoulli $\rho_i \in (0,1)$ random variable. Hence, $P(\gamma_i = 1) = \rho_i$ and $P(\gamma_i = 0) = 1 - \rho_i$. Next, each element ϕ_i is assumed to have the following distribution:

$$\phi_i | \gamma_i \sim (1 - \gamma_i) N(0, \tau_{0i}^2) + \gamma_i N(0, \tau_{1i}^2), \text{ with } \tau_{1i}^2 \gg \tau_{0i}^2 \quad (4)$$

Thus, the conditional prior distribution for each $\phi_i \in \{\Phi_{y,i}, \Phi_{x,i}\}$ is a mixture of two normal distributions with variance hyperparameters $\{\tau_{0i}^2, \tau_{1i}^2\}$ and γ_i controlling the mixture of variances. Following George et al. (2008), the variance hyperparameters are set at $\tau_{0i} = 0.1 \hat{\sigma}_{\phi_i}$ and $\tau_{1i} = 10 \hat{\sigma}_{\phi_i}$. Finally, the prior on the variance σ^2 is:

$$\sigma^2 \sim \Gamma(\alpha_i, b_i) \quad (5)$$

where Γ denotes the gamma distribution whose shape parameter is α_i and scale parameter is b_i . The entire posterior distribution of parameters can be obtained via the Gibbs sampler.

²² See Chapter 4 of Dees et al. (2017).

²³ For more details about the BMA framework for stress testing, see Gross and Población (2015, 2019).

The informative specification of the prior hyperparameter ρ_i accommodates both the risk of model overparameterisation and the persistency of the data.²⁴ The prior conveys extra information about the persistency of the data, with ρ_i being split into two blocks: an autoregressive block $\rho_{y,i}$ and an exogenous block $\rho_{x,i}$. For the autoregressive block, $\rho_{y,i}$ is set to lower values with a higher decay (discount) for distant lags, while for the exogenous block $\rho_{x,i}$ is set to higher values with a lower decay. This implies, for example, that $\rho_{y,1}$ (corresponding to Y_{t-1}) is lower than $\rho_{x,0}$ (corresponding to X_t), while $\rho_{y,2}$ (corresponding to Y_{t-2}) is lower than $\rho_{y,1}$ (corresponding to Y_{t-1}) and, at the same time, lower than $\rho_{x,2}$ (corresponding to X_{t-2}).²⁵

Sign restrictions on the long-run multipliers ensure that the impact of scenario variables affects the expected default rate projections in an economically sensible way. The sign restrictions establishing that the long-run multiplier θ^k (corresponding to the predictor X_t^k) should be positive or negative are implemented by following the steps:²⁶

1. Draw a candidate for the model parameters from the conditional posterior distribution and compute the corresponding long-run multiplier:

$$\sum_{l=0}^{\infty} \frac{\partial E(Y_{t+l})}{\partial X_t^k} = \frac{\hat{\phi}_{x,0}^k + \dots + \hat{\phi}_{x,q}^k}{1 - \hat{\phi}_{y,1}^k - \dots - \hat{\phi}_{y,p}^k} \equiv \theta^k \quad (6)$$

2. Check whether the long-run multiplier θ^k meets the sign restrictions and save the successful candidate.
3. If no candidate satisfies the sign restrictions after 10,000 draws, the indicators that do not meet the sign restrictions are dropped from the equation and the model is re-estimated. This procedure is also known as Bayesian model selection. Then repeat steps 1 to 3 for the new model equation.

Model validation

The predictive performance of the SSVS under a stress test scenario is compared against the BMA/BACE model. The comparison relies on out-of-sample projections for default rates conditional on the baseline and adverse stress test scenarios of 2020 over a three-year period.

The SSVS model offers estimates that are more scenario-sensitive than the BMA/BACE model, especially in cases where the latter struggle to provide scenario-sensitive predictions. Chart 11 illustrates default rates for consumer credit in a selected country conditional on the scenario of the 2020 stress-testing exercise.²⁷ Such a scenario features an adverse path for GDP growth (a key driver of default rate projections) that significantly deviates from its baseline path, thus exhibiting a large baseline-adverse difference in growth of around 6.3% (cumulated across the three-year horizon). Panel a) depicts the projections obtained via BMA/BACE, while panel b) shows the projections estimated via SSVS. The BMA/BACE model generates projections with low scenario sensitivity (i.e., the difference between baseline and adverse projections is rather narrow) and exhibiting large uncertainty (confidence bands around the projections are wide and overlap across scenarios). By contrast, the SSVS model generates projections that are more responsive to the different scenario dynamics and display lower uncertainty.

²⁴ The variable selection framework proposed by George et al. (2008) explicitly addresses overparameterisation, but it does not directly account for the bias emerging from significantly persistent data such as default rate data (the proxy used to model expected default rates or probabilities of default point-in-time).

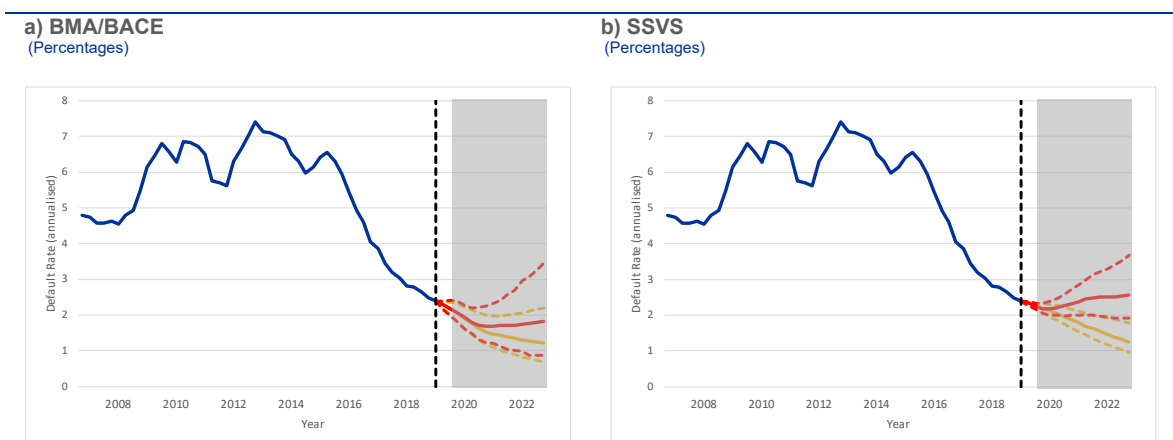
²⁵ When using flat priors, the estimated autoregressive component $\Phi_{y,i} Y_{t-i}$ tends to dominate the exogenous component $\Phi_{x,i} X_{t-i}$. Accordingly, the empirical persistency exhibited by the default rates tends to negatively affect the model's sensitivity to the scenario's severity.

²⁶ Notice that sign restrictions are specified at portfolio level, i.e., for a specific portfolio j , the same set of restrictions is imposed for all countries.

²⁷ The sample length for the historical country-specific default rate varies depending on data availability. In this exercise, the sample length for the mortgage default rate is shorter than for consumer credit.

Chart 11

Conditional projections for default rates on consumer credit: comparison of BMA and SSVS estimates



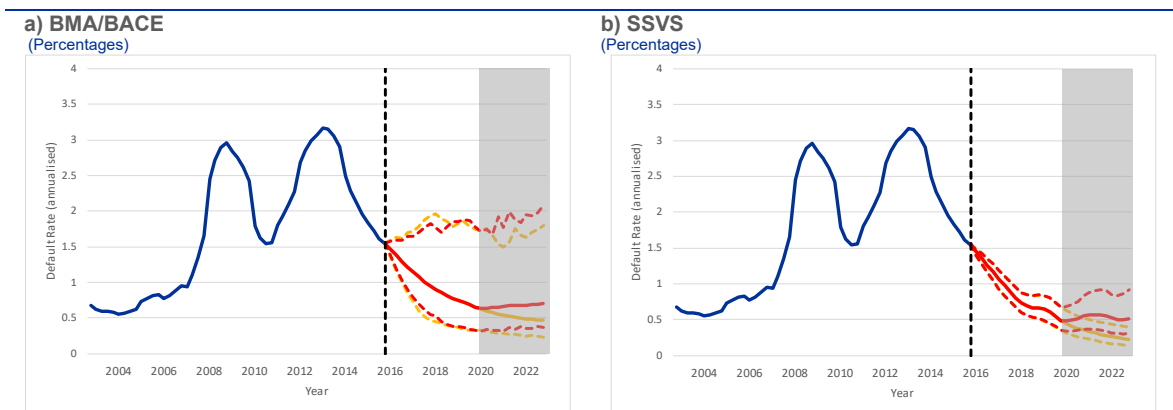
Source: ECB calculations.

Notes: The blue solid line depicts the historical default rate for consumer credit, the red solid line shows the projections conditional on the adverse scenario, and the yellow solid line depicts the projections conditional on the baseline scenario. The dashed red and yellow lines indicate the 25th and 75th percentiles of the forecast distribution. The scenario corresponds to the 2020 stress test scenario. The dashed black vertical line indicates the end of the historical sample for the default rate series. The shaded area indicates the scenario period covering the years 2020, 2021 and 2022. The projections outside the scenario period are computed by conditioning on the realised observations for the macro-financial indicators.

The SSVS model can also generate more stable confidence bands compared with the BMA/BACE framework. Chart 12 displays the second example for the mortgage default rate (for another country). In this case, the BMA/BACE model struggles to produce stable confidence bands over the projection horizon, while the SSVS model generates narrower and stable confidence bands.

Chart 12

Conditional projections for mortgages: comparison of BMA and SSVS estimates



Source: ECB calculations.

Notes: Panel a) shows the case in which the BMA model fails to provide stable estimates (notice the rather explosive confidence bands) and hence is cross-filled. Panel b) shows how the SSVS model is able to provide a stable forecast featuring well-behaved confidence bands. The blue solid line depicts the historical default rate for mortgages, the red solid line shows the projections conditional on the adverse scenario, and the yellow solid line depicts the projections conditional on the baseline scenario. The dashed red and yellow lines indicate the 25th and 75th percentiles of the forecast distribution. The scenario corresponds to the 2020 stress test scenario. The dashed black vertical line indicates the end of the historical sample for the default rate series. The shaded area indicates the scenario period covering the years 2020, 2021 and 2022.

Another comparison concerns projections of the probability of default in the SSVS versus the BMA/BACE model for countries where both frameworks can deliver robust estimates. Chart 13 displays the cross-country distribution of the probability of default multiples for the household segment, conditional on the baseline scenario (panel a) and on the adverse scenario (panel b). The multiples for probabilities of default are computed as the ratio between the annual projected default rate and the starting-point default rate. Overall, the SSVS model produces probability of default multiples with a median close to the BMA/BACE model but including fewer outliers and, in some cases, introducing a slightly higher cross-country dispersion of results.

Chart 13
Cross-country distribution of probability of default multiples



Source: ECB calculations.

Notes: The red dots are medians, the boxes represent the 25th-75th interquartile range, and the whiskers depict the minimum and maximum observations. The charts compare the projected country-level multiples of probability of default for the 2020 stress test adverse scenario. Probability of default multiples are calculated as the ratio of projected probabilities of default for 2020, 2021 and 2022 over the country starting point in 2019 (multiples to T0). Starting-point probabilities of default in 2019 are identical for both the BMA and SSVS models.

3.3.1.2 Quantile model for non-financial corporates at sectoral level

Events such as the COVID-19 pandemic and the Russian invasion of Ukraine highlighted the importance of corporate sectoral heterogeneity as regards credit risk. The panel quantile regressions outlined in this section rely on granular corporate-level data and introduce heterogeneous default levels along with varying degrees of vulnerability of countries and sectors, jointly with potential non-linearities in credit risk estimates. The methodology involves two steps: calculating the corporate default variables and regressing them on scenario-dependent macroeconomic variables in a panel quantile regression framework.

In the first step, granular firm balance sheet data are used to calculate corporate defaults. The granular corporate-level data are taken from Bureau van Dijk's global industry database Orbis, which covers balance sheet variables for around 30 million firms from 2001.²⁸ A corporate default is defined as an event where a firm cannot cover its financial expenses with its cashflows²⁹, whereby the latter are a function of after-tax profits and depreciation at the end of each year (Gourinchas et al., 2020). Based on the number of defaults and non-defaults, the flow default rate *FlowDR* for sector *s* in country *c* at time *t* is calculated as follows:

$$FlowDR_{s,c,t} = \frac{\sum default_{s,c,t}}{\sum nondefault_{s,c,t-1}} \quad (7)$$

It equals the ratio of the number of new defaulted companies per country and sector at time *t* over the total number of non-defaulted companies in the respective country and sector pair a year earlier, i.e., at time *t-1*.³⁰

²⁸ Orbis reports corporate balance sheet data. In stress test applications, the data are projected one year ahead to account for long publication lags.

²⁹ More precisely, a firm is marked as defaulted if the difference between its cashflow and financial expenses is negative. This definition focuses on firms' liquidity and profitability based on an income and cost structure that considers operating expenses. This default definition was discussed with national central bank participants of the working group and validated against available default measures at granular level, such as AnaCredit.

³⁰ The relative frequency of defaulted firms per sector is used, providing an empirical proxy of a probability of default that is observable via firm characteristics until the starting point year (*t*0).

The relative occurrence of the event of default from a sample of firms approximates the 12-month probability of default for each country-sector. The default rates of corporates are calculated separately for firms with loans collateralised by real estate and those that do not have loans secured by real estate.³¹ The resulting dataset captures heterogeneous default levels and reveals varying degrees of vulnerability for different countries and sectors.

The level of default rate flows is validated with other data sources. The distribution of default rate flows is adjusted if the mean deviates significantly from reported country-level data received from national authorities. This adjustment is done by anchoring the mean distribution of default rate flows from Orbis to the mean level of the country-level data reported by national authorities, which maintains the variation from granular data while scaling towards a representative sample.

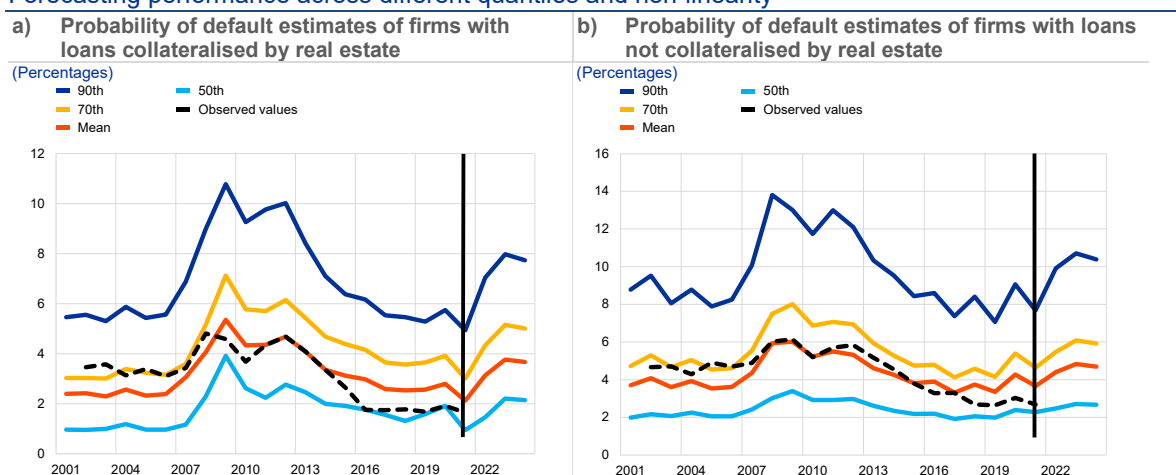
In a second step, the corporate default flows at country and sector level are regressed on macro-financial variables in a panel quantile regression framework (Rios-Avila, 2020; Konietschke et al., 2024). The dependent variable is the probability of default ($PD_{s,c,t}$), proxied by the flow default rate, for sector s (up to NACE2-division breakdown) in country c at time t and separately for loans collateralised and not collateralised by real estate. The specification has the following form:

$$PD_{s,c,t} = \beta_0(\tau) + \beta_1(\tau)Z_{s,c,t} + \beta_2(\tau)X_{c,t} + (\tau)C_{s,c} + \varepsilon_{s,c,t} \quad (8)$$

The estimated coefficients are a function of the evaluated quantile τ , where τ percent of the dependent variable's observations are below the regression line projected from the τ -indexed coefficients. $Z_{s,c,t}$ is the annual growth rate of the country c and sector s gross value added³² at time t , while $X_{c,t}$ is a vector of macro variables for country c at time t , including the unemployment rate, the long-term interest rate changes and house price index growth for loans collateralised by real estate. For loans not collateralised by real estate, $X_{c,t}$ contains the unemployment rate change, the long-term rate, the rate spread change and the stock price index growth. $C_{s,c}$ represents the country and sector fixed effects. Finally, the year 2020 (i.e., the start of COVID-19) is excluded from the estimation sample.

Higher quantiles deliver more conservative estimates under adverse scenarios. Chart 14 depicts the model predictions at aggregate level for firms with loans collateralised and firms without loans collateralised by real estate portfolios, evaluated at the 50th, 75th and 90th percentiles. Expectedly, the estimates at the mean (red line) are very close to the observed flow of default rates (black dashed line). The estimates at the 75th and 90th percentiles capture scenario shocks in tails of the distribution.

Chart 14
Forecasting performance across different quantiles and non-linearity



Sources: Orbis, ECB and ECB calculations.

Notes: The black dashed lines indicate the mean historical sector-level default rate flow from Orbis. The mean has been trimmed at the 95th and 5th percentiles. The blue, yellow and orange solid lines represent estimates from the quantile panel regression, with blue as the 50th, yellow as the 75th and orange as the 90th percentiles. The solid red line represents the estimates from a standard panel regression. The vertical black line separates observed data and calibrated model estimates (to the left of the line) from scenario-conditional model projections (to the right of the line).

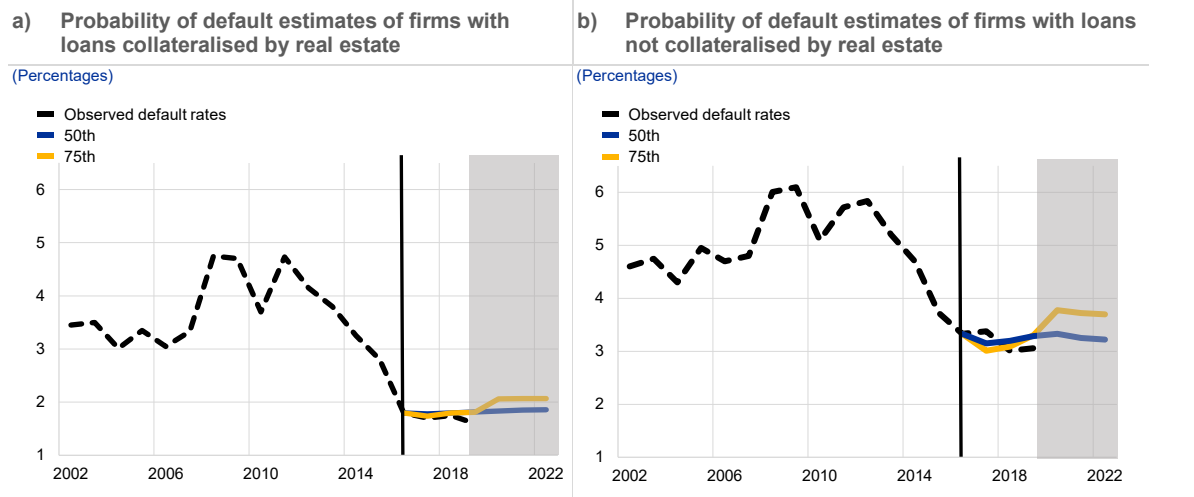
³¹ The allocation is done based on corporate credit registry data from AnaCredit. For this purpose, a firm's outstanding credit is identified as real estate-backed if more than half of all outstanding loans are collateralised by real estate.

³² https://ec.europa.eu/competition/mergers/cases/index/nace_all.html.

An out-of-sample exercise for the period 2020-22 helps to test the predictive performance of models in their current specification. The model is estimated on the sample of data for 2017-19 to build projections conditional on the baseline scenario. Chart 15 shows that the quantile model can provide expected default rates that are sensitive to economic conditions.

Chart 15

Conditional projections for corporates across different quantiles



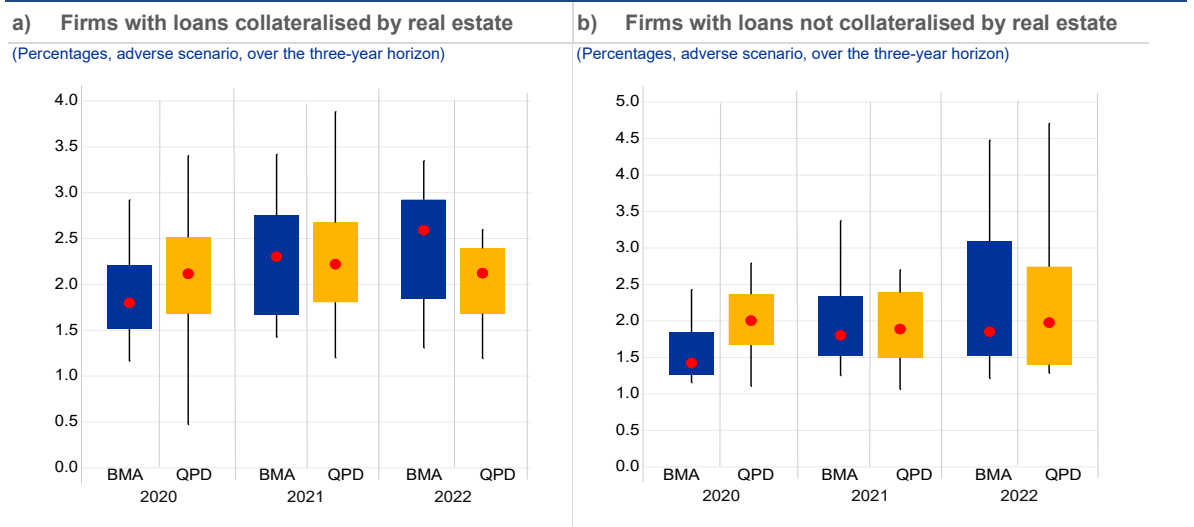
Sources: Orbis and ECB calculations.

Notes: The black dashed lines indicate the mean historical sector-level default rate flow from Orbis. The mean has been trimmed at the 95th and 5th percentiles. The solid lines represent estimates from the quantile panel regression, with blue as the 50th and yellow as the 75th. The vertical black line separates observed data (to the left of the line) and model projections (to the right of the line). The grey-shaded area represents scenario-conditional estimates for the period 2020-22, based on the 2020 EU-wide stress test, while the white part of the chart shows estimates that are driven by realised macro variables for 2017-19.

In addition, the model is validated based on the adverse scenario from the 2020 stress test. To this end, probability of default multiples from the quantile panel regression are compared with those from the previous BMA model. The cross-country distribution displays a similar median and interquartile distribution (Chart 16), while the quantile panel distribution maintains the capacity to suit a larger variety of shocks at a more granular level.

Chart 16

Cross-country distribution of probability of default multiples



Source: ECB calculations.

Notes: For the adverse scenario, the 75th percentile is used. QPD is the panel quantile regression model at the 75th quantile. The red dots are medians, the boxes represent the 25th-75th interquartile range, and the whiskers depict the minimum and maximum observations. The charts compare the projected country-level multiples of probability of default for the 2020 stress test adverse scenario. Probability of default multiples are calculated as the ratio of projected probabilities of default for 2020, 2021 and 2022 over the country starting point in 2019 (multiples to T0). Starting-point probabilities of default in 2019 are identical for both the BMA and QPD models.

3.3.1.3 Expected default rates for non-EU geographies

Default rates for non-EU geographies are linked to macroeconomic developments via bridge equations. The reason for employing bridge equations is that for the non-EU set of countries and regions (as defined under the ESRB scenario), only a reduced set of data and macro-financial scenario variables is available. The approach described below aims to capture cross-country heterogeneity for non-EU country portfolios, while at the same time ensuring consistency in terms of the scenario's impact on probabilities of default between EU and non-EU geographies.

The panel regressions link default rate changes per portfolio type³³ with macroeconomic variables:

$$\Delta\%PD_{c,t}^{TD portfolio} = \beta_1 + \beta_2 GDP\ growth_{c,t} + \beta_3 * \Delta UR_{c,t} + \beta_3 \Delta LTN\ spread_{c,t} \quad (9)$$

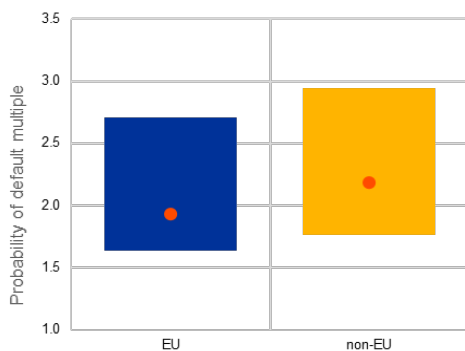
where $\Delta\%PD_{c,t}^{TD portfolio}$ is the year-on-year change in projected probabilities of default and the subscripts c and t denote the country and year, respectively. $GDP\ growth_{c,t}$ is the year-on-year real GDP growth, $\Delta UR_{c,t}$ is the year-on-year change in the unemployment rate and $\Delta LTN\ spread_{c,t}$ is the year-on-year change in the spread of long-term interest rates LTN relative to the German Bund.³⁴

The approach ensures a similar degree of scenario severity between EU and non-EU countries. In Chart 17, the interquartile range of probability of default multiples is depicted for the adverse scenario of the 2021 stress test. The objective of the bridge equations is to account for macroeconomic variables of non-EU geographies, while maintaining a comparable level of impact of the scenario on probabilities of default between EU and non-EU geographies.

Chart 17

Comparison of probability of default multiples for EU countries and non-EU countries

(Probability of default multiple)



Source: ECB calculations.

Notes: The red dots are medians, and boxes represent the 25th-75th interquartile range. The chart compares the projected country-level multiples of probability of default for the 2021 stress test adverse scenario. Probability of default multiples are calculated as the ratio of projected probabilities of default for 2021, 2022 and 2023 over the country starting point in 2020 (multiples to T0).

³³ Panel regressions are estimated separately for consumer credit, mortgages, financials, non-financial corporates for real estate-related and non-real estate-related portfolios.

³⁴ The macroeconomic variables such as GDP, UR and LTN were found to be sufficient in summarising the overall macroeconomic scenario for non-EU countries.

3.3.2 Transition probabilities

With the introduction of the IFRS 9 framework, there was a need for a method to project transition probabilities over the scenario horizon.³⁵ The transition probabilities follow the EBA methodology for the “no cure” assumption constraint, where the cures from stage 3 are set to zero (i.e., $TP^{3 \rightarrow 1}$ and $TP^{3 \rightarrow 2}$ are zero). The projection of the remaining transition probabilities is derived from the scenario paths for the default probability.

$$TP_t = \begin{matrix} S1 \\ S2 \\ S3 \end{matrix} \begin{matrix} S1 & S2 & S3 \\ \left[\begin{array}{ccc} TP_t^{1 \rightarrow 1} & TP_t^{1 \rightarrow 2} & TP_t^{1 \rightarrow 3} \\ TP_t^{2 \rightarrow 1} & TP_t^{2 \rightarrow 2} & TP_t^{2 \rightarrow 3} \\ 0 & 0 & 1 \end{array} \right] \end{matrix} \quad (10)$$

The default probability is decomposed into transition rates to Stage 3 $TP_{T_0+h}^{1 \rightarrow 3}$ and $TP_{T_0+h}^{2 \rightarrow 3}$ using a distance-to-default transformation.³⁶ Accordingly, the scenario paths for $TP_{1 \rightarrow 3}$ and $TP_{2 \rightarrow 3}$ are as follows:

$$\phi^{-1}(TP_{T_0+h}^{1 \rightarrow 3}) - \phi^{-1}(TP_{T_0}^{1 \rightarrow 3}) = \phi^{-1}(PD_{T_0+h}) - \phi^{-1}(PD_{T_0}) \quad (11)$$

$$\phi^{-1}(TP_{T_0+h}^{2 \rightarrow 3}) - \phi^{-1}(TP_{T_0}^{2 \rightarrow 3}) = \phi^{-1}(PD_{T_0+h}) - \phi^{-1}(PD_{T_0}) \quad (12)$$

where ϕ^{-1} denotes the standard normal inverse cumulative distribution function. The values for PD_{T_0} , $TP_{T_0}^{1 \rightarrow 3}$ and $TP_{T_0}^{2 \rightarrow 3}$ correspond to bank-specific starting points for expected default rates and transition probabilities, respectively. The normal inverse transformation ensures that transition probabilities are in the $[0,1]$ interval.

The projection of the remaining elements of transition matrices, namely $TP_{1 \rightarrow 2}$ and $TP_{2 \rightarrow 1}$, entails the estimation of bridge equations at country and portfolio level. Two equations capture the historical relationship between $TP_{1 \rightarrow 2}$ and $TP_{2 \rightarrow 1}$ and $TP_{1 \rightarrow 3}$ and $TP_{2 \rightarrow 3}$, respectively:

$$\phi^{-1}(TP_t^{1 \rightarrow 2}) = a + b \times \phi^{-1}(TP_t^{1 \rightarrow 3}) + \varepsilon_t \quad (13)$$

$$\phi^{-1}(TP_t^{2 \rightarrow 1}) = c + d \times \phi^{-1}(TP_t^{2 \rightarrow 3}) + \varepsilon_t \quad (14)$$

The coefficients b and d are expected to be positive and negative, respectively. Empirically, higher transition rates from stages 1 to 3 are associated with higher transition rates from stages 1 to 2 since both correspond to a deterioration of the credit quality. Following the same reasoning, higher transition rates from stages 2 to 3 are associated with lower transition rates from stages 2 to 1. In detail, for the projection of $TP_{1 \rightarrow 2}$ and $TP_{2 \rightarrow 1}$, bridge equations are estimated for regressions of $TP_{1 \rightarrow 2}$ on $TP_{1 \rightarrow 3}$ series as well as of $TP_{2 \rightarrow 1}$ on $TP_{2 \rightarrow 3}$. The slopes from these regressions are used to project the respective transition rates conditional on the macroeconomic scenario at country and portfolio level. Only model estimates with an R^2 higher than 10% and a positive (and negative) value for the slope from the $TP_{1 \rightarrow 2}$ vs $TP_{1 \rightarrow 3}$ (and $TP_{2 \rightarrow 1}$ vs $TP_{2 \rightarrow 3}$) regression, respectively, are retained. The countries and portfolios without retained estimates or not providing time series are cross-filled by the EU median.

The distance-to-default transformation below is then used to derive the paths for $TP_{T_0+h}^{1 \rightarrow 2}$ and $TP_{T_0+h}^{2 \rightarrow 1}$:

$$\phi^{-1}(TP_{T_0+h}^{1 \rightarrow 2}) - \phi^{-1}(TP_{T_0}^{1 \rightarrow 2}) = b(\phi^{-1}(TP_{T_0+h}^{1 \rightarrow 3}) - \phi^{-1}(TP_{T_0}^{1 \rightarrow 3})) \quad (15)$$

$$\phi^{-1}(TP_{T_0+h}^{2 \rightarrow 1}) - \phi^{-1}(TP_{T_0}^{2 \rightarrow 1}) = d(\phi^{-1}(TP_{T_0+h}^{2 \rightarrow 3}) - \phi^{-1}(TP_{T_0}^{2 \rightarrow 3})) \quad (16)$$

Finally, the scenario paths for the transition probabilities $TP_{1 \rightarrow 1}$ and $TP_{2 \rightarrow 2}$ are obtained by difference, ensuring that each row of the matrix adds up to 1.

$$TP_{T_0+h}^{1 \rightarrow 1} = \max(1 - TP_{T_0+h}^{1 \rightarrow 2} - TP_{T_0+h}^{1 \rightarrow 3}, 0) \quad (17)$$

$$TP_{T_0+h}^{2 \rightarrow 2} = \max(1 - TP_{T_0+h}^{2 \rightarrow 1} - TP_{T_0+h}^{2 \rightarrow 3}, 0) \quad (18)$$

³⁵ The transition probabilities are used as input for the top-down lifetime loss rate projections. The baseline marginal transition matrices after year three (and until the maturity of the loan) are assumed to remain constant, while the corresponding adverse parameters are set to linearly revert to their baseline value over the course of six years.

³⁶ For a detailed explanation of this transformation, please see Section 3.3.1.

For sovereign exposures transition rates, the top-down methodology assumes the values submitted by banks, following the relationships below:

$$0 \leq TP_{T_0+h}^{i \rightarrow j} \leq 1, \sum_j TP_{T_0+h}^{i \rightarrow j} = 1, h = 1,2,3, \text{ for both baseline and adverse} \quad (19)$$

$$TP_{adverse, T_0+h}^{2 \rightarrow 1} \leq TP_{adverse, T_0}^{2 \rightarrow 1}, h = 1,2,3 \quad (20)$$

$$TP_{adverse, T_0+h}^{1 \rightarrow 2} \geq TP_{adverse, T_0}^{1 \rightarrow 2}, h = 1,2,3 \quad (21)$$

$$\frac{Exp_{S1} \times TP_{T_0+h}^{1 \rightarrow 3} + Exp_{S2} \times TP_{T_0+h}^{2 \rightarrow 3}}{Exp_{S1} + Exp_{S2}} = pitPD_{T_0+h} \quad (22)$$

3.3.3 Loss given default of loans

3.3.3.1 Loans collateralised by real estate

The structural model of loss given default for household and non-financial corporate loans collateralised by real estate aligns the value of loan collateral with the evolution of real estate prices. Specifically, the value of commercial real estate collateral is aligned with commercial property prices and the value of residential real estate with residential property prices. The loss given default is modelled as a function of the bank loan-to-value ratio (LTV), the probability of cure and the loss given liquidation (LGL), as follows:

$$LGD = (1 - \text{Probability of Cure}) \cdot LGL + AdmCosts \quad (23)$$

where *AdmCosts* is a constant reflecting typical administrative costs of real estate transactions. As described in STAMP€, LGL can be derived from the LTV and the expected sales ratio (E(SR)), which is defined as the ratio between recovery and collateral value. This can be described as $LGL = MAX\left(\frac{\text{Loan-Recovery Value}}{\text{Loan}}, 0\right) \leftrightarrow MAX\left(\left(\frac{\text{Loan-Recovery Value}}{\text{Loan}} / \text{Collateral Value}\right), 0\right) \leftrightarrow MAX\left(\frac{\text{LTV}-E(\text{SR})}{\text{LTV}}, 0\right)$.³⁷

There is a level of uncertainty around the reported collateral value, which may be overvalued, deviating from realised market values, due to outdated valuations or adverse market conditions leading to declines in real estate prices. Therefore, assuming that the expected sales ratio (E(SR)) is normally distributed, and considering the relation above between the recovery value and the LTV, the E(SR) can be expressed as follows:

$$E(SR) = \mu \left[\Phi\left(\frac{\text{LTV}-\mu}{\sigma}\right) - \Phi\left(\frac{-\mu}{\sigma}\right) \right] + \frac{\sigma}{\sqrt{2\pi}} \left[e^{-\frac{\mu^2}{2\sigma^2}} - e^{-\frac{(\text{LTV}-\mu)^2}{2\sigma^2}} \right] + \text{LTV} \left[1 - \Phi\left(\frac{\text{LTV}-\mu}{\sigma}\right) \right] \quad (24)$$

where LTV denotes the indexed LTV ratio at the point of sale, μ represents the mean of the sales ratio distribution, σ indicates the standard deviation of sales ratio distribution and $\Phi(\cdot)$ denotes the cumulative probability distribution function of the standard normal distribution. The expected sales ratio is bounded between 0 and the LTV. The specification of the sales ratio reflects the uncertainty around bank reported collateral values. For instance, as long as the sales ratio varies around its mean even over-collateralised loans can generate losses. In this approach, parameter mean (μ) has to be found, to thereby let the LGD fit the observed bank starting point loss given default, conditional on the LTV ratio and sales ratio. For this purpose, a grid combination of probability of cure (or cure rates), loss given default and LTV parameters, derived from previous stress test exercises, are used to find the μ and align it with the banks' reported starting points.

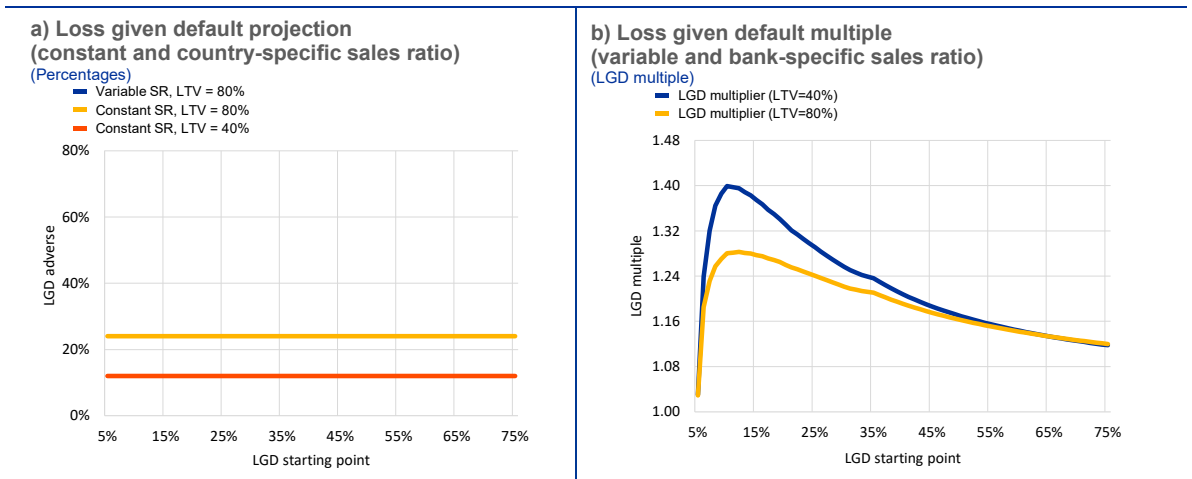
The LTV ratio forward paths are related to the evolution of real estate prices (HP_t), as follows:

$$LTV_t = LTV_0 \frac{HP_0}{HP_t} = \frac{LTV_0}{\frac{HP_t}{HP_0}} = \frac{LTV_0}{\frac{HP_0 + HP_t - HP_0}{HP_0}} = \frac{LTV_0}{1 + \frac{HP_t - HP_0}{HP_0}} = \frac{LTV_0}{1 + \Delta HP} \quad (25)$$

³⁷ The inclusion of the max operator is based on the legal framework in most EU countries, where any surplus from selling collateral beyond the defaulted borrower's debt obligation to the bank should be returned to the borrower.

The specification allows for relatively higher increases in the loss given default for banks with a low starting-point loss given default, as opposed to banks with a high starting-point loss given default.³⁸ Chart 18 shows the projected loss given default and respective multiple conditional on a house price shock from an adverse stress test scenario under different assumptions for the initial LTV ratio. Panel a) of Chart 18 shows the projections with a constant and country³⁹-specific sales ratio as earlier used in STAMP€. The projected loss given default under the adverse scenario is independent of the bank's starting-point loss given default. Panel b) shows the projections from the current model with a bank-specific sales ratio. The loss given default multiples are lower for banks with high starting points, accounting for banks' heterogeneity.

Chart 18
Bank-specific calibration of the sales ratio



Source: ECB calculations.

Notes: Panel a): Loss given default (LGD) projections under the adverse scenario for a bank-specific and constant sales ratio (SR) for different LTV values of 40% and 80%. Panel b): LGD multiples are expressed relative to the bank's starting-point LGD ($LGD_{adverse}/LGD_{t0}$) applied to a bank-specific SR for LTV values of 80% and 40% and a cure rate of 30%.

3.3.3.2 Loans not collateralised by real estate

The approach to modelling the loss given default (or point-in-time loss given default) of exposures not collateralised by real estate property considers both country-level and bank-level heterogeneity.⁴⁰ By using bank data from previous stress tests, it is possible to obtain an estimate of the scenario sensitivity of loss given default across the three portfolios: credit consumer, non-financial corporates for loans not collateralised by real estate and financials. The model has the following form:

$$LGD_{c,t}^{x \rightarrow 3} = \beta_0 + \beta_1 GDP\ growth_{c,t} + \beta_2 \Delta UR_{c,t} \quad (26)$$

where $LGD_{c,t}^{x \rightarrow 3}$ is the loss given default multiple calculated as the ratio of the bank's projected loss given default over its starting-point loss given default ($\frac{LGD_{scen}}{LGD_{t0}}$) and $x=\{1,2,3\}$ denotes the losses given default ($LGD^{1 \rightarrow 3}$, $LGD^{2 \rightarrow 3}$ and $LGD^{3 \rightarrow 3}$). $GDP\ growth_{c,t}$ is the cumulative gross domestic product growth over the three years of the scenario, and $\Delta UR_{c,t}$ is the unemployment rate change over the three years of the scenario, while the constant is denoted by β_0 .⁴¹ The loss given default sensitivities to economic activity and unemployment rate (coefficients β_1 and β_2) are aligned with the average estimates obtained from the literature (Georgescu, Galow and Ponte Marques, 2024; Bellotti and Crook, 2012; Caselli and Querci, 2008; Konečný et al., 2017). The scenario-conditional shift in the loss given default is applied in a distance-to-default space to ensure the bank's starting-point dependency.⁴²

³⁸ The relative increase in the loss given default under the adverse scenario is expected to be lower for very high bank loss given default starting values compared with the very low bank loss given default starting values. This is because high starting point loss given default values are assumed to reflect conservative estimates of collateral values, implying limited scope for further devaluation.

³⁹ Calculated as the exposure weighted average from stress test exercises reported by banks and aggregated at country level.

⁴⁰ The earlier approach to modelling forward paths of loss given default for non-real estate-related exposures involved applying a fixed parameter to the T0 bank starting-point loss given default.

⁴¹ Other macroeconomic variables were excluded from the regression analyses since they were not significant.

⁴² For a detailed explanation of this transformation, please see Section 3.3.1.

The new top-down model provides comparable projected losses given default to three alternative approaches. The results from the model are benchmarked against the results derived from the alternative approaches in Table 6. The estimated outcome from the ECB model compares well with the stressed, downturn and adverse loss given default parameters, and, in line with expectations, the downturn loss given default projections are the most conservative. This reflects the provisions of the Basel II framework, which requires banks to estimate and use loss given default reflecting downturn conditions, as long as these are more conservative than the long-run loss given default average.

Table 6

Comparison of top-down estimates with other alternative approaches for non-financial corporate loans not collateralised by real estate under the adverse scenario* (A-IRB portfolios only)

Top-down LGD unsecured*	LGD stressed cure rate**	Downturn LGD (REA)***	LGD 13 adv (SCEN)***
31.0%	27.8%	31.9%	29.6%

Sources: Participating banks and ECB calculations based on data from the 2018 and 2021 stress tests.

Notes: * For the analysis, the adverse scenario set-up from the 2018 and 2021 stress tests 2018 was employed. ** Projected LGD levels based on the chosen model specification. *** The LGD stressed cure rate corresponds to $LGD_{adv} = ((1 - Probability\ of\ cure) * Loss - Given\ Liquidation)$. Under this set-up, starting-level losses given default and cure rates of past stress test exercises are used to derive a proxy for the loss given liquidation. A stressed loss given default is estimated by scaling the cure rate with a factor equal to the inverse of the ratio $\frac{LGD_{downturn}}{LGD_{10}}$ for unsecured non-financial corporate non-real estate-related portfolios under the advanced internal ratings-based (A-IRB) regulatory approach. **** Both downturn losses given default and losses given default under the adverse scenario are reported by banks.

3.3.4 Lifetime loss rates

The IFRS 9 projections of lifetime loss rate parameters are incorporated into the stress horizon conditioned on both baseline and adverse scenarios. There are three point-in-time risk parameters related to the lifetime loss rate:

- $LRLT_t^{1 \rightarrow 2}$ refers to the lifetime expected loss rate of those exposures that start the year in stage 1 and end it in stage 2;
- $LRLT_t^{2 \rightarrow x}$ refers to the lifetime expected loss rate for exposures that begin and end the year in stage 2 regardless of the stage they end up in eventually during their lifetime ($LRLT_t^{2 \rightarrow 2}$ includes exposures that begin and end the year in stage 2 and remain in stage 2);
- $LRLT_t^{3 \rightarrow 3}$ refers to the lifetime expected loss associated with exposures that start the year in stage 3. Note that due to the “no cure” constraint, stage 3 exposures cannot migrate to another stage.

where the lifetime loss rate for new stage 2 assets ($LRLT_t^{1 \rightarrow 2}$) is set equal to lifetime losses for existing stage 2 assets, i.e., ($LRLT_t^{2 \rightarrow x}$). Accordingly, it is assumed that once an exposure has migrated to stage 2 it has the same risk characteristics as those exposures which are already in stage 2. The lifetime loss rate for stage 3 assets $LRLT_t^{3 \rightarrow 3}$, is set equal to $LGD_t^{3 \rightarrow 3}$ over their lifetime.

The lifetime loss rate parameters rely on the estimates of the expected cumulative loss. The latter is calculated according to the following formula:

$$ECL_{(t+1,M),12}^{lifetime} = \sum_{s=t+1}^M EAD_s \times (LGD_s^{2 \rightarrow 3} \times (EAD_s/100)) \times TP_s^{2 \rightarrow 3\ Marginal} \quad (27)$$

where EAD_s is the exposure at default at time s , LGD_s is the point-in-time loss given default ($LGD_s^{2 \rightarrow 3}$) at time s , M is the maturity of the portfolio and $t \in (1,2,3,4)$ is the time, as the calculations are repeated for different years under the scenario. The term $(EAD_s/100)$ refers to the decay factor for $LGD_s^{2 \rightarrow 3}$. $LGD_s^{2 \rightarrow 3}$ is assumed to decay at the same pace as the exposure at default reflecting the fact that the LTV ratio decreases in line with the amortisation of the exposure. The last term in the formula ($TP_s^{2 \rightarrow 3\ Marginal}$) is the marginal, or conditional, probability of migrating to stage 3 (probability of default for stage 2 assets).

The decay factor assumes that the exposure at default (EAD)⁴³ falls linearly after the initial three-year scenario. Starting from year 4, the portfolio goes down over its residual lifetime along with the normalised formula:

$$EAD_s = \begin{cases} 100 & \text{if } s \in (1,2,3,4) \\ EAD_{s-1} - \frac{100}{M+(t-4)} & \text{if } 5 \leq s \leq M \end{cases} \quad (28)$$

where $EAD_0 = 100$ and M refers to the maturity of the exposure. Under the adverse scenario, the reversion of EAD to baseline is assumed from year 4.

⁴³ Conservative prepayments are not included in the calculation of exposure at default over time.

The marginal probability of migrating to stage 3 $TP_s^{2 \rightarrow 3 \text{ Marginal}}$ is conditional on survival up to the reference period. It is defined as:

$$TP_s^{2 \rightarrow 3 \text{ Marginal}} = Prob(D_s = 1, D_k = 0; t \leq k < s) = TP_s^{2 \rightarrow 3} \underbrace{\prod_{k=t}^{s-1} (1 - TP_k^{2 \rightarrow 3})}_{\text{cumulative PIT survival probability at time (year) } k} \quad (29)$$

where $TP_k^{2 \rightarrow 3}$ is the incremental (unconditional) probability of migrating to stage 3 as described in Section 3.3.2, D_s, D_k are indicator variables taking the values 1 and 0, respectively, in case the loan survived in the previous period, and 0 and 1 in case the loan defaulted in the previous period. This implies that annual point-in-time expected credit losses are summed up until the residual maturity (M) of the portfolio in question. At each point in time, only the share of the portfolio that has not defaulted in previous periods is considered for the calculation of the expected losses.

This approach to compute the marginal probability of default ($TP_s^{2 \rightarrow 3 \text{ Marginal}}$) considers the transition from stage 2 to stage 1 along the maturity of the loan.⁴⁴ It relies on the information on transition matrices, with transition rates from stage 2 to stage 3 ($TP_t^{2 \rightarrow 3}$) taking into account migration from stage 2 to stage 1 in line with the EBA methodology (see transition matrix in equation (10)). More precisely, assuming that transition matrices evolve according to a Markov process, the cumulative $TP_t^{2 \rightarrow 3}$ becomes $TP_t^{\text{Cumulative}} = \prod_{s=1}^t TP_s$ (30)

The marginal transition rate $TP_t^{2 \rightarrow 3 \text{ Marginal}}$ at time t can be obtained from the cumulative transition matrix as follows:

$$TP_t^{2 \rightarrow 3 \text{ Marginal}} = TP_t^{2 \rightarrow 3 \text{ Cumulative}} - TP_{t-1}^{2 \rightarrow 3 \text{ Cumulative}} \quad (31)$$

Hence, cumulative transition matrices are projected over the lifetime of the loan. From year 4 of the adverse scenario, every element of the transition matrix is computed such to ensure its convergence to the baseline scenario over a six-year period.

Finally, benchmarks for loss rates are calculated according to the following formula:

$$LRLT_t^{1 \rightarrow 2} = \frac{ECL_{(t,M)}^{1 \rightarrow 2 \text{ lifetime}}}{EAD_0} \quad (32)$$

$$LRLT_t^{2 \rightarrow 2} = \frac{ECL_{(t,M)}^{2 \rightarrow 2 \text{ lifetime}}}{EAD_0} \quad (33)$$

where $EAD_0 = 100$.

3.3.5 Validation framework for impairment models

An important new element of the ECB top-down credit risk framework is the validation framework, including two types of out-of-sample exercises. The forward-looking predictions from top-down models that were derived during past EU-wide or euro area-wide stress-testing exercises or, alternatively, in a pseudo out-of-sample forecast going back to the same time point, are compared with their actual realisations. In the first case, the ability of models to match actual data for credit risk parameters is assessed over a three-year period and employing baseline scenarios from past stress-testing exercises. In the latter case, it is assessed either employing baseline scenarios from past stress-testing exercises or actual realised macro-financial data, depending on data availability for reference variables and the intention of the performance test. Looking ahead, the analysis is to be expanded to other credit risk variables and categories.

⁴⁴ Allowing for migration between stage 1 and stage 2 for the projection of lifetime rates appears justified from an economic point of view, with high-risk exposures migrating back to low-risk status. While the EBA methodology does not allow cures from stage 3 to performing, transitions from stage 2 back to stage 1 are explicitly foreseen.

Ex post validation: back-testing analysis

The back-testing analysis speaks to the ability of credit risk benchmarks, as considered in past stress-testing exercises, to accurately capture future credit risk developments. The back-testing looks at annual values of portfolio-level impairments, an aggregate variable summarising the performance of all models jointly, and statistics which compare the actual bank credit risk losses from the plainly top-down assessment. The analysis involves baseline impairment projections from the 2018 EU-wide stress test and central scenario impairment projections from the 2020 vulnerability analysis. The projected and actual impairments are compared at the end of a reference year and separately for different portfolios. The realised impairments of euro area banks for the years 2018, 2019 and 2020 are obtained from the implementing technical standards (ITS) on supervisory reporting.⁴⁵ The impairments reported by banks are therefore compared with baseline projections for the most recent years of the scenario (e.g., 2018 stress test scenario and respective top-down projections are compared with realised impairments in 2018 and 2019; the 2020 vulnerability analysis is compared with realised outcomes for the same year). This comparison in the initial years of the stress test ensures a closer alignment between the baseline scenario and the realised macro-financial indicators, as well as the composition of bank balance sheets.⁴⁶

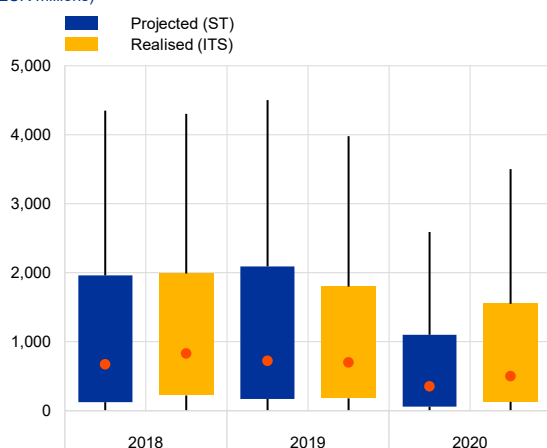
The outcome of the back-testing analysis points to an overall high degree of concordance between top-down impairment projections and their realisations (Chart 19). Realisations in 2018 and 2019 are compared with the outcomes of the 2018 stress test, and in 2020 with those of the 2020 vulnerability analysis. A simple correlation between past bank-level projections of impairments on exposures to households and to non-financial corporations (NFCs) and the actual data is in the range of 92-96% and a rank correlation in the range of 90-95% (Table 7). It can therefore be concluded that the top-down models capture the relative size of impairment flows within the sample of banks. At the same time, the top-down models tend to project somewhat higher impairment flows for household and corporate sub-portfolios. This, however, can be largely explained by the fact that the top-down calculations are tailored to the EBA methodology, which by construction has a conservative bias (e.g., no cures from stage 3, perfect foresight assumption for loss given default and loss rate projections).

Chart 19

Top-down stock of impairment projections versus banks' realised stock of impairments

Projected versus realised impairments

(EUR millions)



Source: Participating banks, ECB and ECB calculations based on ITS supervisory data for realised impairments and stress test data for projected impairments (2018 and 2020 stress tests and vulnerability analysis for the pandemic).

⁴⁵ For the purpose of this analysis, the supervisory data includes banks' realised impairments at amortised cost from stage 1 to stage 3 (table FINREP 04.04.1), which exclude partial or total write-offs. The reported stock of impairments from FINREP is compared with the starting-point stock of impairments plus impairment projections from stress tests.

⁴⁶ The top-down projections assume a static balance sheet composition; thus, this assumption is more accurate in the initial years of the stress-testing exercise.

Table 7
Correlation and rank correlation between top-down projections versus banks' realised impairments

		2018	2019	2020
Correlation	Households	0.94	0.92	0.95
	Non-financial corporations	0.94	0.93	0.96
Rank correlation	Households	0.95	0.95	0.93
	Non-financial corporations	0.90	0.90	0.90

Source: ECB calculations based on ITS supervisory data for realised impairments and stress test data for projected impairments (2018 and 2022 stress tests and vulnerability analysis for the pandemic).

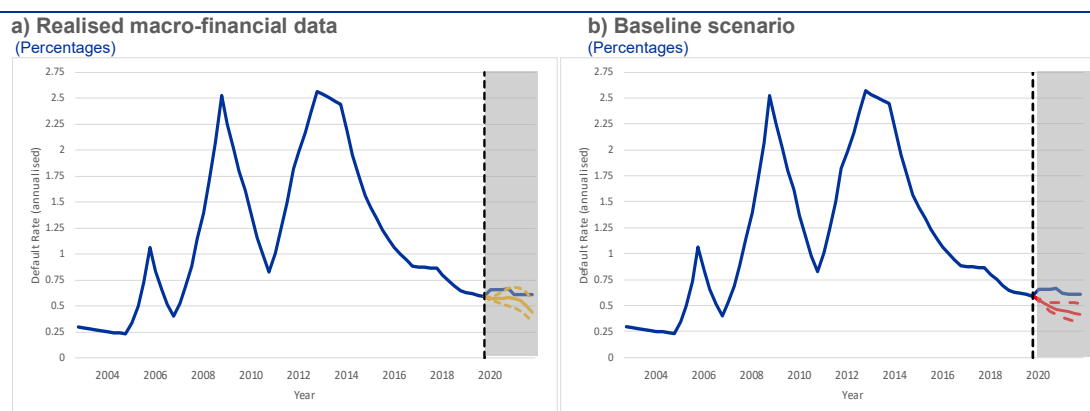
Ex ante validation: out-of-sample analysis

The ex ante analysis provides an alternative metric to test the predictive performance of models in their current specification. It relies on pseudo out-of-sample projections, where the current model specification is estimated (the parameters are updated) based on the data up to a past reference date. The projections from the model are then assessed against the actual realisations of the outcome variables. This type of analysis is a relevant criterion for phasing in new models or fine-tuning existing set-ups. There are two complementary ways to run an ex ante analysis. The first considers projections based on the already realised macro-financial variables. The second considers projections based on baseline scenarios from past stress tests (similarly to an ex post analysis). While the latter analysis offers a more accurate out-of-sample set-up, the former separates forecast errors in a top-down model from those inherited from the past baseline scenario.

The performance of the SSVS model is tested in both versions of the ex ante analysis. The first out-of-sample projections is generated conditional on the realised macro-financial indicators (Chart 20, panel a), while the second set of projections is generated conditional on the baseline scenario of 2020 EU-wide stress-testing exercise (Chart 20, panel b).

The ex ante test provides evidence to support the adequate forecasting performance of the SSVS model. The SSVS projections closely track the realised default rates in the out-of-sample period (panel a). As expected, the projections tend to be more accurate when the scenario measurement error is excluded from the projections, although the projections conditional on the scenario (hence including its measurement error) are still properly capturing the default rate dynamics.

Chart 20
Conditional projections for mortgages: SSVS estimates



Source: ECB calculations.

Notes: The chart shows the forecasts produced via the SSVS model. The blue solid line depicts the historical default rate for mortgages, while the black dotted vertical line indicates the end of the sample used for the estimation of the model. The yellow solid line shows the out-of-sample projections conditional on the realised macro-financial indicators, while the dashed yellow lines indicate the 25th and 75th percentiles of the forecast distribution. The red solid line shows the out-of-sample projections conditional on the baseline scenario for the 2020 stress test, while the dashed red lines indicate the 25th and 75th percentiles of the forecast distribution. The shaded grey area indicates the out-of-sample projection period.

3.4 Credit risk: regulatory parameters

The top-down risk weight calculations aim to replicate and challenge the risk exposure amounts reported by banks for both standardised and internal ratings-based approaches. The top-down framework is calibrated to project regulatory parameters with appropriate sensitivity to scenarios, thereby considering macroeconomic variables, while still accounting for banks' specificities by considering bank-level variables. This is done for the following segments: real estate-collateralised portfolios (mortgages, non-financial corporates) and non-real estate-related exposures (consumer credit, non-financial corporates, financials). In detail, the ECB estimates the following regulatory parameters:

- Risk weights for the standardised approach
- Risk weights for the internal ratings-based approach
 - Probabilities of default
 - Loss given default

3.4.1 Standardised approach parameters

The top-down risk exposure amount for the standardised approach is computed as the product between the risk weight for a given portfolio and the corresponding exposure at default amount (EAD). At the same time, risk exposure amount calculations are distinguished between performing (non-defaulted) and non-performing (defaulted) exposures. More formally:

$$\text{▪ Risk exposure amount of non-defaulted loans (nondef): } REA_{nondef,t,STA} = RW_{nondef,t} \cdot EAD_{nondef,t} \quad (34)$$

$$\text{▪ Risk exposure amount of defaulted loans (def): } REA_{def,t,STA} = RW_{def,t} \cdot EAD_{def,t} \quad (35)$$

3.4.1.1 Risk weights for the standardised approach

Two regression equations support the derivation of the top-down risk weights under the standardised approach. The estimation uses data from previous stress tests (2018 and 2021) and is performed through a feasible generalised least squares (FGLS) approach, which allows for asymptotically efficient estimates in the presence of autocorrelation (AR(1)) within panels, cross-sectional correlation and heteroskedasticity across panels. Both micro and macro indicators were selected as explanatory variables for risk weights based on their significance, driven by their influence on the risk weight outcomes.⁴⁷ The equations read:

$$\begin{cases} RW_{nondef,STA,t3} = \beta_0 + \beta_1 RW_{nondef,STA,t0} + \beta_2 \Delta NPE_{REA} + \beta_3 \Delta HPI \\ RW_{def,STA,t3} = \beta_0 + \beta_1 RW_{def,STA,t0} + \beta_2 \Delta CovRatio_{SCEN} + \beta_3 \Delta UR \end{cases} \quad (36)$$

where $RW_{STA,t0}$ is the bank risk weight starting point (t0) for the standardised approach, separately for non-defaulted and defaulted exposures.⁴⁸ ΔNPE_{REA} is the percentage point difference in the non-performing exposure ratio (from the EBA risk exposure amount template)⁴⁹ and $\Delta CovRatio_{SCEN}$ is the percentage point difference in the NPL coverage ratio.⁵⁰ ΔHPI_{MACRO} and ΔUR_{MACRO} are the cumulative changes in the country-specific house price index and unemployment rate over the three-year horizon of a scenario, respectively. The constant is denoted by β_0 .

⁴⁷ The objective is to capture the relationship between macroeconomic variables/scenarios and both collateral revaluation and rating downgrades, as these changes are mirrored in risk weights for the standardised approach.

⁴⁸ The main arguments for country-bank level aggregation are the (i) similar behaviour of portfolios as a consequence of the adverse macroeconomic scenario evolution and (ii) deterioration in collateral values due to the macroeconomic conditions, which lead to increased risk weights.

⁴⁹ As sourced from the EBA risk exposure amount template: $\frac{EAD(non-perf)_{Adverse}}{(EAD(perf)+EAD(non-perf)_{Adverse})} - \frac{EAD(non-perf)_{Actual}}{(EAD(perf)+EAD(non-perf)_{Actual})}$.

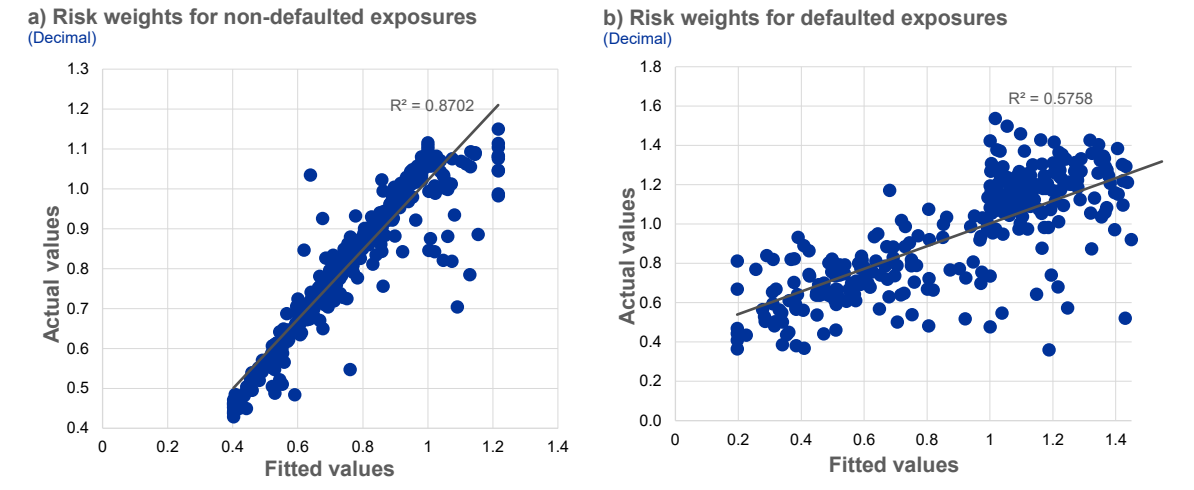
⁵⁰ $\frac{Prov(S3)_{Adverse,EoY3}}{EAD(S3)_{Adverse,EoY3}} - \frac{Prov(S3)_{Adverse,BoY1}}{EAD(S3)_{Adverse,BoY1}}$.

The estimates indicate that an increase in unemployment and a decrease in house prices are strongly correlated with an increase in risk weights. In addition, a rise in defaulted exposures and a decrease in the coverage ratio under the adverse scenario are significantly related with an increase in risk weights, reflecting the deterioration in the credit quality of borrowers and the corresponding higher riskiness of the loan portfolio. To validate the stability of these results, the regressions were also estimated using an ordinary least squares (OLS) approach with robust standard errors and standard errors clustered by bank. Internal results confirm the stability of the FGLS coefficients for both OLS specifications. Additionally, to validate further the performance of the regression, Chart 21 depicts the actual risk weights plotted against fitted values for both non-defaulted (panel a) and defaulted exposures (panel b).

In the final step, estimated risk weights are subjected to a set of caps and floors. The caps and floors ensure adequate conservativeness of the top-down view and remove outliers. The projected risk weights are floored to banks' starting point values, while caps are set at portfolio level⁵¹ and informed by the CRR.⁵²

Chart 21

Actual values compared with fitted values for the risk weights of the standardised approach



Source: ECB calculations.

Note: The chart compares actual and fitted values for the risk weights of the standardised approach for the 2021 stress test adverse scenario.

3.4.2 Risk exposure amount for internal ratings-based approach

The top-down risk exposure amount for the internal ratings-based approach is calculated according to the provisions of Articles 153 and 154 CRR. For non-defaulted exposures, the top-down projected risk exposure amount is calculated by multiplying the increase in risk weights (RW) and respective exposure amount (*NonDefExp*) with the bank starting point value:

$$REA_{t,NonDef,IRB} = \frac{RW_t}{RW_0} \cdot \frac{NonDefExp_t}{NonDefExp_0} \cdot REA_{t_0,NonDef,IRB} \quad (37)$$

The risk weight for defaulted exposures in the IRB advanced approach follows Article 153 CRR ($RW_t = \max(0; 12.5 \cdot (LGD_{Reg,def}^{TD \text{ Downturn}} - ELBE))$), where the best estimate of expected loss for defaulted exposures (ELBE) is used in accordance with Article 181(1)(h).

⁵¹ The caps for the SME non-defaulted portfolios include the effect of the SME supporting factor. The SME supporting factor is usually applied as an adjustment that reduces final calculated risk-weighted exposures, decreasing in turn the implied risk weight.

⁵² See <https://eur-lex.europa.eu/legal-content/en/TXT/?uri=celex%3A32013R0575>.

3.4.2.1 Risk weights for the internal ratings-based approach

Projections of the regulatory probability of default and loss given default draw on the provisions of the CRR⁵³ and account for bank and country specificities. The regulatory probability of default is estimated as the moving average between point-in-time probability of default (as used in the calculation of impairments) and the banks' starting-point value for the regulatory probability of default. The length of the moving average time window corresponds to the sensitivity of the regulatory probability of default to the point-in-time parameter. The latter is related to the country-specific "probability of default cycle length" and is based on the country's loan workout⁵⁴ collected from the supervisory targeted review of internal models (TRIM).⁵⁵ More formally, regulatory probabilities of default are estimated as follows:

$$PD_{Reg,t}^{TD} = \max\left(\frac{1}{y}\sum_{i=1}^t PD_{Pit,t}^{TD} + \left(\frac{y-t}{y}\right) PD_{Reg,0}^{Bank}, \frac{1}{y}\sum_{i=1}^t PD_{Pit,t}^{Bank} + \left(\frac{y-t}{y}\right) PD_{Reg,0}^{Bank}, PD_{Reg,t}^{Bank}\right) \quad (38)$$

where the *TD* and *Bank* subscripts refer to top-down and bank projections, respectively. $PD_{Reg,t}$ is the regulatory probability of default in year t of the stress test horizon, and $PD_{Pit,t}$ is the point-in-time probability of default in year t of the stress test horizon. y is the country-specific probability of default cycle length (in years) as implied by the supervisory review.

The top-down projections of regulatory loss given default represent a sufficiently conservative economic downturn effect.⁵⁶ They are estimated as the maximum between top-down and bank projections. For non-defaulted loans, the specification has the form:

$$LGD_{Reg,nondef,t}^{TD\ Downturn} = \max\left[W_{avg}(LGD_{1\rightarrow 3,t}^{TD\ Pit}, LGD_{2\rightarrow 3,t}^{TD\ Pit}); W_{avg}(LGD_{1\rightarrow 3,t}^{Bank\ Pit}, LGD_{2\rightarrow 3,t}^{Bank\ Pit}); LGD_{Reg,nondef,t}^{Bank,Downturn}\right] \quad (39)$$

For defaulted loans, it is the following:

$$LGD_{Reg,def,t}^{TD\ Downturn} = \max\left[LGD_{3\rightarrow 3,t}^{TD\ Pit}, LGD_{3\rightarrow 3,t}^{Bank\ Pit}, LGD_{Reg,def,t}^{Bank\ Downturn}\right] \quad (40)$$

where $LGD_{Reg,t}^{Bank,Downturn}$ is the bank regulatory downturn estimate for the loss given default, W_{avg} denotes an exposure-weighted average across IFRS 9 stages 1 and 2, and $LGD_{X\rightarrow 3,t}^{TD\ Pit}$ and $LGD_{X\rightarrow 3,t}^{Bank\ Pit}$ are the point-in-time loss given default top-down and bank estimates, respectively. Accordingly, the top-down estimates of the regulatory loss given default include the downturn component required by the CRR by taking the most conservative value between point-in-time and regulatory parameters, while accounting for country and portfolio specificities. The derived top-down benchmarks allow to challenge counterintuitive cases where the downturn parameter is lower than the point-in-time parameter in banks' projections.

The validation of the top-down framework in the internal ratings-based approach shows a high comparability overall with bank estimates. To validate the top-down framework, Chart 22 compares the top-down risk exposure amount of the internal ratings-based approach with bank submissions, using the metrics:

$$Impact\ CET1^{REA} = \frac{CET1_{t0}}{REA_{t0}} - \frac{CET1_{t0}}{REA+\Delta REA} \quad (41)$$

where $CET1$ and REA denote the $CET1$ capital and total risk exposure amount, respectively, of a bank at the beginning of the exercise, and ΔREA the projected change in the risk exposure amount as a result of the macroeconomic scenario. The comparison shows that the top-down framework is equally successful as banks' own projections in accounting for bank-level specificities under the adverse scenario.

⁵³ See Articles 180 181 CRR.

⁵⁴ A workout in the context of a financially distressed obligor generally means an attempt by the bank to resolve a defaulted loan, for example through restructuring agreements, cures, transfers or judicial measures. To this end, it is considered the amount of losses that is based on the cash flows observed between the time of default and the time a resolution may take place (i.e., it is worked out).

⁵⁵ See TRIM report: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.trim_project_report~aa49bb624c.en.pdf.

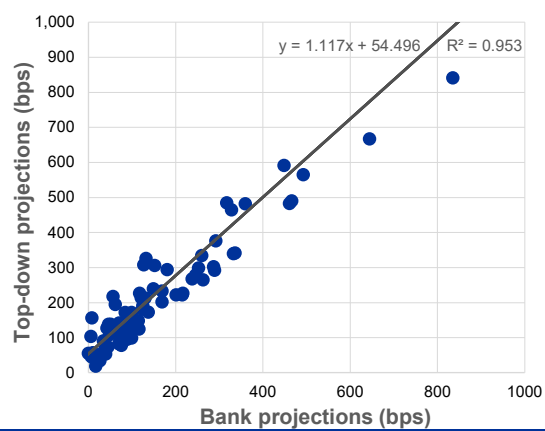
⁵⁶ The Basel framework defines loss given default as a downturn loss given default (Article 181 CRR), i.e., a loss given default referring to a crisis period for each jurisdiction. This is estimated by banks as: (1) the maximum loss given default experienced for a portfolio during an economic cycle (for long time series), (2) the downturn loss given default calibration based on estimated impact using historical loss data (haircut or extrapolation approach); or (3) the long-run average loss given default plus an add-on of 15 percentage points (for short time series). More information is available at:

<https://eba.europa.eu/documents/10180/2551996/Final+Report+on+Guidelines+on+LGD+estimates+under+downturn+conditions.pdf>.

Chart 22

Top-down and bank risk exposure amount projections in terms of impact on CET1

(Basis points)



Source: ECB calculations.

Note: The chart compares top-down and bank risk exposure amount projections for the risk weights of the internal ratings-based approach for the 2021 stress test adverse scenario.

3.5 Profitability

Profitability models include the top-down models for net interest income (NII), net fee and commission income (NFCI) and dividend income. The evolution of performing exposures net of non-performing loans (NPLs) is determined by the credit risk models. Projections for all three profitability models enter the calculation of banks' net profits. The main changes in the profitability models compared with STAMP€ are compiled in Table 8.

Table 8
Top-down profitability model developments

<p>1. Net interest income: additional models for debt securities and non-EU countries:</p> <ul style="list-style-type: none"> ▪ New models for debt securities projecting yields conditional on the macroeconomic scenario and analogous to the interest rate margin rate models at rating class level ▪ Added interest rate models for nine non-EU countries <p>2. Net interest income: switch from margin models to interest rate models</p> <ul style="list-style-type: none"> ▪ Models are now estimated with the interest rate instead of interest rate margins as a dependent variable ▪ Interest rate margin is derived ex post as the difference between the interest rate and the scenario reference rate 	<p>3. Net fee and commission income</p> <ul style="list-style-type: none"> ▪ Model is now estimated with macro variables weighted by bank-specific country weights as predictors ▪ Dependent variable is now based on FINREP time series (the previous version of the model relied on Bankscope data) ▪ Variables selected by the LARS procedure and that are not statistically significant are dropped <p>4. Dividend income</p> <ul style="list-style-type: none"> ▪ Dynamic panel fixed effect equations modelling dividend income as a function of macroeconomic variables
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Source: ECB.

3.5.1 Net interest income

Interest income is the main income source of banks. Interest income and expense are determined as the product of the interest rate and outstanding amounts. Interest income is driven by the reference rate, the margin over the interest rate and the outstanding amounts on interest-bearing assets. Throughout this section, the interest rate margin is defined as the spread between the interest rate and the reference rate in the same interest rate fixation period. This definition follows the logic of the EBA methodology, according to which banks are required to decompose the interest rate into the reference rate and the margin component. The NII model focuses on interest rates on loans, debt securities and deposits.

The ultimate output of the NII top-down model is to produce projections of the interest rate margin. The current approach focuses on the projection of interest rates,⁵⁷ which are then translated into interest rate margins by deducting the maturity matched reference rates along the scenario horizon.

Modelling of interest rates⁵⁸ relies on the BMA approach. The projections are performed separately for nine portfolios in 28 EU countries and eight non-EU countries. For loans, the portfolios considered on the asset side are corporate loans, household mortgages and consumer credit. In addition, the top-down models include three debt security portfolios: corporate debt securities, financial institutions and other debt securities. The portfolios considered on the liabilities side are corporate sight deposits, household sight deposits and term deposits.

The rationale for using the BMA approach is to address model uncertainty. While extensive empirical evidence shows that interest rates are driven by macroeconomic variables (Hanzlík and Těplý, 2022; Alessandri and Nelson, 2015), the BMA approach is agnostic about the set of variables most relevant for predicting interest rates. Additionally, the BMA modelling approach offers the possibility to impose restrictions on the sign of selected coefficients for explanatory variables. As a result, equations for which the coefficients have an undesired sign receive a weight of zero. These restrictions are informed by economic theory and empirical evidence. For example, higher short-term rates and sovereign spreads are expected to lead to higher lending rates and implicitly higher margins for loans as banks pass the increase in funding costs and country risk to their customers. Similarly, banks are expected to face higher costs on deposits as market rates increase.

⁵⁷ In the earlier approach, the modelling focused directly on interest rate margins. See Dees et al. (2017).

⁵⁸ The earlier approach had a disadvantage related to the combination of multicollinearity and restrictions on coefficients. The high correlation between the reference rate and the interest rate variables led to an unstable coefficient sign for these variables. As a result, sign restrictions imposed in the BMA framework could result in the exclusion of models with desirable statistical properties.

The BMA method first defines the model space as all possible combinations of variables and their lags. Each equation is estimated as an ARDL model:⁵⁹

$$\Delta i_t = \alpha + \sum_{q=1}^Q \rho_q \Delta i_{t-q} + \sum_{g=1}^G \beta_g X_g + \sum_{g1=1}^G \beta_{g1} X_{g1,t-1} \dots + \gamma D_{i,t} + \xi_t \quad (42)$$

where X is set of explanatory variables, indexed by g and including changes in long-term and short-term interest rates, the spread to the sovereign yield, GDP growth, unemployment, inflation and changes in residential property prices. The dummy variables $D_{i,t}$ capture the COVID-19 shock and take the value 1 in June 2020 and June 2021, and 0 otherwise. Q refers to the maximum lag of the dependent variable, ρ_q refers to the autoregressive coefficient at lag q , while β_g and β_{g1} refer to the coefficient estimates for the variable g and its first lag respectively. A model search is performed in a predefined “segment” or subset of the model space.⁶⁰ The parameters defining the size of each segment are the maximum number of predictors, their lags as well as the maximum number of autoregressive lags. Within each segment of the model space, the BMA method estimates a large set of equations for changes in interest rate and then aggregates these equations to a posterior model using the Bayesian criterion as weight.

Interest rate time series for loans and deposits are sourced from the MIR database for EU countries and the database of national central banks for non-EU countries. For debt securities, the country-level corporate bond yields for financial and non-financial companies for different rating classes are used instead of interest rates. The macro variables are obtained from Eurostat for EU countries and the World Economic Outlook (WEO) database for non-EU countries.

The second step is to translate the projections of interest rates into interest rate margins. Interest rate margins equal the projected interest rates minus the maturity-matched⁶¹ reference rates along the scenario horizon:

$$im_t = i_t - ref_t \quad (43)$$

The revamped approach to modelling interest rate margins leads to only slightly lower margin projections than the earlier approach, still applied in the 2021 stress test. The panel a) of Chart 23 compares the projections for loans and deposits under the new approach and the previous one, which applied the BMA method directly to interest rate margins.⁶² Both models are estimated conditional on the adverse scenario of the 2021 stress test. The change in specification was motivated by concerns about econometric robustness under the margin modelling approach. The lower margins under the new approach could indicate that the upward bias in margins resulting from the old model specification has decreased. In addition, the in-sample forecasting properties improve, with the root mean square error (RMSE) decreasing across all segments, in particular for consumer credit (panel b) of Chart 23).

⁵⁹ For comparison, the STAMP€ approach assumed the modelling of interest rate margins according to $i_t - ref_t = \alpha + \sum_{q=1}^Q \rho_q i_{t-q} + \sum_{q=1}^Q \zeta_q ref_{t-q} + \sum_{g=1}^G \beta_g X_g + \sum_{g1=1}^G \beta_{g1} X_{g1,t-1} \dots + \xi_t$.

⁶⁰ This segmentation of the model space is performed in order to ensure that the estimation remains tractable.

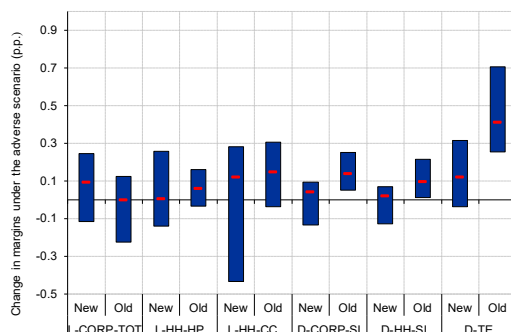
⁶¹ The maturity is proxied by the interest rate fixation period.

⁶² The earlier approach had a disadvantage related to the combination of multicollinearity and restrictions on coefficients. The high correlation between the reference rate and the interest rate variables led to an unstable coefficient sign for these variables. As a result, sign restrictions imposed in the BMA framework could result in the exclusion of models with desirable statistical properties.

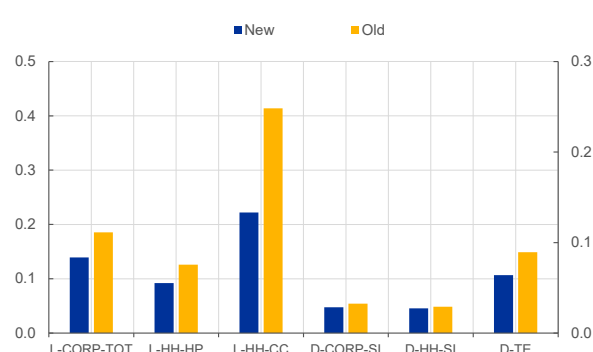
Chart 23

Comparison of margin projections between the new approach and projections

a) Change in margins under the adverse scenario
(Percentage points)



b) Root mean square errors of margin projections
(Percentage points)



Sources: 2021 stress test adverse scenario and ECB calculations.

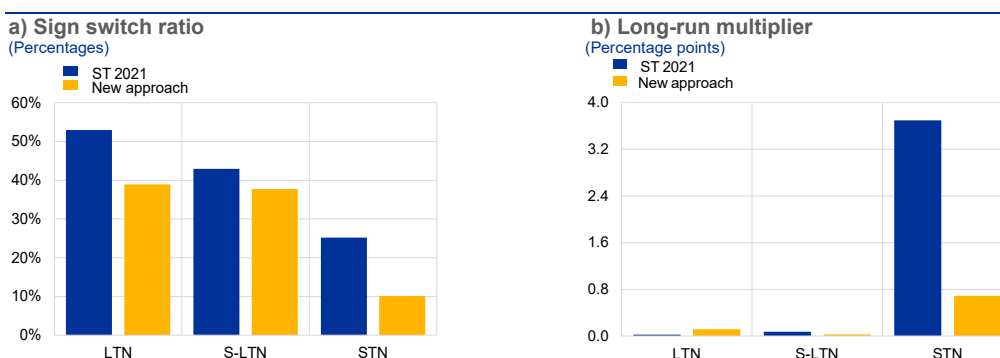
Notes: Panel a) shows the interest rate spread changes in each year of the adverse scenario reported relative to December 2019 values. L-CORP-TOT refers to margins for corporate loans, L-HH-HP to mortgages and L-HH-CC to consumer credit. D-CORP-SI refers to spreads for corporate sight deposits, D-HH-SI to household sight deposits and D-TE to total term deposits. The projections under the new approach and old approach (2021 stress test) are conditional on the 2021 stress test adverse scenario. The interquartile range refers to the country distribution of margin projections. Panel b) compares the in-sample RMSE.

The new modelling approach for net interest margins improves model robustness by reducing the impact of sign restrictions. The sign switch ratio in the panel a) of Chart 24 shows the number of posterior models in which a particular variable was excluded due to a negative sign divided by the total number of posterior models. The blue bars show the sign switch ratio under the old approach (“ST2021”), while the yellow bars refer to the new specification. The coefficient sign of the long-term nominal yield (LTN) was particularly unstable: it was set at 0 in around 53% of the posterior models due to unmet sign restrictions. Furthermore, the coefficients of the LTN spread (S-LTN) and short-term interest rate (STN) were set at 0 in 43% and 25% of the posterior models respectively. The sign restrictions are much less binding under the revised interest rate model approach: the LTN sign switch ratio drops to 39%, while the STN sign switch ratio drops to 15%. Overall, the coefficient sign restrictions have a lower and hardly material impact on projections under the new compared with the old approach.

The new approach also translates well in the improved behaviour of the long-run multipliers for the explanatory variables.⁶³ Panel b) of Chart 24 shows the long-run multipliers for the interest rate variables: the blue bars show the coefficients from the margin model, while the yellow bars show the interest rate coefficients under the new approach shown in the interest rate equation (42). Under the old approach, both the short-term interest rate (STN) and the reference rate were included as predictors, while the latter is omitted under the new approach. The very high STN coefficient of 3.7 under the old approach is inflated by the high correlation between the STN and the reference rate. The relevance of multicollinearity is confirmed by a drop in the STN coefficient of a similar magnitude when the margin equation under the old approach is estimated without the reference rate: on average, the long-run multiplier drops from 3.7 in the presence of the reference rate to 0.89 without the reference rate. Under the new approach, the coefficient of the short-term interest rate drops to 0.7, consistent with other pass-through coefficients reported in the literature.

⁶³ The long-run multiplier for variable g is computed as the ratio between the sum of the coefficients of variable g and its lags divided by the sum of the autoregressive coefficients.

Chart 24
Coefficient sign stability and long-run multipliers



Sources: 2021 stress test adverse scenario and ECB calculations.

Notes: The numerator of the sign switch ratio for variables is the average number of posterior models in which the variable has a negative sign before the sign restriction is applied divided by the total number of models. STN, S-LTN and LTN refer to the short-term interest rate, the sovereign spread and the long-term nominal yield respectively.

3.5.2 Net fee and commission income

The contribution of NFCI to revenues for most euro area banks is second only to NII. Furthermore, it has gained importance in the low interest rate environment. The top-down model reflects the sensitivity of NFCI to changes in macroeconomic conditions and relies on Kok et al. (2019).

The estimation is based on a two-step approach. First, the least angle regression (LARS) algorithm is applied to select the most relevant variables for predicting the NFCI ratio (Efron et al., 2004). The second step is to use an econometric panel approach to estimate the link between the ratio of NFCI over total assets (%) and the macro variables that were selected in the first step.

The LARS-based preselection of explanatory variables in the first step of the approach keeps the model relatively sparse and circumvents over-fitting. The initial pool of potential explanatory variables includes 14 variables, therein the lagged dependent variable, both contemporaneous and lagged values of the Itraxx index, the short-term interest rate, the stock market return and real GDP growth. Of these, the LARS algorithm selects five significant variables to include in the estimation step.⁶⁴

The second estimation step panel introduces a bias-corrected least square dummy variable (LSDVC) regression:

$$NFCI_{it} = \alpha_0 + \sum_{j=1}^p \alpha_1 NFCI_{it-1} + \sum_{j=0}^r \sum_{k=1}^4 \alpha_{3,k} X_{k,it-j} + \varepsilon_{it} \quad (44)$$

where $NFCI_{it}$ is the net fee and commission income over total assets (%) for bank l at time t , and X_t is the set of macroeconomic variables mentioned above and their lags. NFCI data was obtained from FINREP, while macroeconomic variables were obtained from the ECB Statistical Data Warehouse (SDW). Sourcing the NFCI from long-term supervisory data (FINREP) marks an improvement over the previous econometric model, allowing the sample coverage to be extended. Previously, the model covered a sample of 102 euro area banks located in 19 countries. Now, it covers 126 European banks including non-SSM countries. The collection of supervisory data across all relevant jurisdictions was coordinated by the EBA.⁶⁵ The LSDVC estimator is more efficient than the generalised method of moments (GMM) estimator and corrects for the Nickel bias. The Nickel bias is the bias arising in dynamic fixed effects models due to the correlation between the time-invariant fixed effects and the error term.⁶⁶ Chart 25 shows the change in NFCI in the 2023 stress test baseline and adverse scenario implied by equation (44).

⁶⁴ The selection procedure is re-run before each stress test exercise, and the list of variables selected may change. Nevertheless, past experience has shown that the LARS outcome is relatively stable and consistently ensures that all relevant variables are included in the estimation.

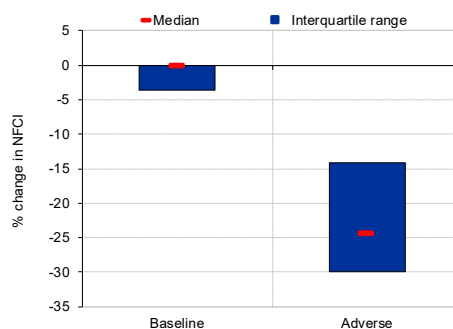
⁶⁵ Many improvements to NFCI projection models were undertaken in the context of the EBA's efforts to introduce more top-down elements in the EU-wide stress-testing exercise. A group of experts from different European central banks and supervisory authorities were tasked with providing recommendations for the existing framework to be used as a robust model for the projections of individual banks' NFCI in the regular stress-testing exercise.

⁶⁶ See Nickel (1981), "Biases in Dynamic Models with Fixed Effects", *Econometrica*, Vol. 49, Issue 6, pp. 1417-1426.

Chart 25

Changes in NFCI under the adverse and baseline scenarios

(Percentages)



Source: ECB calculations.

Notes: Changes in NFCI relative to December 2022 values under the baseline and adverse scenarios. The scenario refers to the 2023 stress test. NFCI in each year of the scenario was derived from the estimation described in equation (44).

Importantly, the explanatory variables are derived by weighting country-level macro-financial variables with the geographical breakdown of individual bank assets. In the earlier model, bank-level NFCI was linked with the macroeconomic variables relevant only to the countries where the bank is headquartered. However, the latter did not accurately capture the sensitivity to macroeconomic conditions of banking groups with a significant cross-border exposure. In the current version of the model, time-varying geographic weights are estimated based on the FINREP F20.04 country exposures for the period 2014-21 and kept constant at 2014 values for the period 20-2013. Geographic weights are kept constant along the scenario horizon for the purpose of deriving scenario projections.

3.5.3 Dividend income

Top-down projections of dividend income are derived on the basis of a bank-level panel regression estimated with the LSDVC estimator. The regression explains the dividend income over assets⁶⁷ as in Lintner (1956) and Gross et al. (2021):

$$DI_{it} = \alpha_0 + \sum_{j=1}^p \alpha_1 DI_{it-j} + \sum_{j=0}^r \sum_{k=1}^4 \alpha_{3,k} X_{k,it-j} + \varepsilon_{it} \quad (45)$$

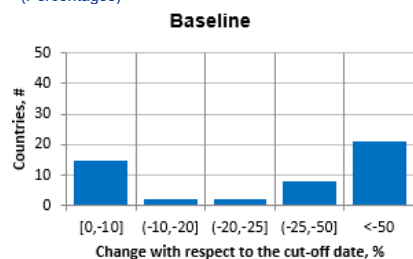
where DI denotes dividend income over assets in bank i at time t , which is explained by its lagged value and macroeconomic indicators (X), the slope of the yield curve, GDP growth, the change in short-term interest rate, inflation and stock market return. Chart 26 shows the percentage change in dividend income in the 2023 stress test baseline and adverse scenario, as implied by equation (45).

⁶⁷ The regression uses the dividends/total assets ratio as a dependent variable rather than the dividends/net income ratio, as total assets are more stable than earning flows.

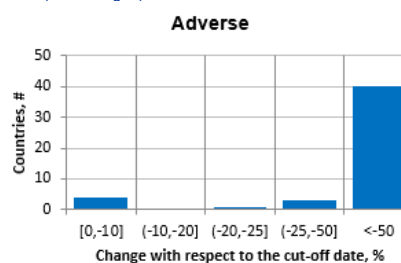
Chart 26

Changes in dividend income under the adverse and baseline scenarios

a) Change in dividend income,
baseline scenario
(Percentages)



b) Change in dividend income,
adverse scenario
(Percentages)



Source: ECB calculations.

Notes: Changes in dividend income relative to December 2022 values under the baseline and adverse scenarios. The y-axis shows the number of countries with a change in dividend income in each bucket. The scenario refers to the 2023 stress test. Dividend income in each year of the scenario was derived from the estimation described in equation (45).

The dataset covers 3,386 banks located in euro area countries⁶⁸ spanning the period 2011-20. Banks with fewer than five observations for the dependent variable were removed from the sample. Macroeconomic variables are sourced from the ECB SDW database. All variables are winsorised to limit the effect of outliers on the estimation results.

⁶⁸ However, the information on bank-level dividend income is not available for all jurisdictions.

3.6 Market risk

The market risk top-down models produce the stressed impacts related to full revaluation, liquidity and model uncertainty, counterparty credit risk (CCR) and net trading income. The top-down models are generally adapted to the EU-wide stress-testing methodology and related data collections. They cover all positions held at fair value (and related hedges), which are classified into the following accounting categories according to IFRS 9:

- fair value through profit or loss (FVPL);
- fair value through other comprehensive income (FVOCI);
- amortised cost positions being part of a hedge accounting relationship (AC).

The projections of market risk use dedicated higher-frequency stress test scenarios. The calibration of an adverse market risk scenario links to the general macro-financial scenario but features two specificities:

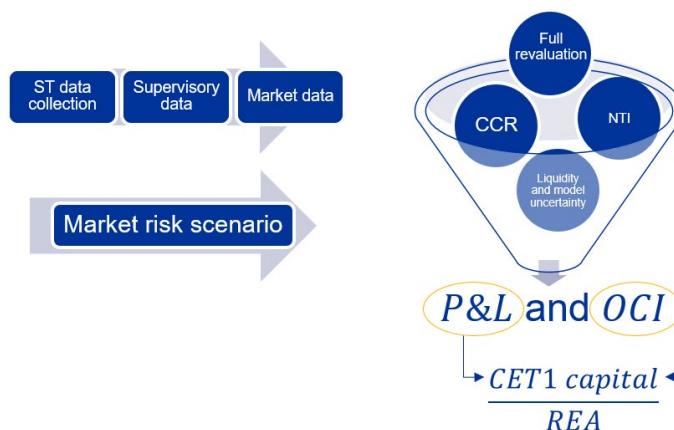
- **Instantaneous shocks:** market risk shocks are instantaneous and materialise in the first quarter of the first year of the projected horizon;
- **Large set of risk factors:** many financial variables are included in the scenario, providing high granularity (e.g., a high number of tenors for government bond spreads) and additional information (e.g., inflation, corporate bond spread, volatilities, etc.).⁶⁹

Risk factors included in an adverse market scenario cover interest rate, credit spreads, equity, foreign exchange, inflation, commodities and funds.

Aside from the top-down models directly used during stress-testing exercises, the market risk infrastructure includes additional tools to compute gains and losses stemming from assets held at fair value. Specifically, the SHS-G and EPIC tools compute bank-level sensitivities to different risk factors for security and derivative holdings, respectively and independently from stress test data (Appendix 8.2.5 and 8.2.6). Finally, the infrastructure includes a new quantile model on net trading income.

The output of the market risk models contributes to the overall capital depletion via profit and loss and the capital account (Figure 9).

Figure 9
High-level overview of top-down market risk computation



Source: ECB authors.

In recent years, model development focused on expanding the coverage of market risk categories and increasing the accuracy of earlier models. The new models were developed to project the stressed impact on liquidity and model uncertainty reserves and to forecast net trading income and client revenues. For pre-existing models, the modelling efforts included increasing the scope and accuracy of the full revaluation model and fine-tuning the CCR model. For an overview of modelling activities, see Table 9.

⁶⁹ As a reference, consider the [2023 EU-wide stress test market risk scenario](#).

The main changes to the market risk methodology compared with STAMP€ are compiled in Table 9.

Table 9
Top-down market risk model developments

<p>1. Full revaluation:</p> <ul style="list-style-type: none"> Extended to include non-linear sensitivities and additional (with respect to the stress test scenario) risk factor impacts reported since the 2021 EU-wide stress test (building on the granularity of first-order and second-order sensitivities reported in the EU-wide stress test), and project risk impact for other than held-for-trading assets; <p>2. Liquidity and model uncertainty:</p> <ul style="list-style-type: none"> A new top-down model (replacing the STAMP€ set-up where the liquidity reserve was a function of the derivative fair value) that relies on the information collected from commercial data providers (e.g., Bloomberg and Reuters) on bid-ask spreads for relevant risk factors at the most granular level. The approach takes into consideration the riskiness of the portfolio and incorporates the detailed information provided in other parts of the market risk templates, i.e., the split between L1, L2 and L3 assets and the sensitivities as reported by banks in EBA/SSM stress test templates. 	<p>3. Counterparty credit risk (CCR):</p> <ul style="list-style-type: none"> The model computes CCR for the two most vulnerable counterparties (of the ten largest counterparties reported by banks) by controlling for credit ratings and including counterparty fixed effects that capture counterparties' specificities and credit mitigation mechanisms.⁷⁰ <p>4. Net trading income (NTI):</p> <ul style="list-style-type: none"> The model focuses on the client revenues component of NTI and leverages on banks' submissions in previous stress tests. It is based on a dynamic panel model that controls for banks' trading activity. An additional NTI top-down benchmark projects total adverse NTI and represents a second layer of analysis for the stress-testing exercise.
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Source: ECB.

In the EBA methodology, banks are divided into two categories: comprehensive approach (CA) and trading exemption (TE). TE banks are exempt from reporting the full revaluation impact for items held with a trading intent and their related hedges. CA banks have no trading exemption and are required to project client revenues and the full revaluation impact for items held for trading.

3.6.1 Full revaluation

The top-down full revaluation model estimates adjusted gains and losses due to market stress impact on assets booked at full or partial fair value. The revaluation of fair value assets makes up the main contribution to market risk losses in most stress-testing exercises. The model computes the impacts for the first year of the adverse forecast horizon⁷¹ for each bank and item⁷².

The recent extensions of the model acknowledge the non-linear nature of banks' fair value portfolios and capture the impacts of risk factors not reported in the EU-wide stress test templates. Since 2021, the model has included second-order sensitivities and additional risk factors, consisting of three computation parts:

1. first-order approximation (FOA) gains and losses derived on the basis of delta⁷³ sensitivities;
2. second-order approximation (SOA) including the impact from gamma⁷⁴ and vega⁷⁵ sensitivities and providing an estimate of total gains and losses;
3. adjusted gains and losses considering additional risk factors and additional gamma and vega sensitivities (not included in 1 or 2 above).

⁷⁰ STAMP€ modelled the bank-level top CCR exposure via the interaction of derivative notionals and scenario shocks. It then derived the provision for the default of the two most vulnerable counterparties via expert judgement on the relation between the largest CCR exposure and the two most vulnerable ones.

⁷¹ In accordance with the prescribed EBA methodology, the shock applied to the full revaluation of fair value items is realised within the first year of the stress test.

⁷² Portfolio items are classified according to balance sheet side, IFRS 9 standards for financial holdings, hedged/hedging role, FINREP classification of financial holdings, derivative holdings specificity (linear or optional), long or short positions.

⁷³ Delta sensitivity represents the change in the derivative value given a change in the derivative's underlying.

⁷⁴ Gamma sensitivity represents the change in the option's delta given a change in the derivative's underlying.

⁷⁵ Vega sensitivity represents the sensitivity of the value of an option with respect to the underlying's volatility.

The linear FOA of the change in a bank's holdings value is computed as:

$$FOA_{item} = \sum_j \Delta_{item}(j) \times Shock(j), \forall j \in J \quad (46)$$

where J is the full set of risk factors reported in the scenario, and $\Delta_{item}(j)$ is the change in the value of the portfolio ($item$) following a unit change in risk factor (j) and is reported by the bank. $Shock(j)$ for the risk factor (j) is derived from the market risk stress test scenario. The risk factors reported in the scenario cover different categories (i.e., interest rates, equity, foreign exchange, commodity, inflation, credit spreads, etc.), different regions (i.e., euro area, North America, Asia), different geographies (i.e., Ireland, Italy, USA, Japan) and different risk factor specificities (i.e., different tenors for interest rates).

Total impact is calculated as the SOA for CA banks. The latter is represented by the sum of the FOA and the shock sensitivities captured by gamma and vega parameters:

$$SOA_{item} = FOA_{item} + \sum_j Vega_{item}(j) \times Volatility_Shock_{item}(j) + \sum_j 0.5 \times Gamma_{item}(j) \times Gamma_Shock_{item}(j)^2 \quad (47)$$

where $\Gamma_{item}(j)$ is the second-order sensitivity and $Vega_{item}(j)$ is the first-order sensitivity to volatility. They are reported by banks with a lower level of granularity than delta sensitivities, for the two categories interest rates and equity and for the two regions European Union and United States⁷⁶. Moreover, CA banks can also report additional gamma and vega sensitivities that can be included in the total impact computation. SOA is not computed for TE banks as they are not required to report gamma and vega sensitivities.

While the vega shocks are provided in the scenario, the gamma shock is computed for the relevant items and geographies as a weighted average of more granular market risk scenario shocks, where the weights are the absolute values of the delta sensitivities:

$$Gamma_Shock_{item}(j) = \left(\sum_s \sum_g \frac{Shock(j_{g,s})}{\sum_s \sum_g |\Delta_{item}(j_{g,s})|} |\Delta_{item}(j_{g,s})| \right) \quad (48)$$

where $\Delta_{item}(j_{g,s})$ considers all the item-specific deltas for interest rates or equity and the geographies (g) within the European Union or United States, and interest rate tenors (s). Given that the current portfolio composition for each specific instrument is not known, the weighting scheme is an approximation used to compute the relevant shock (for instance, a delta of an option not only depends on the notional but also on the comparison between the spot price and strike price).

The linear first-order gains and losses include impacts stemming from additional risk factors reported by banks.⁷⁷ Banks report impacts from two types of additional risk factors: (i) more granular risk factors than those included in the scenario, e.g., different types of oil as part of the oil risk factor; and (ii) risk factors not included in the scenario, e.g., correlation risk. Both can have a material impact on bank-level full revaluation results.⁷⁸

The final top-down revaluation impact is therefore computed as follows:

$$Revaluation\ impact_{item} = ARF_{item} + SOA_{item} \quad (49)$$

where ARF_{item} represents the reported additional impacts for a specific item.

The top-down model is effectively able to capture the idiosyncrasies of banks' full revaluation impacts. Chart 27 presents the results for the 2021 stress-testing exercise, comparing the top-down model results (y-axis) and banks' bottom-up projections (x-axis) by bank approach (CA/TE). To allow for peer comparison, impacts are presented in terms of basis points of the risk exposure amount. The chart shows a high degree of correlation between the two sets of results.

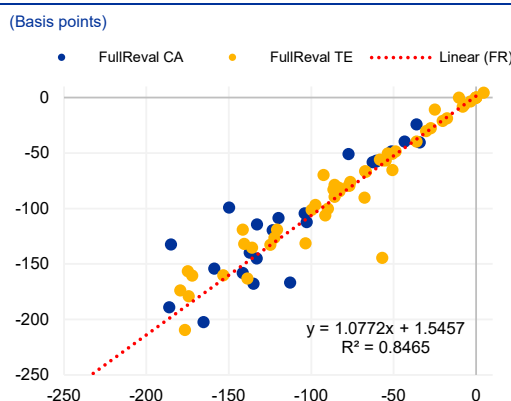
⁷⁶ Only comprehensive approach (CA) banks are subject to this reporting requirement.

⁷⁷ Additional risk factor impacts are reported separately so that there is no double counting.

⁷⁸ An example of additional risk factors reported during the 2021 EBA stress test was the emerging market sovereign "Colombia 5 Years Sovereign CDS".

Chart 27

Top-down and bank impacts on CET1 ratio from full revaluation



Sources: 2021 stress test and ECB calculations.

Notes: X-axis: bank results; y-axis: top-down results; risk exposure amount (bps). Results are reported by bank approach: comprehensive approach (CA) and trading exemption (TE).

For the 2023 stress test, a new template on leveraged finance for full revaluation has been included in the data collection for a limited sample of banks.⁷⁹ Leveraged finance has become a relevant topic from a supervisory perspective following a prolonged period of low interest rates. The scope of this new template is to focus specifically on items in the underwriting pipeline, and its structure is similar to the main full revaluation template.⁸⁰ The leveraged finance underwriting pipeline is a subset of the fair value items revalued in the full revaluation template. Although, gains and losses on these items are already included in equation (49), the additional template facilitates gain and loss projections at a more granular level.

3.6.2 Market liquidity and model uncertainty reserve

Market liquidity affects the cost of transforming assets into cash. One measure of market liquidity is the bid/ask spread, i.e., the difference between the highest bid price and the lowest ask price of an asset. This spread measures the variable transaction cost added to fixed transaction costs such as fees.

The top-down model of market risk reserves estimates the impact of an exogenous widening in the bid-ask spread on fair value and prudential reserves for all items within the market risk scope.⁸¹ In terms of accounting adjustments (i.e., fair value adjustments, IFRS 13), the widened bid-ask spread concerns only the fair value adjustment for liquidity, model risk and market price uncertainty. For prudential adjustments (additional valuation adjustment, Article 105 CRR and EBA/RTS/2014/06), calculations consider only the adjustments related to market price uncertainty, close-out cost and model risk. Other valuation adjustments defined in Article 105 CRR (unearned credit spreads, early termination, investing and funding cost, operational risks and future administrative costs) are not covered.⁸²

The top-down model computes the impact of a bid-ask spread liquidity shock for all fair value levels (L1, L2, L3) and of a model uncertainty shock for L2 and L3 instruments. The model uncertainty shock to L2 and L3 instruments is additive to the liquidity shock. The fair value level-based shocks are as follows:

$$Shock_l = \begin{cases} X\% & \text{if } l = L_1 \\ X\% + Y\% & \text{if } l = L_2 \\ X\% + Z\% & \text{if } l = L_3 \end{cases} \quad (50)$$

where l ranges across exposure levels (i.e., L1, L2 and L3), X represents the market liquidity shock, while Y and Z represent the model uncertainty shocks for L₂ and L₃ respectively. All shocks are derived from the relevant bid-ask spreads.

⁷⁹ Banks were selected according to the relevance of leverage finance in their business activities.

⁸⁰ The key differences from the main full revaluation template are that (i) banks are not required to report sensitivities to equity and funds, and (ii) banks are not required to report additional gamma and vega sensitivities.

⁸¹ See EBA methodological note 2023 stress test (Par. 289).

⁸² See EBA methodological note 2023 stress test (Par. 290).

To consistently challenge the stress test impact on liquidity reserves submitted by banks, the top-down model is developed starting from the following formula:⁸³

$$\text{Impact_stressed_Reserve}_l^{item} = \sum_{j \in \text{Risk Factors}} \text{Spread (Bid – Ask)}_{j,l} \times \text{Shock}_l \times \text{Exposure}_{j,l}^{item} \quad (51)$$

where *item* ranges across held-for-trading, mandatory or optional FVPL, and FVOCI portfolios. It is assumed that the relevant exposure can be broken down by risk factors⁸⁴ *j*, which have different sensitivities. The relevant risk factor categories (classified according to their FINREP class) include debt instruments, interest rates, equity, credit and foreign exchange.⁸⁵ A bid-ask spread *Spread* (Bid – Ask)_{*j,l*} is assessed within each of the categories (e.g., equity) and for the most relevant risk factors *j* (e.g., German stocks), using market data.

Market quotes are used to obtain the portfolio bid-ask as the product of risk factor bid-ask multiplied by the risk factor sensitivity:

$$\text{Spread (Bid – Ask)}_{j,l} = \sum_{l \in \text{FV level}} \sum_{j \in \text{Risk factors}} \left(\frac{\text{Bid – Ask}}{2} \right)_j \times \text{Sensitivity}_j \quad (52)$$

where sensitivity is the change in one unit of exposure given a 1% change in the risk factor.⁸⁶ The sensitivity for fixed income instruments is the duration (first-order sensitivity) sourced from market data. The risk factor-specific bid-ask is obtained from market prices and applied to interest rate, credit, equity and exchange rate portfolios.

The exposure value for each risk factor is estimated in a few steps. The first step is the estimation of the share exposed to each risk factor (*Share*_{*j*}^{*item*}) for each accounting portfolio item in scope (i.e., held for trading, mandatory or optional FVPL, FVOCI). Risk factor delta sensitivities provided by the bank and described in the previous section are used to imply a risk factor share for each portfolio item. The relevant delta(s) can be deduced depending on the breakdown of the FINREP accounting items (e.g., equity, interest rate, etc.). For example, for those portfolio rows related to debt instruments, the delta(s) associated with interest rate swap rate shocks are divided by the associated duration to compute the exposure value for each risk factor. The *Share*_{*j*}^{*item*} is the relative weight of each risk factor in each accounting portfolio item.

The next step concerns the calculation of weights of L1, L2 and L3. These are calculated using portfolio notional amounts submitted in the full revaluation template and computed for each item in the full revaluation template as:

$$\text{Weight}_l^{item} = \frac{\text{Notional_Exposure}_l^{item}}{\text{Notional_Exposure}_{Tot}^{item}} \quad (53)$$

The final step is the estimation of bank-specific total exposure (*Exposure_Tot*^{*item*}) for each accounting item in monetary value. It considers risk factor exposure and portfolio composition. Following the EBA methodology, the exposure amount to be considered for bonds is the nominal value. For exchange-traded derivatives, interest rate swaps and foreign exchange swaps, it is the notional value of the instrument, while for equities, the fair value is used.⁸⁷ Once the overall exposure for each accounting item is determined, the risk factor-specific and liquidity level-specific exposures are calculated:

$$\text{Exposure}_{j,l}^{item} = \text{Exposure_Tot}^{item} \times \text{Weight}_l^{item} \times \text{Share}_j^{item} \quad (54)$$

Overall, the approach reflects the risk composition of banks' portfolios in terms of types of assets, risk drivers and complexity of derivatives (i.e., L1, L2, L3).

⁸³ Following the EBA methodology as described in Box 15.

⁸⁴ The risk factors considered reflect those reported in the market risk scenario.

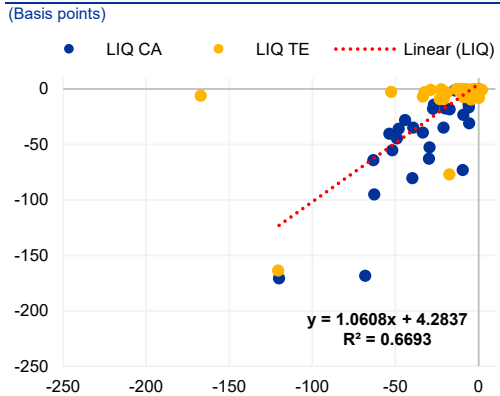
⁸⁵ The “commodity” risk factor category is not considered because of its very low exposure.

⁸⁶ The top-down model employed during the 2018 stress tests was based on a fixed elasticity of stressed reserves combined with liquidity shocks for different types of assets. The framework did not reflect the composition of the portfolio across different asset classes and different types of assets (i.e., L1, L2 and L3). This represented a substantial shortcoming of the model, which the new model tries to solve using the information provided by banks in the full revaluation template and with market data.

⁸⁷ Notional and fair value amounts are sourced from the full revaluation template for the relevant accounting portfolio items.

Chart 28 displays the top-down model fit with respect to banks' final projections in the 2021 stress test. The R-squared value is approximately 67%. The comparison with banks' projections reveals that the top-down model is a good fit for most banks in the sample. For a small number of banks, the top-down model projection is slightly more conservative, mainly for banks applying the comprehensive approach. In these cases, it highlights areas where a deeper dive into bank projections might be warranted.

Chart 28
Top-down and bank impacts on CET1 ratio from liquidity and model uncertainty reserves



Sources: 2021 stress test and ECB calculations.

Notes: X-axis: bank results; y-axis: top-down results. Results are reported by bank approach: comprehensive approach (CA) and trading exemption (TE).

3.6.3 Counterparty credit risk

Counterparty credit risk (CCR), as defined in Article 272 CRR, reflects the risk that a counterparty defaults before the final settlement of a transaction. The top-down methodology follows the EBA methodological note, where CCR provisions are computed for the default of the two most vulnerable counterparties among the ten largest ones in terms of stressed CCR exposures. A loss will occur if the value of the bank exposure to the defaulting counterparty is positive.

The methodology follows two steps. First, an empirical regression model projects the stressed CCR exposure net of stressed collateral. Second, the provisions related to the two most vulnerable counterparties are calculated given the bank's submitted losses given default and credit valuation adjustments (CVAs).

The stressed CCR exposure is projected using a cross-sectional non-linear regression. The stressed CCR is regressed on the initial CCR level and other relevant variables leveraging on the data submitted by banks in the EU-wide stress tests in 2016, 2018 and 2021, FINREP and market data:

$$\begin{aligned} Stressed_{CCR_{i,k,t}} = & \alpha_0 + \alpha_1 Initial_{CCR_{i,k,t}} + \alpha_2 Initial_{CCR_{i,k,t}}^2 + \sum_{l \in \theta} \beta_l NOT_{i,T}^l \times SHOCK_t^l + \gamma_1 IG_{k,T} + \\ & \gamma_2 Tier_{i,T} + \gamma_3 CA_{i,T} + \gamma_4 NOT_{i,T}^{IR} \times Positive IR shock dummy_t + \gamma_5 Initial_{CCR_{i,k,t}} \times \\ & Tier_i + \varepsilon_{i,k,t} \end{aligned} \quad (55)$$

where the subscripts i , k , t , T and l stand for bank (i), counterparty (k), scenario (t), stress test wave (T) and FINREP asset class category (l), respectively. $Initial_{CCR_i}$ is the initial CCR exposure before the application of adverse scenario shocks in each of the EU-wide stress tests. NOT is the vector of the notional amounts of derivatives reported by asset class $\theta = \{Equity,^{88} FX, Commodities, Interest Rates, Credit\}$. $SHOCK$ is the vector of scenario shocks. Shocks are common across banks and counterparties, and they vary under adverse scenarios (2016, 2018, 2021), while notional derivatives vary among banks and stress tests. CA dummy is equal to 1 when a bank follows the comprehensive approach and 0 otherwise. IG dummy is equal to 1 for those counterparties belonging to the credit quality steps 1 and 2. $Tier^{89}$ dummy captures the size of the bank, and $Initial_{CCR} \times Tier$ is the interaction between the initial CCR and the bank's tier, which adjusts for the non-linear effect of larger banks. $Positive IR shock dummy$ takes the value of 1 if a positive interest rate shock for is envisaged for bank i ; it is introduced to adjust for the non-linear effect of negative interest rates in two of the scenarios.

⁸⁸ The shock to equity is the only one that differs from country to country.

⁸⁹ Tiering classifies banks according to their total assets compared with the overall sample.

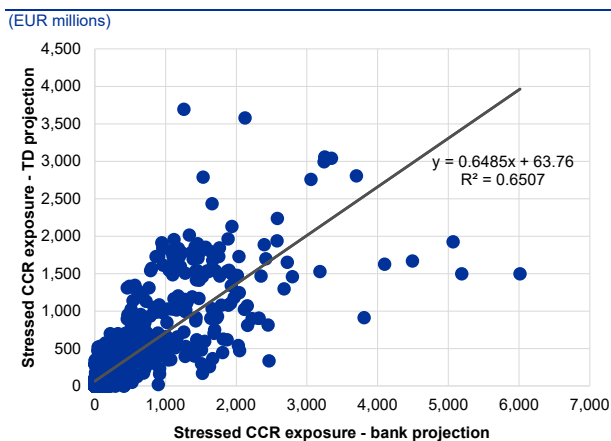
Stressed CCR exposure is first dependent on the initial CCR exposure. A squared term is introduced to account for the non-linear relationship between stressed CCR exposure and initial exposure. A positive coefficient suggests that as the initial CCR exposure grows, the marginal effect results in a larger stressed exposure. Dummies are included in the regression to account for the credit quality of the counterparty, which in turn affects the CCR provision. Bank-specific dummies are also included to account for the type of bank (comprehensive approach or trading exemption) and for the size of the bank, with larger, market risk-focused banks generally having a higher stressed exposure. Negative shocks to interest rates have a more pronounced effect on stressed CCR exposure, so an interest rate dummy interacted with the notional amount is included to account for this asymmetry.

The regression is estimated with the pooled OLS approach. This estimator was chosen from three tested alternatives (*pooled OLS*, *Ridge* and *LARS* regression) on the basis of its best out-of-sample forecasting performance measured by RMSE. The sets for training and testing data were randomly identified, ensuring that the proportions were 70% training data and 30% testing data.

The regression relies mainly on the final bank submissions and risk factor shocks from past stress tests. Since 2016, the EBA methodology has required the assumed default of two of the bank's weakest counterparties. As such, the model projects the stressed CCR exposure for each counterparty and can be extended to any number of counterparties reported by the bank. The information on derivative notionals broken down by asset class (end of 2015, end of 2017, end of 2020) is sourced from FINREP. The ECB ratings database provides information on raw ratings data from four rating agencies, namely Fitch, Moody's, Standard & Poor's and Dominion Bond Rating. The market risk scenario differs across stress tests and is accounted for in the regression model.

The model performs well, especially for the largest banks. Chart 29 shows the comparison between top-down and bottom-up stressed CCR exposures (net of stressed collateral) for the ten largest counterparties in the 2016, 2018 and 2021 stress tests. The model has an R-squared value of 65.07%.

Chart 29
CCR model performance



Sources: 2016, 2018 and 2021 stress tests, and ECB calculations.
Notes: The stressed CCR exposure is net of stressed collateral (after application of the market risk shock).

3.6.4 Net trading income and client revenues

A large share of banks' net operating income in the euro area arises from non-interest income and therein net trading income (NTI).⁹⁰ More precisely, NTI stands for "gains or (-) losses on financial assets and liabilities held for trading and trading financial assets and trading financial liabilities"⁹¹. Given the nature of financial markets, trading income can also be a relatively volatile income source for banks. As a result, it is an important component of market risk during stress-testing exercises.

The top-down infrastructure includes two different models related to NTI. The first model focuses on the client revenues component of NTI, while the second models total NTI via a quantile approach. The two models are complementary in nature. In the EU-wide stress test, the client revenue model is used to challenge banks' client revenues projections, a subcomponent of NTI. It follows a panel regression approach and projects a conditional mean. Conversely, the quantile model empirically estimates and forecasts the full NTI distribution conditional on an adverse scenario. It can therefore be used at a more aggregate level to assess the likelihood of the overall NTI impact in the stress test, especially when the projection is far from the median. In addition, the quantile model is estimated on supervisory data reported quarterly, which allows the model to be used outside of the EU-wide stress test to estimate expected losses and tail risk measures under adverse scenarios.

3.6.4.1 Client revenues model

Client revenues (*ClientRev*) include income that banks generate as intermediaries in transactions performed on behalf of their clients. They include (i) a retained portion of or a mark-up on the bid-ask spread, generated from market making or trading activities on behalf of external clients; (ii) prime service revenues; and (iii) underwriting fees charged by the bank on a debt underwriting or a debt issuance by a corporate client booked in the trading book.⁹² For the first year of the stress test horizon, client revenues affect banks' profits and losses as a component of NTI. NTI and client revenues are related according to the following equation:

$$NTI(Adverse)_{Y_1} = ClientRev(after\ cap)_{Y_1} - \Delta ReserveLiquidity(HFT)_{Tot,Y_1} - \Delta ReserveCVA_{Tot,Y_1} - P\&LFullReval(HFT\&Economic\ hedges)_{Tot,Y_1} \quad (56)$$

where *ClientRev(after cap)* is described in equation (58), $\Delta ReserveLiquidity(HFT)_{Tot}$ is the impact from fair value and prudential reserves on held-for-trading items, $\Delta ReserveCVA_{Tot}$ is the impact from CVA reserves (net of eligible CVA hedges) and $P\&LFullReval(HFT\&Economic\ hedges)_{Tot}$ is the impact stemming from the revaluation of items held for trading and economic hedges. From the second year of the stress test horizon onward, the only component of adverse NTI is the *ClientRev(after cap)*; the remaining components of the right-hand side of equation (56) are assumed null.

In line with the EBA methodology, client revenues after caps are computed as follows:

$$ClientRev(after\ cap)_{Y_1} = \begin{cases} NTI(Baseline)_{Y_1} & if\ NTI(Baseline) < 0 \\ Min(ClientRev_{projected,Y_1}, 0.75 \times ClientRev_{Y_0}, 0.75 \times NTI(Baseline)) & if\ NTI(Baseline) \geq 0 \end{cases} \quad (57)$$

where $NTI(Baseline)$ is computed as an average of historical NTI and $ClientRev_{projected,Y_1}$ is the projected client revenues reported by the bank before the methodological cap applies⁹³.

⁹⁰ In the recent 2021 EU-wide stress-testing exercise, the year 1 impact from gains and losses from financial assets held for trading accounted for 50 basis points (of the risk exposure amount) across all banks and 75 basis points across global systemically important banks in 2021. The total market risk impact was 102 basis points at the end of the exercise.

⁹¹ Please note that this is the definition used in the 2021 EBA methodological note. The definition changed for the 2023 stress test, but the 2021 definition is used for the purpose of this report.

⁹² See paragraph 228 of the EBA 2021 methodological note.

⁹³ On the contrary, TE banks do not have to project client revenues and are therefore computed with a haircut applied to the baseline NTI (if the latter is positive).

The top-down model estimates client revenues on a quarterly basis and aggregates them to compute the client revenues before caps (*ClientRev_{projected}*) in the first year of the stress test horizon. The regression model reads as follows:

$$ClientRev_{i,t} = \beta_0 + \beta_1 ClientRev_{t-1} + \beta_2 ClientRev_{t-2} + \sum_{l \in \theta} \alpha_l NOT_{i,l,t-1} + \sum_{l \in \theta} \gamma_l SHOCK_l \cdot NOT_{i,l,t-1} + DUMMY + \varepsilon_{i,t} \quad (58)$$

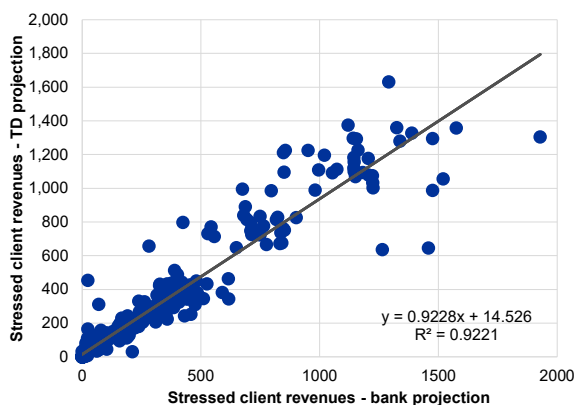
where the subscripts *i*, *t* and *l* stand for bank (*i*), quarter (*t*) and FINREP asset class category (*l*) respectively. *ClientRev* represents banks' reported historical client revenues from the fourth quarter of 2015 to the fourth quarter of 2020 on a quarterly basis, and *NOT* is the variable representing the notional value of derivative exposures (reported by categories $\theta = \{Equity, FX, Commodities, Interest Rates, Credit\}^{94}$), which should capture the different weights of asset classes/risk factors and is expressed in millions. *SHOCK* is the variable representing the change in the risk factor included in the market risk scenario. *DUMMY* is a variable defined using k-means as a clustering algorithm to cluster banks according to two variables: average client revenues and average total notional amounts in derivatives. This allows the fixed effect associated with each bank to be captured.

The model is estimated using the pooled OLS approach. The estimator was chosen from three alternatives (pooled OLS, panel OLS with fixed effects and panel OLS with random effects) applied to a sample of banks with the comprehensive approach and for which average client revenues were different from zero, using the lowest RMSE as a selection criterion.

From the second quarter of the first year of the stress test horizon, top-down projections are estimated under the assumptions of a constant balance sheet and zero shocks in line with EBA methodology. For this purpose, a second lag was added to the *ClientRev* variable to avoid having constant estimates beyond the first quarter.

Chart 30
Client revenues model performance

(EUR millions)



Sources: 2018 and 2021 stress tests, and ECB calculations.

Note: Stressed client revenues reported by banks (x-axis) versus stressed client revenues computed via the TD model (y-axis).

The model reliably captures the dynamics of stressed client revenues. Chart 30 shows an R-squared value equal to 92.2%. The model is also unbiased, since it has residuals that are randomly scattered around zero.

⁹⁴ Variables are chosen to be broadly representative of the risk factor. For interest rates, the five-year euro area swap is selected. The shock to equity differs at country level, depending on the domicile of the bank and the country-relevant equity index. The global oil index is used as a proxy for the commodity shocks. The EUR/USD is used for foreign exchange and the five-year overall iTRAXX index for the credit shock.

3.6.4.2 Net trading income: quantile approach

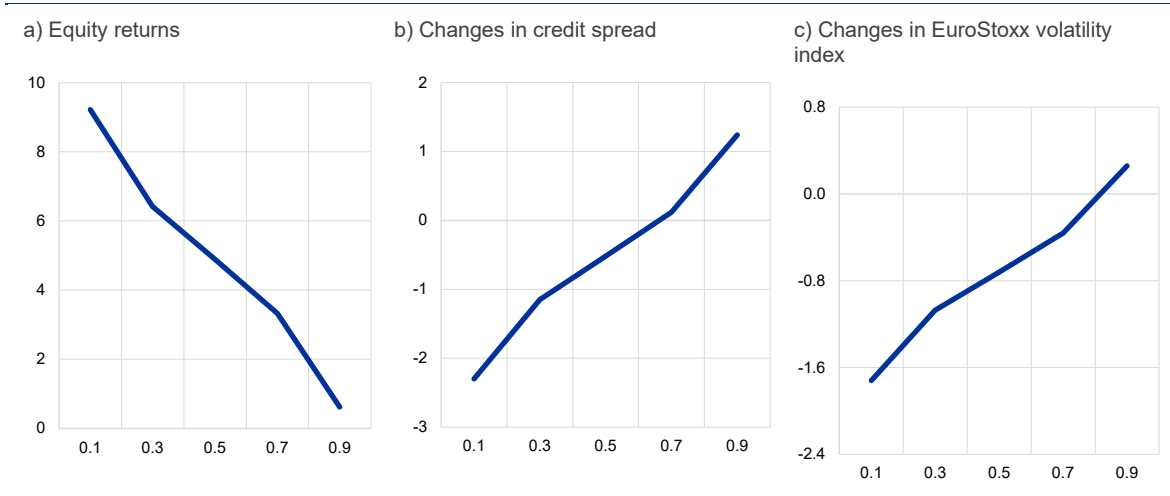
A quantile regression approach can be used to project the NTI distribution under stress. This methodology, as detailed in Cappelletti et al. (2021), forecasts the entire distribution rather than only a mean impact. The quantile approach allows for the measuring of risk metrics such as tail loss estimates and their corresponding probabilities. This methodology is complementary to the approach presented in the previous sections and takes a holistic view of NTI.

The model can be used to challenge banks' NTI projections at an aggregate level and evaluate the likelihood of the impact, especially when the projection is far from the median. The volatile nature of trading income can lead to increased downside tail risk, i.e., the risk that a bank experiences an extreme trading loss. Extreme returns cause “fatter” tails than a normal distribution would predict. Interlinkages between financial risk factors and trading income indicate that financial crisis and adverse market shocks can produce left tail events, which could have a damaging impact on the trading portfolio.

The quantile model can identify where shocks have asymmetric effects on NTI, especially in the tails of the distribution, examples of which are shown in Chart 31. Chart 31 shows the coefficients across the net trading income over total assets (NTI/TA) distribution for three of the independent financial variables included in the quantile regression: changes in credit spread, stock returns and changes in the EuroStoxx volatility index. In each case, the sensitivity of NTI/TA changes across the percentiles of the distribution. The negative coefficients in the lower quantiles suggest that when NTI/TA is low (in the left tail of the distribution), the widening credit spread and increased volatility can intensify losses. The quantile coefficients for the equity index show that lower percentiles of the NTI/TA distribution are highly sensitive to changes in equity prices, intuitively implying that negative equity returns have a negative impact on NTI/TA.

Chart 31

Quantile regression coefficients for the 10th, 30th, 50th, 70th and 90th percentiles of the NTI/TA distribution



Source: Cappelletti et al., 2021.

Notes: The 10th, 30th, 50th, 70th and 90th percentiles are displayed on the x-axis. The y-axis shows the quantile regression coefficients for each independent financial variable.

The relationship between NTI/TA and macro-financial risk factors is captured by a fixed effects quantile dynamic regression model. The macro-financial factors are restricted to those provided in previous EU-wide stress test scenarios and are broken down into interest rate, credit spread, equity, commodity, foreign exchange and volatility. The model is estimated semi-parametrically using the method of moments technique proposed by Machado and Santos Silva (2019) and following Covas, Rump and Zakrajšek (2014). The bank-level data are collected from FINREP and COREP supervisory reporting, while risk factor data are sourced from market data providers.

The conditional quantiles are estimated for quantiles ranging from the 10th to 90th percentiles with 10 percentage point increments.

$$NTI/TA_{i,t+1} = \alpha_i + X'_{i,t}\beta + (\delta_i + X'_{i,t}\gamma)U_{i,t} \quad (59)$$

The quantile τ is given as

$$QNTI/TA_{i,t+1}(\tau|X_{i,t}) = (\alpha_i + \delta_i q(\tau)) + X'_{i,t}(\beta + \gamma q(\tau)) \quad (60)$$

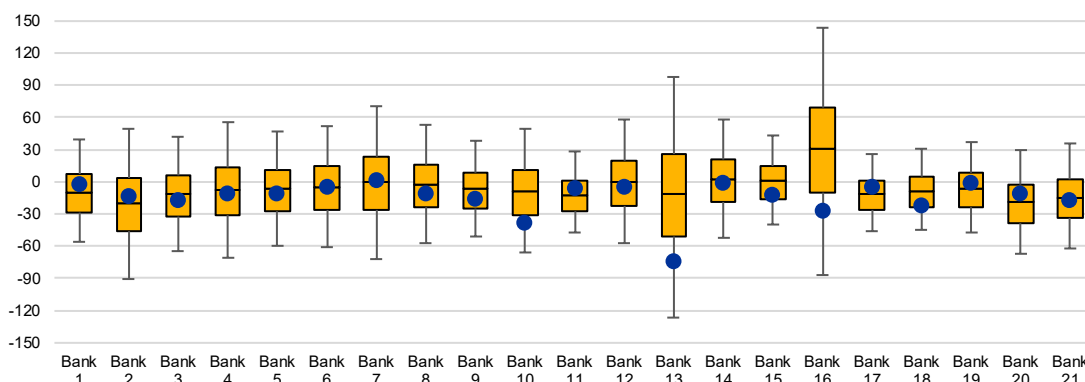
where i indexes banks in the sample and t the time period. $NTI/TA_{i,t+1}$ is net trading income over total assets, $X'_{i,t}$ is a set of explanatory risk factors and bank-specific controls, $(\alpha_i, \beta, \delta_i, \gamma)$ are unknown coefficients and $U_{i,t}$ is an unobserved random variable independent of X . $\alpha_i + \delta_i q(\tau)$ is the quantile- τ fixed effect for individual i , and $\beta + \gamma q(\tau)$ is the quantile- τ slope. Included in $X'_{i,t}$ are bank-specific controls, risk-weighted assets over total assets and equity over total assets, together with a time dummy. On estimation, a strong and asymmetric impact of the risk factors on the tails of the NTI/TA distribution is found.

The model is used to compute the one-year impact for the sample of CA banks in the 2021 stress test. The sum of the four-quarter projections is calculated using shocks provided in the market risk scenario and compared with the final projections provided by banks. Forecasting the entire distribution gives a range of plausible impacts. Chart 32 below shows that most bank impacts projected in 2021 lie close to the top-down projected median and all fall within the distribution.

Chart 32

Adverse projected net trading income over total assets for comprehensive approach banks

(Basis points)



Sources: 2021 stress test, supervisory data, market data and ECB calculations.

Notes: The box represents the 30th and 70th percentiles, while the minimum and the maximum are the 10th and 90th percentiles. Bank values are represented by the blue dots.

4 Macro-micro interactions and macroprudential stress testing

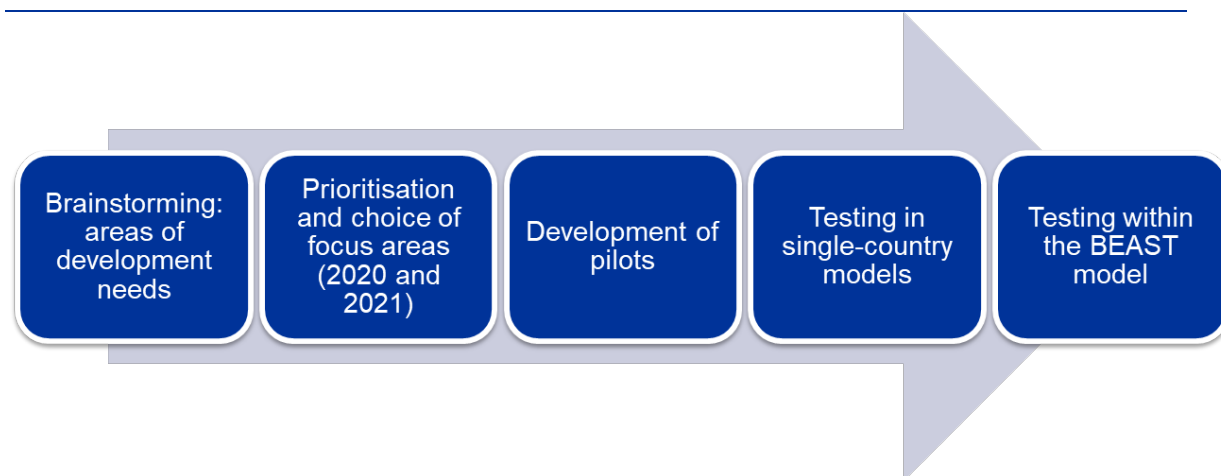
The macro-micro work stream focused on enhancing the effectiveness of macroprudential stress testing. It pushed this agenda forward on three fronts. First, it adopted the ECB BEAST model as its primary operational framework. Over the course of several years, the work stream diligently evaluated the model's properties and identified any shortcomings. This led to tangible advancements in the model's mechanisms, leveraging national expertise and datasets. Furthermore, the model served as a reference point for discussing emerging challenges in macroprudential stress testing, facilitating the establishment of a wish list and the formulation of best practices for various modelling solutions.

Second, the work stream served as a hub for macroprudential stress testing modellers from member institutions, actively monitoring the evolution of macroprudential stress testing within the policy process. To this end, it fostered knowledge exchange and cross-pollination of ideas among European institutions invested in developing robust macroprudential stress-testing frameworks. Concurrently, the work stream explored the applications of macroprudential stress testing in assessing central bank vulnerability, policy evaluation and communication.

Third, the work stream undertook several analytical investigations involving its members and engaged in discussion on a wide range of analytical works relevant for macroprudential stress testing. These analytical endeavours encompassed various topics, including bank lending decisions, the interplay between solvency and funding, and the modelling of exceptional macro-financial events like the COVID-19 pandemic.

The analytical work revolved around annually updated priority areas, as illustrated in Figure 10. Members collectively established these priority areas, drawing inspiration from the BEAST model structure and addressing challenges arising from economic developments such as the COVID-19 crisis. These priority areas were categorised into those focusing on modelling aggregate macro-financial dynamics (macro priorities), those focusing on bank behaviour (micro priorities) and studies dedicated to understanding the functioning of feedback loops. The priority areas served as the basis for conducting dedicated investigations or engaging in in-depth discussions on members' works within the work stream forum.

Figure 10
Macro-micro interactions timeline



Source: ECB.

The structure of this section is as follows. Subsection 4.1 provides an overview of the uses and role of macroprudential stress testing, highlighting the main ECB stress-testing exercises conducted in the past five years. Subsections 4.2 and 4.3 succinctly present the BEAST model and two of the amplification mechanisms that the work stream focused on (real economy feedback loop and funding/solvency feedback loop). Subsection 4.4 gives an overview of the four conducted pilot exercises, while subsections 4.5 and 4.6 discuss each of them in more detail, with more emphasis put on the COVID-19 dummies and treatment of shock periods, and the modelling of lending dynamics with a one-equation approach.

4.1 Uses and role of macroprudential stress testing

The primary objective of macroprudential stress testing is to provide a framework for assessing the resilience of the banking system. Macroprudential stress testing aims to determine whether the banking system can withstand shocks and whether there is a risk of amplification. Unlike standard microprudential stress tests that focus on individual banks, macroprudential stress tests examine the banking sector as a whole and assess the system's ability to handle stress without disrupting credit flow to the real economy.

A complementary goal of macroprudential stress testing is to enhance the understanding and measurement of systemic risk. It offers insights into the economic rationale behind observed and projected developments in both the banking system and the real economy. To achieve this, macroprudential stress testing must consider various specific features, such as the endogeneity of risk, the potential for systemic risk amplification through feedback loops affecting the real economy or contagion within the financial sector, non-linearities and strategic decision-making processes.

Furthermore, macroprudential stress testing can be used for ex ante impact assessments of macroprudential policies and other regulatory interventions. This is possible because macroprudential stress-testing models encompass the relevant transmission channels. For example, these models should capture banks' reactions to changing capital requirements and the systemic risk transmission channels that macroprudential policies aim to address. By incorporating elements like coordination failures between banks and banks' behavioural responses to shocks (such as de-risking or deleveraging), macroprudential stress testing allows for the evaluation of the necessity and impact of regulatory interventions, such as the calibration of countercyclical capital buffers.

Table 10 provides a summary of the macroprudential stress-testing exercises conducted within the ECB's macroprudential modelling framework over the past four years. The introduction of the new model framework, BEAST, occurred alongside the 2018 EU-wide stress-testing exercise. This exercise utilised a dynamic balance sheet perspective and incorporated the real economy-banking sector feedback loop. Subsequently, macroprudential stress-testing exercises were conducted in 2021 and 2022 using the BEAST model. The BEAST model has also been employed for regular banking sector analysis under adverse and baseline scenarios as part of the Financial Stability Review. In 2021, amidst the COVID-19 pandemic, the macroprudential stress test considered the implementation of various supervisory and government mitigation policies. This acknowledgement of the exceptional circumstances allowed for a comprehensive assessment of the resilience and stability of the banking sector in the face of the pandemic and the measures put in place to mitigate its impact. More recently, the macroprudential stress-testing framework has also been utilised to examine the interactions between monetary policy changes and financial stability. Specifically, a growth-at-risk and inflation-at-risk approach has been employed to forecast potential risks and their impact on the banking sector over a one-to-three-year period.

Table 10
Applications of macroprudential stress tests conducted through the lens of the BEAST model

	Main stress test policy exercises	Description	Sources
2018	Macroprudential stress test	Prepared on the back of the 2018 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)
2019	Baseline and adverse scenario analysis in the Financial Stability Review	A stand-alone scenario analysis employing September 2020 ECB staff projections as a baseline and native adverse scenario selection methods to reflect conjectural risks.	Published as ECB (2019)
2020	Macroprudential stress test	Prepared on the back of the 2020 SSM vulnerability analysis and enriched with the solvency-funding costs feedback loop, taking account of COVID-19 mitigation policies and NPL coverage expectations.	Published in Budnik et al. (2021a)
2020	Pilot macroprudential climate stress test	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. (2022a)
2021	Macroprudential stress test	Prepared on the back of the 2021 EU-wide stress test, with improved modelling of non-standard monetary policy transmission mechanisms.	Published as Budnik et al. (2022a); see also Budnik and Groß (2021)
2022	Baseline and adverse scenario analysis	A stand-alone adverse scenario analysis employing June 2022 ECB staff projections and native scenario selection methods to reflect risks stemming from the Russian invasion on Ukraine.	
	Regular assessment of the macro at risk to support the monetary policy process	Quarterly evaluation of the one-to-three-year-ahead growth-at-risk and inflation-at-risk forecasts to assess changes in financial stability.	
2022	Interest rate sensitivity analysis	Assessment of 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.	Published as Budnik et al. (2022b)

Source: ECB.

To meet the expectations of an effective macroprudential stress test, the underlying modelling framework should fulfil several prerequisites. First, it should provide a comprehensive assessment of the stability of the entire banking sector, rather than focusing solely on individual institutions. Further, it should allow banks to adjust their balance sheet in line with the economic scenario, since such mechanisms play an important role in amplifying systemic risk. Thus, the model should explicitly incorporate the behavioural reactions of banks, including potential non-linearities. Furthermore, the framework should incorporate selected mechanisms that contribute to the build-up or propagation of systemic risks. This may involve capturing feedback loops between the banking sector and the real economy or interactions among banks.

The work stream also discussed other operational requirements for macroprudential stress testing. Building a new macroprudential stress-testing framework involves addressing trade-offs between the desire for consistency, micro-foundations and data fit and capturing relevant details (sufficient level of granularity), while maintaining a manageable level of complexity. Second, to ease effective communication of the macroprudential stress test, a model should be able to provide an economic narrative. The communication of a macroprudential stress test can become a potent policy tool, and modelling frameworks that can provide such a narrative behind the results are often favoured by policymakers and practitioners.

4.2 The BEAST model

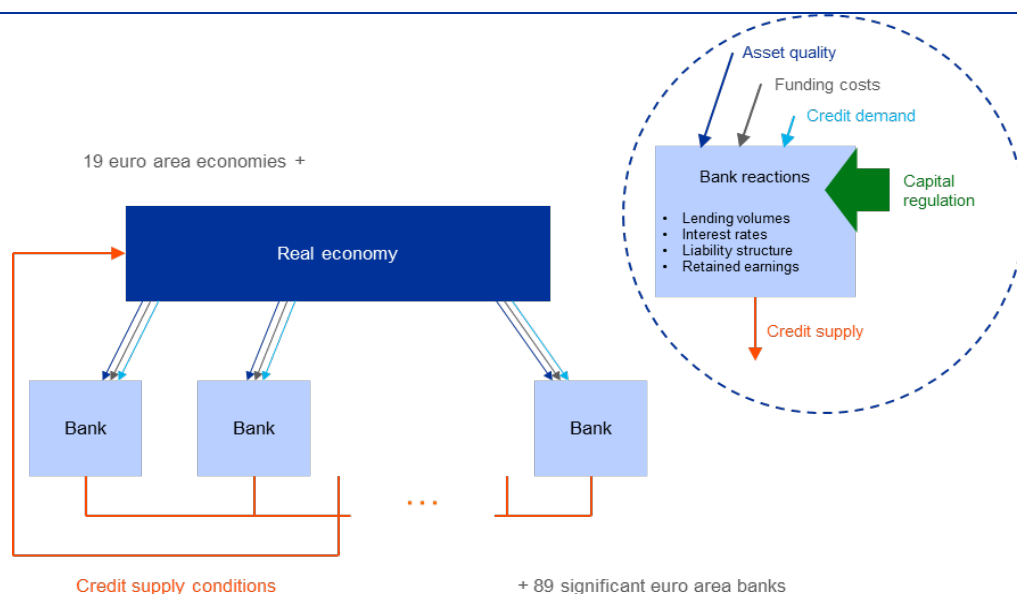
The BEAST model is a comprehensive semi-structural model designed to assess the resilience of the euro area banking system from a macroprudential perspective. It combines the dynamics of approximately 90 major euro area banks with the economies of 19 euro area countries. The BEAST model employs a semi-structural approach, integrating empirical and structural elements within a single system.

The model provides a detailed representation of both sides of banks' balance sheets and their profit and loss accounts to accurately capture the diversity among banks. On the asset side, the model distinguishes between different loan portfolios, equity exposures and securitised portfolios. It also incorporates the three IFRS 9 asset impairment stages and tracks risk weight developments. The liability side of the balance sheet captures equity dynamics as well as the dynamics of wholesale and retail funding. For each bank, the model breaks down profitability and solvency dynamics, considering the impact of credit, market and operational risks, NII and dividend payouts.

A significant portion of the model consists of equations that translate scenarios into the impact on banks' balance sheets and profitability. These equations are derived from microdata-based bank sensitivities, which assess the effect of macro-financial variables on flows between the three IFRS 9 asset impairment stages, loss given default and loss rate parameters, risk weights, revaluation losses, funding costs and NFCI. These equations share similarities with the top-down models described in Section 3.

Additional bank-level equations within the model capture banks' behavioural responses (Figure 11). Banks adjust their lending volumes, loan pricing, profit distribution policies and liability structure in response to changes in general economic conditions, considering their own financial situation. Their lending decisions are influenced by their capital targets, which are determined by regulatory capital requirements and buffers. Other factors affecting lending, dividend distributions and loan pricing include asset quality, profitability and funding structures. Banks follow a pecking order in their funding composition, tapping retail and institutional deposits first, followed by the wholesale market. On the wholesale market, they can either secure funding by posting collateral at a rate close to the risk-free rate or issue unsecured debt with an additional credit spread. The model's bank-level equations, capturing both parameter sensitivities and behavioural responses, are derived empirically based on different bank-level or transaction-level datasets.

Figure 11
Schematic illustration of the macro-micro BEAST model



Source: Budnik et al. (2020).

The macroeconomic module of the BEAST model captures the dynamics of each euro area economy, taking into account trade spillovers among them. The model estimates the dynamics of individual euro area economies using a structural panel vector autoregressive model with Bayesian methods. Long-run priors are introduced to stabilise the long-term dynamics of the system, aligning them with long-run trends across the 19 euro area economies. Additionally, there is a block of cross-country trade spillovers that link import volumes to foreign demand variables and export prices to foreign price variables. This configuration allows for a reduced-form multi-country set-up, providing a description of the real economy.

The BEAST model integrates all macro-financial and bank-level equations and solves them as one system. This approach ensures internal consistency and enables simultaneous feedback mechanisms. Moreover, the model can generate confidence forecasts of macroeconomic and banking sector conditions. Its semi-structural design allows for the incorporation of various sources of information available during the forecast-building process. This includes the most recent macroeconomic data as well as detailed information on banks' balance sheets and profit and loss accounts. The model can also incorporate forward-looking information, such as ECB staff macroeconomic projections of macro-financial variables for up to three years and information about upcoming macroprudential and supervisory policies.

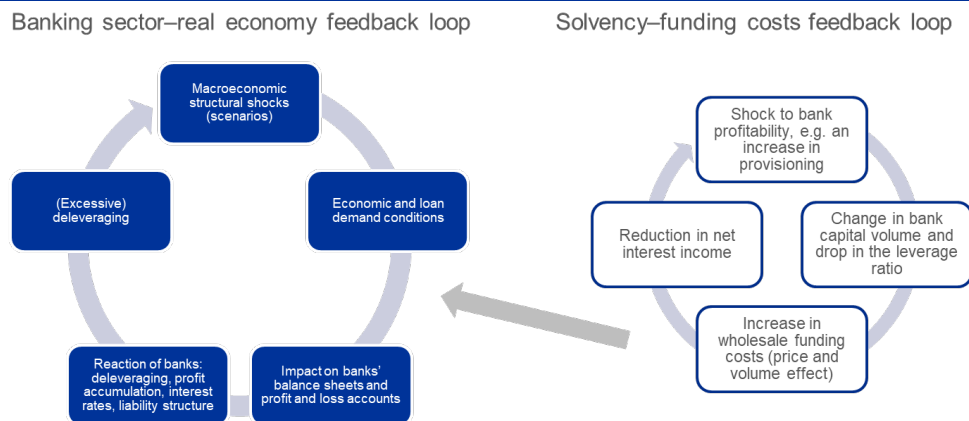
4.2.1 The banking sector-real economy and solvency-liquidity feedback loops

The BEAST model incorporates two macro-financial amplification mechanisms, with a particular focus on the feedback loop between the banking sector and the real economy. Figure 12 illustrates the steps involved in both feedback loops. Regarding the banking sector-real economy feedback loop, macroeconomic shocks initially affect the real economy, leading to changes in economic conditions. These changes, in turn, affect the quality of bank assets and credit demand conditions. Based on the adjustments to their balance sheets, banks have the ability to rebalance their assets, modify prices and adjust liabilities.

The central element of the banking sector-real economy feedback loop lies in the actions taken by banks to rebuild their capital levels. In normal economic conditions, banks typically align their credit volumes and interest rates with changes in aggregate credit demand. However, in adverse economic conditions, banks strive to restore their capital levels, and factors influencing credit supply become more significant. In these cases, negative credit supply shocks can emerge, exacerbating the initial macro-financial shocks and further worsening the economic outlook. The banking sector and the real economy continuously interact with each other, although they are discussed separately for clarity. The model incorporates this feedback loop by aggregating the non-linear elements of bank credit supply responses, representing excessive deleveraging, and translating them into a credit supply shock that affects the euro area economies.

Figure 12

Schematic illustration of BEAST's main amplification mechanisms: the real economy-banking sector and solvency-liquidity feedback loops



Source: Budnik et al. (2021a).

Another amplification mechanism in the BEAST model is the funding-solvency feedback loop. When a bank experiences a negative shock to profitability, its solvency position becomes weaker. Higher levels of leverage make the institution more susceptible to default risk, resulting in an increase in its credit spread on unsecured funding. As unsecured wholesale funding becomes more expensive, it raises the bank's interest expenses. This, in turn, has an adverse impact on the bank's capital by eroding its NII. Additionally, the bank passes on a portion of the increased funding cost to its borrowers, resulting in reduced demand for new lending and further squeezing the bank's income base (Schmitz et al., 2017). Particularly under adverse macroeconomic scenarios, where risk margins are elevated across the board, this funding-solvency feedback loop can have a substantial impact on the financial outcomes of banks. Overall, the funding-solvency feedback loop highlights how the interplay between funding costs, profitability and solvency can create a reinforcing cycle that affects the stability and performance of banks, especially in challenging economic conditions.

4.2.2 Stochastic simulations

An important step in the evolution of the model was its extension to stochastic simulations. This extension allows for the exploration of scenario uncertainty by looking at alternative futures of the macro-financial environment and of the banking sector and selectively assessing developments in the tails of distributions. The stochastic simulations also facilitate the assessment of parameter uncertainty, encompassing both macro-financial and banking aspects, while providing ranges of uncertainty for model results to account for potential limitations in the empirical identification of various model equations.

Scenario uncertainty is captured by repeatedly drawing values from the distributions of macro-financial shocks. These distributions are identified during the estimation process of the macro-financial block and stored for future reference. Using Monte Carlo draws, values are selected from each shock distribution, considering the covariance structure between them, to generate multiple macro-financial scenarios. The model offers two approaches for shock selection: parametrised multi-normal distributions and bootstrapping methods based on residuals from the macro-financial block.

Parameter uncertainty is assessed by performing parallel repetitive draws from the distributions of model parameters. Similar to macro-financial shocks, these parameter distributions are identified and stored alongside the mean estimates during the estimation process. Parameter draws are conducted separately for the macro-financial block and the banking block. In the former, the draws account for the covariance structure among parameters describing the dynamics of each individual euro area country, while in the latter, they consider the covariance structure of parameters within the same model equation, such as bank lending or interest rate equations.

Stochastic simulations offer great versatility and can be applied to various scenarios. They can be employed around predetermined scenarios, while additional functions like pruning help to focus on economically viable simulations. Pruning involves examining simulated paths at each time point during the simulation and removing unstable ones. Stochastic scenario selection procedures enable the choice of simulation families with shared economic narratives, such as economic booms or recessions, housing market trends or market liquidity pressures.

4.2.3 The role of frictions in modelling the banking sector

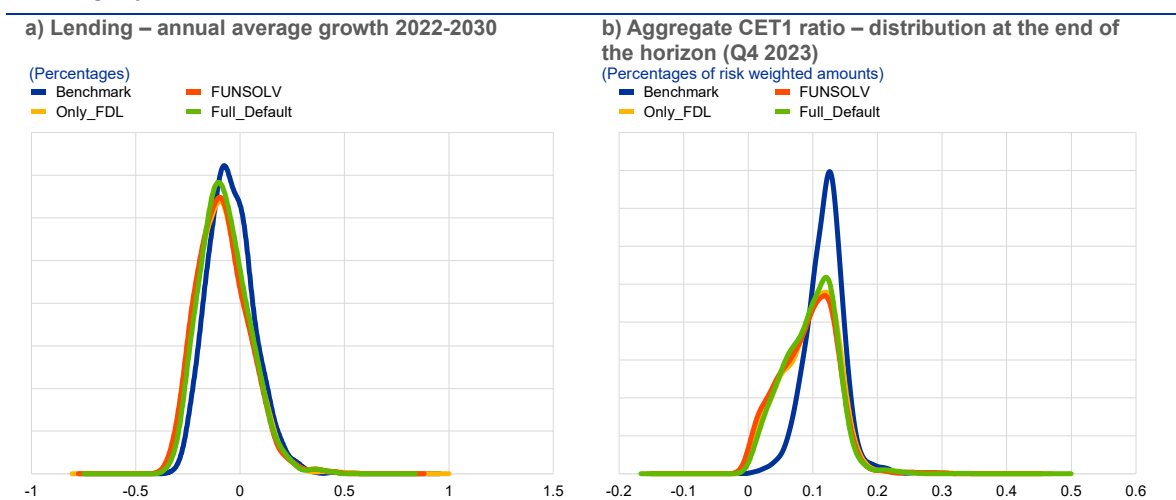
The model incorporates two feedback loops involving the banking sector, the zero lower bound condition for money market interest rates and other non-linearities in the banking block. These elements contribute to the richness of the model's mechanics. To understand their relative roles in generating model dynamics, stochastic simulations are conducted, comparing the resulting distributions of variables of interest with different frictions selectively included or excluded. Specifically, the analysis focuses on the real economy-banking sector feedback loop, the solvency-liquidity feedback loop and the zero lower bound condition. Close to or at the zero lower bound, the propagation of different shocks, including monetary policy, in the macro-financial system can be substantially affected (Brunnermeier and Koby, 2018; Eggertsson et al., 2019; Darracq Pariès et al., 2023). For instance, the transmission of market interest rates to bank deposit rates and therefore to banks' funding costs can be significantly hampered.

The role of different frictions and other non-linearities in the model can be assessed by model stochastic simulations. The benchmark simulations include only non-linearities related to economic reasonability, for example the impossibility of issuing negative new loans and regulatory limits, such as the non-linear formulas for risk weights and gradually tightening maximum distributable amount restrictions. Panel a) of Chart 33 depicts the distribution of average annual lending growth over the eight-year horizon in benchmark simulations. The distribution exhibits subtle positive skewness and somewhat shorter tails compared with a normal distribution.

The feedback loop between the real economy and the banking sector shifts the distribution to the left and increases its variance. The skewness of the distribution turns subtly negative. The addition of the funding-solvency feedback loop has a moderate and intuitive impact on the average annual lending distribution. It further increases its variance, restores the skewness to its initial positive position and thickens the tails. Lastly, the inclusion of the zero lower bound restriction subtly increases the mean and reduces the variance of the distribution. The variance of the distribution remains significantly higher than in the benchmark case, while its tails become even thinner than in the benchmark. Overall, it is the real economy-banking sector feedback loop that has the most substantial effect on lending dynamics.

Chart 33

Growth of average annual euro area lending to the non-financial private sector and the CET1 capital ratio in an eight-year-ahead model solution



Source: ECB calculations.

Notes: Benchmark: results from the model version without additional frictions, i.e., no real economy-financial sector feedback loop, no solvency-funding feedback loop and no zero lower bound. Only_FDL: results from the model version with real economy-financial sector feedback loop only. FUNSOLV: results from the model version with the real economy-financial sector feedback loop and solvency-funding feedback loop. Full_Default: model version with all three frictions included.

The real economy-banking sector feedback loop also has a significant impact on the distribution of the solvency rate. Panel b) of Chart 33 presents the average euro area CET1 rate at the end of the eight-year simulation horizon. The benchmark CET1 ratio distribution is relatively strongly and symmetrically centred around its mean, which reflects strong bank solvency rates still boosted by policies implemented during the COVID-19 pandemic. However, the introduction of the real economy-banking sector feedback loop shifts the mean of the distribution to the left, brings about a clear negative skewness, sharply increases the variance and thickens the tails of the distribution. Other frictions have a much less pronounced impact on the solvency distribution. The funding-solvency feedback loop amplifies the effects of the real economy-banking sector feedback loop, while the zero lower bound slightly narrows the CET1 ratio distribution. Overall, tracking the changes in solvency distributions confirms the role of macro-financial frictions in amplifying scenario adversity and speaks to the ability of a macroprudential stress-testing model to provide more conservative estimates of solvency while accounting for these frictions.

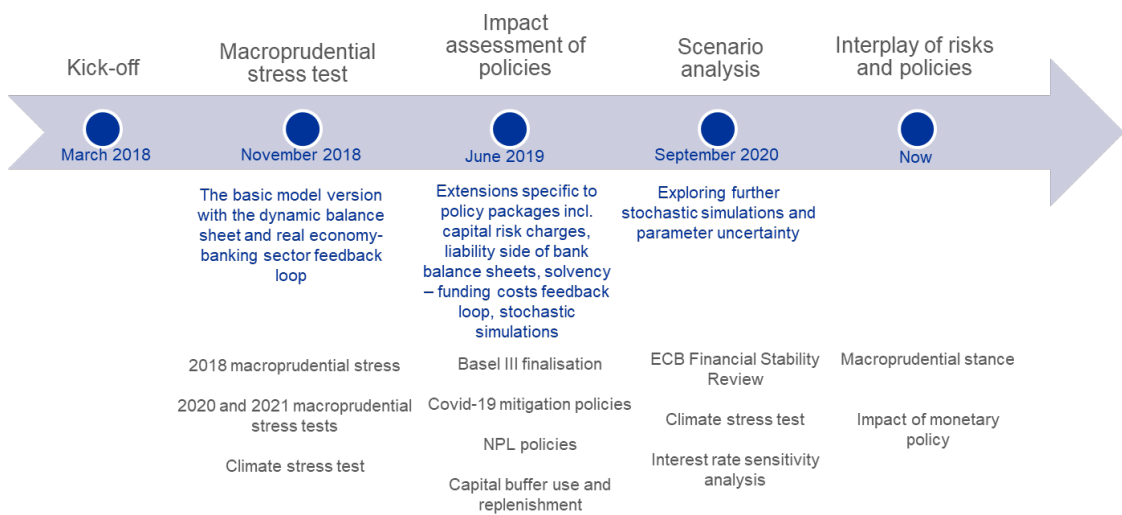
4.3 Towards the workhorse model

BEAST originated as the first semi-structural macroprudential stress-testing model for the euro area banking sector. Its objectives were twofold. First, to establish a new ECB framework for macroprudential stress testing that emphasised the feedback loop between the real economy and the banking sector while acknowledging the heterogeneity of banks. Second, to explore the extent to which a semi-structural set-up can support assessments of financial stability, leveraging its demonstrated advantages in inflation forecasting. In both endeavours it followed earlier works by Kitamura et al. (2014) for Japan and Krznar and Matteson (2017) for Brazil, and preceded that of Catalán and Hoffmaister (2020) for Indonesia. All of these authors developed practical semi-structural policy models for stress testing a country’s banking system. The major difference between their approaches and BEAST was the latter’s far richer level of granularity and its acknowledgement of banks’ international activities. The initial application of BEAST to macroprudential stress testing occurred only six months after its development began, which demonstrated its ability to deliver on its fundamental promise. The first macroprudential stress test in 2018 provided estimates of the amplification that would have occurred under an adverse scenario and delved deeper into the heterogeneous lending and solvency dynamics across banks.

About a year after its inception, the concept of expanding BEAST and gradually developing it into a workhorse model started to take shape (Figure 13). The notion of a workhorse model was borrowed from the practices of forecasting and monetary policy departments in central banks. It refers to a model that is extensively applied beyond its primary purpose of inflation forecasting to policy simulations, impact assessments and scenario analyses. The path towards establishing BEAST as a workhorse model involved iterative adjustments and its application to various analytical problems.

The next step in the model’s development involved its application to cost-benefit assessments of regulatory and prudential policies. Evaluating the impact of policies generally entailed conducting stochastic simulations using the model. This approach allowed outcomes to be studied in the tails of the distributions, capturing at-risk measures and extracting the resilience-building effects of policies. Additionally, stochastic simulations facilitated the design of multiple counterfactual scenarios, such as prospective future recessions where capital buffers would be released.

Figure 13
Evolution of BEAST towards a workhorse model



Source: ECB authors.

Various scenario and sensitivity analyses played a crucial role in validating and expanding the model mechanisms of BEAST. For instance, the interest rate sensitivity analysis conducted in 2021 led to further improvements in modelling the pass-through of interest rates into banks' balance sheets from the extension of the market risk block. The assessments integrated into the ECB Financial Stability Review helped identify both the strengths and limitations of BEAST as a model for forecasting bank profitability, enabling benchmarking against numerous other models and the forecasts of individual banks.

The experiences gained from policy and scenario analysis facilitated the application of BEAST to novel problem areas, such as measuring macroprudential policy stance or assessing the impact of monetary policy on financial stability. While these are still evolving challenges, BEAST, with its detailed banking block, capacity to capture the effects of multiple prudential, regulatory and macro-financial policies, and stochastic set-up, has proven to be a powerful tool for assessing the dynamic impact of policies on the tails of distributions or examining specific financial stability risks like fragmentation and their relationship to implemented policies.

BEAST serves as a prime example of a model that evolved in response to dynamic and diverse policy requirements. This evolution resulted in a framework that is highly flexible and adaptable while retaining its original semi-structural set-up with individual banks. From a practical standpoint, BEAST's broad range of applications has justified the investments made in its maintenance and updates, which are substantial given the scale of the model.

4.4 Other macroprudential stress-testing frameworks

The work stream witnessed and discussed the evolution of alternative macroprudential stress-testing models. Most models follow the modular approach, where existing stand-alone top-down stress-testing models are put together with a macroeconomic infrastructure and solved sequentially. Almost all macroprudential models summarised in Table 11 account for selected dynamic balance sheet aspects and can be applied to the study of bank deleveraging in tandem with their solvency and profitability developments. At the same time, acknowledging the feedback between the banking sector and the real economy is the ambition of only one of the models (Banca d'Italia).

Table 11
Summary of progress on national models⁹⁵

Institution	Name	Aim	Overview and model assumptions
Banco de Portugal	Model for the Assessment of Profitability and Solvency (MAPS)	Top-down approach to assess the profitability and solvency of the largest banking groups over a three-year horizon.	The model projects the main items of the balance sheet and profit and loss statement and the regulatory capital of each banking group, in line with macroeconomic projections. Bank credit and deposit volumes evolve in line with the scenario considered, although the model does not account for potential feedback effects between the banking sector and the real economy.
Banque de France	Stress Testing Tool Resources for Micro and Macroprudential analysis (STORM ²)	A set of models is integrated into a unique and coherent framework in order to analyse bank resilience both on microprudential and macroprudential levels.	STORM is composed of a set of econometric and accounting equations that allow for the projection of capital ratios conditional on different macroeconomic scenarios. Two macroeconomic models complement this core block: <ul style="list-style-type: none"> - a semi-structural model called ALIENOR (Couaillier et al., 2019) is used to generate the adverse scenarios. - a macroeconomic general equilibrium model inspired by Gerali et al. (2010) and estimated on French data (Bennani et al., 2017) is used to assess the impact of possible macroprudential activations calibrated on the basis of the results of the solvency block of STORM² (e.g., shortfalls in terms of CET1 ratios).
Deutsche Bundesbank		Tool to monitor potential deleveraging in the banking system and its implication for financial stability.	The tool brings together results from sectoral stress tests relevant for the banking system – for example, in the real estate market, financial markets and the corporate sector (Barasinska et al., 2019; Falter et al., 2021; Memmel and Røling, 2021). It also considers the potential impact of credit substitution, i.e., unused lending capacities of sufficiently capitalised banks after the realisation of second-round effects. The tool provides a range of possible outcomes regarding deleveraging. To explicate the importance of macroprudential buffers, the tool allows for two alternative assumptions, the use or non-use of macroprudential buffers, in the specification of bank lending to non-financial corporations.

⁹⁵ The table covers models that were discussed during the work of the Working Group on Stress Testing.

Institution	Name	Aim	Overview and model assumptions
Banca d'Italia	'Macro' stress testing framework (MSTF)	The MSTF aims to capture the feedback effects between the banking sector and the real economy.	<p>The macro model serves two purposes:</p> <ul style="list-style-type: none"> - capture the feedback effects between the banking sector and the real economy - derive internally consistent projections for variables that are not part of the original scenario <p>The top-down model (TDST) follows a modular approach. It relies on a combination of different blocks to estimate the impact of a change in macroeconomic conditions on the balance sheets and profitability of Italian banks. It involves three types of risks: credit, market (including sovereign) and interest income.</p> <p>The model incorporates two important assumptions: balance sheet items are supposed to remain constant, and a floor is applied to risk-weighted assets.</p>
Banca Națională a României		Macroprudential stress testing framework	<p>The stress-testing framework is comprised of six main modules – credit risk, new loans, interest rate margins, fees and commissions (estimated through BMA), market risk and operational risk, as well as an external satellite model of interbank contagion.</p> <p>The approach is based on realistic assumptions: a dynamic balance sheet hypothesis (according to which banks adapt their lending volumes depending on the macroeconomic changes), upcoming changes in regulations (e.g., CRR quick fix transitional arrangements) and robust estimation of risk parameters.</p>

Source: ECB.

4.5 Pilot exercises and other focus areas

An important part of the work stream's activities was cross-country analyses of high relevance for macroprudential stress testing. The areas of these analyses were identified jointly by the members and can be subdivided into works focusing on the macro-financial (macro) and bank-level (micro) analyses. Table 12 summarises these pilot exercises, their motivation, methodology applied and main findings.

To model aggregate macro-financial dynamics, two pilot exercises were carried out. The first focused on a distinct dynamic of lending to private households and to NFCs, which can affect the identification of credit supply shocks. The second related to the challenges of modelling the exceptional magnitude of shocks amid the COVID-19 pandemic.

The other two pilot exercises revolved around improving the identification of bank lending equations by employing national datasets. In the BEAST model, the identification of bank-level loan volume equations relies on relatively small datasets, and as a result the model makes strong assumptions while combining loan demand and supply factors.⁹⁶ These data limitations can be overcome by using granular national datasets that reflect a longer history of lending by banking institutions. Furthermore, this analysis fulfils a number of member institutions' pressing analytical needs.⁹⁷ The first, referred to as the one-equation approach, was inspired by the corresponding equations in BEAST. However, both loan demand and supply factors were included in the same estimation step.⁹⁸

⁹⁶ Equations of bank lending volumes in BEAST are estimated in two stages. In the first stage, one estimates the impact of credit demand factors on lending volumes while controlling for the credit supply side. In the second stage, one estimates the impact of credit supply factors while controlling for credit demand trends. The resulting equation explaining the overall lending dynamics in BEAST puts together the parameters and explanatory variables from the two stages after dropping the cross-referencing control variables.

⁹⁷ Although precluded from a multi-country panel study due to confidentiality reasons, work stream members were able to include all relevant supply and demand factors within the same model estimation.

⁹⁸ This is not possible with the historical samples available to the ECB due to the short horizon of consolidated bank-level reporting information. To overcome data shortages, the process of estimating lending dynamics in BEAST separates the impact of credit demand and credit supply factors into two equations. The demand-side equation is later reinterpreted as an autoregressive component and the supply-side equation as a medium-run relationship.

Table 12
Summary of exercises

Level	Exercise	Goal/motivation	Methodology	Conclusions/findings
Macro	Splitting of household and corporate lending information in SVAR	How can the distinction between lending to households and NFCs affect the properties of identified credit supply shocks?	<p>Single-country structural VARs for selected euro area countries (Italy, Germany, France) with main macro-financial variables (real GDP, HICP, Euribor) and different measures of lending volumes and interest rates to the non-financial private sector. The structural credit supply shocks in each VAR were identified with zero and sign restrictions.</p> <p>Comparison of impulse response functions between SVARs with (i) overall lending volumes and interest rates to the non-financial private sector, (ii) household lending volumes and interest rates, (iii) corporate lending volumes and interest rates to a credit supply shock defined on any of the credit definitions.</p>	<p>The responses to a credit supply shock defined for overall and disaggregated lending (household and corporate lending separately) are similar both in shape and magnitude.</p> <p>Accordingly, there is no strong evidence of potential benefits from the inclusion of disaggregated information on households' and NFCs' lending compared with the aggregate (as relates to the transmission of credit supply shocks).</p>
Macro	Factoring in of COVID-19 episode in SVARs	How should the data from the pandemic period be treated in estimates of dynamic models?	<p>Single-country structural VARs⁹⁹ for selected euro area countries (France, Germany, Italy, Spain) with six quarterly macro-financial variables (real GDP, HICP, Euribor, long-term interest rate, bank loan volumes to the private non-financial sector, spread of bank loan rate to the private non-financial sector over Euribor). A structural credit spread shock identified recursively with the credit spread ordered last.¹⁰⁰</p> <p>Two different approaches to tackle the COVID-19 episode: (i) homoscedastic Bayesian VAR models where COVID-19 observations identified as outliers (by inspecting the multivariate regression residuals) are dummied out, (ii) Lenza and Primiceri (2022) model using a BVAR with stochastic volatility. The VAR estimation was expanded with three stochastic parameters affecting the volatility of the shocks arriving between Q1 2020 and Q3 2020.</p> <p>Comparison of impulse responses (i) between the model estimated on the data up to Q4 2019, (ii) by including COVID-19 data without treatment, (iii) by including dummied out COVID-19 data, (iv) and applying the Lenza and Primiceri (2020) treatment of COVID-19.</p>	<p>The empirical identification using unaltered data from the COVID-19 period is not useful for macroprudential analysis. VAR models that include data gathered throughout the COVID-19 crisis and apply no special treatment to these data points produce very different inference about an identified structural credit spread shock.</p> <p>The two approaches, dummied out and stochastic volatility, deliver structural inferences that are comparable to models estimated only on pre-COVID-19 data.</p>
Micro	Loan volume equations with loan demand and supply factors	Simultaneously accounting for loan demand and supply factors while modelling bank loan volumes	<p>Univariate bank-level panel equations of lending volumes (log differences), separately for consumer, mortgage and corporate lending for several EU banking sectors (Greece, Lithuania, Croatia, Italy, Slovenia, Ireland and Poland). The right-hand variables included loan demand business cycle factors (real GDP, house prices) and bank-specific loan supply factors (profitability, capital adequacy, pricing policy, ownership, NPL clean up strategy).</p> <p>The country models were estimated twice: with and without applying dynamic homogeneity conditions.</p>	<p>Common patterns of significant inertia in lending volumes across countries. Heterogenous outcomes regarding the significance of different loan supply factors, including the impact of bank capitalisation. Furthermore, importance of country-specific factors in capturing loan dynamics, e.g., NPL policies in Greece, bank ownership in Croatia.</p> <p>In most of the cases, the results of the version with dynamic homogeneity were close to the results of the unconstrained regressions.</p> <p>The simultaneous equations approach yielded economically meaningful results.</p>
Micro	Modelling of lending dynamics with one-equation approach	Modelling of simultaneous loan volume and pricing decisions of banks	<p>Two-equation panel system of equations with mortgage loan volumes and interest rate margins (over SWAP rates) as left-hand variables (building on Behrendt, 2016). Exogenous variables included a rich selection of loan demand and supply factors. Estimates were conducted for two euro area banking sectors (Austrian and Belgian).</p> <p>Estimators (OLS/FE, 2SLS and 3SLS) successively applied and the last of them chosen as the benchmark.</p>	<p>Higher funding costs and higher cost of equity (CoE) feed into the price of loans. The gross margin is an important explanatory variable of loan volumes.</p> <p>The following variables turned out to be other significant determinants of higher new mortgage lending: lower credit standards, the size of the bank, the size of the bank's management buffer above capital requirements (for AT: the Tier 1 ratio), the non-bank loan concentration (in % TA), lower systemic risks.</p>

Source: ECB.

⁹⁹ The analysis relies on homoscedastic Bayesian VAR models with a Minnesota-style prior as in Bańbura, Giannone and Reichlin (2010). The number of lags of the endogenous variables included in the VAR (one to four lags) and the choice of the prior tightness hyperparameter ($\lambda=0.1, 0.2, \dots, 1$) are set by maximising the marginal data density.

¹⁰⁰ This ordering implies that all variables other than the spread are assumed to react to the spread shock only after the initial period.

The first pilot exercise explored the implications of potentially different lending dynamics for household and non-financial corporates across the business and financial cycles (see also Table 13). In the BEAST model, the identification of credit supply shocks and the feedback loop between the banking sector and the economy relies on an aggregate measure of country-level bank lending to the non-financial private sector. Separating the two lending sectors could potentially bring to light important cross-sector and cross-country differences in the transmission of credit supply shocks, which would then propagate into the working of the feedback loop. However, the evaluation based on country-level structural Bayesian vector autoregression (VAR) models did not show significant differences in model responses to credit supply shocks defined for overall and sector-specific lending. The responses obtained from the estimation of models with overall lending to the non-financial private sector and those with household or corporate lending turned out similar in both shape and magnitude. Accordingly, potential benefits from the inclusion of disaggregated information on lending to households and NFCs were not evident.

The other macro-financial pilot study focused on capturing the effect of the COVID-19 period in structural VAR models. The COVID-19 pandemic resulted in an unprecedented downturn in euro area economies triggered by a combination of extreme demand and supply shocks. The magnitude of COVID-19 shocks posed the question whether the data from the pandemic period should be treated as conventional observations or as outliers distorting the parameter estimates. The existing data history included only a few economic crises with little resemblance to the pandemic. The scoping analysis by work stream members confirmed that VAR models that included data gathered throughout the COVID-19 crisis and applied no special treatment to these data points produced very different inference about an identified structural credit spread shock.

The pilot exercise involved estimating simple structural Bayesian VARs with alternative approaches to factoring in COVID-19 information. The first approach quantified how unusual the COVID-19 observations were and dummied out those identified as outliers in the VAR estimation. The identification of outlier observations was informed by inspecting the multivariate regression residuals. The second approach followed Lenza and Primiceri (2020) and introduced stochastic volatility for shocks occurring between the first and third quarters of 2023. The two approaches that were considered to address this issue proved to be almost equally successful. VAR models that included data gathered throughout the COVID-19 crisis and applied no special treatment to these data points produced very different inference about an identified structural credit spread shock. However, either dummied out observations identified as outliers or ex ante allowing for shock volatility to be inflated throughout the pandemic delivered structural inferences that were comparable to models estimated only on pre-COVID-19 data.

The third pilot exercise involved estimating bank-level loan volume equations acknowledging both loan demand and supply factors. The determinants of loan volumes were tested separately for consumer, mortgage and corporate loans. The country estimates revealed some common patterns but also a relatively high cross-country heterogeneity. Among common patterns, a high degree of inertia in lending volumes was consistently found in all country studies. Autoregressive terms were in all cases positive and significant, and highest for household mortgage lending. Banks' capitalisation, which has a strong and significant impact in the BEAST loan supply equation, had a positive (though not significant) impact on lending in Greece and Italy. However, in Lithuania there was the unexpected result that capital surplus has an imprint on lending. This reflected the fact that in the Lithuanian banking system lending decisions in most cases were not affected by low capital buffers. After the global financial crisis, the Lithuanian banking sector became well-capitalised. NPL policies proved to be an important factor in explaining loan volume dynamics in Greece, while domestic or foreign bank ownership turned out to be relevant for the dynamics of Croatian loans. Altogether, the exercise revealed the need to know and recognise challenges of individual banking sectors along with their history.

The final pilot examined the simultaneity of lending volumes and price decisions within the same empirical system. The model captured the impact of loan demand and supply on equilibrium volumes and interest rates. The simultaneous equations approach yielded economically encouraging results. The loan interest rate turned out to be an important explanatory variable of the demand for loan volumes. Higher funding costs and the cost of equity had a positive impact on the price of loans and a negative impact on loan demand. New mortgage lending depended positively on lower credit standards, the size of the bank, the size of the bank's management buffer above capital requirements, the non-bank loan concentration and lower systemic risks.

All pilot exercises translated into adaptations of the BEAST model. The conclusions from the first pilot exercise supported the identification of credit supply shocks based on the dynamics of lending to the non-financial private sector. The other macro pilot exercise led to the inclusion of the COVID-19 episode in the estimates underlying the model macro block. The two micro pilots inspired the improvement of bank lending equations.

Table 13
Summary of exercises

Level	Exercise	BEAST adaptation
Macro	Splitting of corporate and household lending information in SVAR	Continued joint treatment of lending to non-financial private sector (without distinguishing between household and corporate lending) in the macro block.
Macro	COVID-19 dummies and treatment of shock periods	Inclusion of COVID-19 episode in estimates of the macro block, applying the identification of outlier periods and the dummifying-out method as in the pilot exercise.
Micro	One-system approach for loan volume dynamics	Inclusion of the leverage ratio (next to the risk-weighted bank capital ratio) in bank lending volume equations.
Micro	Modelling of lending dynamics with one-equation approach	Inclusion of (lagged) bank-level interest rates in the bank-level lending volume equations (to control for the simultaneity of volume and pricing decisions). Adapted specification of loan interest rate equations with more emphasis on the role of the average cost of funding and bank leverage.

Source: ECB.

4.6 Other focus areas

Not all analyses relevant for macroprudential stress testing could be translated into pilot exercises involving coordinated efforts by multiple work stream members. However, the work stream continued discussing them, usually drawing on works conducted in member institutions. Table 14 summarises some of these activities. In terms of modelling macro-financial dynamics, the topics of interest included capturing structural changes in the banking sector leading to the increasing role of market-based finance and growing holdings of corporate bonds by banks, and modelling non-linearities. A focus area that resulted in changes to the BEAST core modelling platform was multiple experiments with structural shock identification.

Regarding the dynamics of the banking sector, a relatively high proportion of the discussions resulted in gradual changes in BEAST. Examples of focus areas which ultimately translated into tailored adaptations of the model were the relevance of relative risk weights for the substitution of loans between sectors and the importance of bank funding structure and costs. The recognition of the latter in particular resulted in the far-reaching revision of bank liability structure in the model, the introduction of regulatory limits on liquidity and the feedback loop between solvency and liquidity. Less direct inspirations concerned the importance of the costs of equity, NPL management and capital thresholds for bank deleveraging incentives. All of these considerations were incorporated in BEAST, though not in the full scope initially postulated (and tested).

Table 14
Summary of other priority areas

Level	Exercise	Goal/motivation	Activities/methodologies considered	Conclusions/findings
Macro	A broader (than lending) definition of bank credit	An investment project can be funded via a bank loan or via a bond purchased by a bank. The definition of bank lending could therefore be expanded beyond loans to bonds, promissory notes and other legal forms of exposure.	Discussions of analytical works on the relevance of market-based credit to non-financial corporates, the substitution and transmission of shocks to market-based financing versus loans, and supply and demand factors driving corporate bond issuance.	

Level	Exercise	Goal/motivation	Activities/methodologies considered	Conclusions/findings
Macro	Identification of structural shocks by different combinations of zero and sign restrictions	Assessment of the robustness of the structural shock identification strategy in BEAST and other models.	The analytical works focused on the identification of two shocks in particular: credit supply and standard monetary policy. The baseline identification strategy for both shocks was extended to consider additional zero and sign restrictions while maintaining the same set of endogenous variables. For instance, for standard monetary policy shocks these were (i) positive restriction on equity prices on impact, (ii) positive restriction on bank loans on impact, (iii) zero restrictions on import volumes and export prices on impact, and (iv) positive restrictions on inflation (HICP) (Uhlig, 2005) and/or real GDP (Christiano et al., 1996) on impact.	Moderate revisions of the identification strategy for selected structural shocks in BEAST.
Macro	Non-linear specification of the macro block	Non-linear specification could help to generate state dependent dynamics in crisis times.	The work stream discussed two alternative approaches to modelling macro-financial non-linearities: local projection methods in VAR models with non-linearities related to vulnerabilities (smooth transition switching model implemented in Banque de France's STORM) and stochastic volatility. The latter approach was tested directly in BEAST with terms related to risk indicators.	The non-linear specifications, though highly relevant in capturing asymmetries in business and financial cycles, can – at times – compromise the stability of models.
Micro	Impact of changes in relative risk weights on lending decisions of banks	Banks may substitute lending in response to changes in relative risk weights between sectors.	The loan supply reaction function of banks in the BEAST model was extended by adding portfolio-average relative risk weight information. Additionally, the relative risk weights per sector were interacted with an indicator variable for a capital shortfall realisation to capture the non-linear substitution from high-risk weight sectors to less capital-intensive sectors.	Relative risk weights significantly enter the loan supply equations for household sectors and are associated with a negative sign, indicating that sectors with higher relative risk weights experience a reduction in bank loan supply, further amplified by capital shortfalls.
Micro	Varying definition of regulatory capital thresholds relevant for deleveraging	The initial BEAST definition of threshold capital requirements does not distinguish between hard requirements and buffers. However, the lending reaction of banks can be different for different capital thresholds.	Testing the hypothesis based on the data proved challenging due to the scarcity of data on events where banks cut into their hard capital requirements. However, the BEAST capital thresholds were revised to map the hypothesis on an ex ante basis.	The revision of the BEAST capital thresholds resulted in (i) banks cutting into their voluntary capital buffers (but not into their regulatory capital buffers), limiting their profit distribution; (ii) banks cutting into their regulatory capital buffers but not into hard requirements, enter a non-linear path of deleveraging; and (iii) banks cutting into their hard requirements, stopping new lending.
Micro	Equity financing	BEAST assumes that equity financing is costless for banks, while evidence suggests that equity financing can be costlier than debt financing.	The topic was addressed by: (i) revising studies measuring cost of equity (CoE) and its relevance for lending, and (ii) including a measure of CoE in BEAST and re-testing the model properties. In the first step, CoE was introduced in BEAST as an endogenous variable and a function of – inter alia – dividend distributions. In the second step an investigation was conducted into how CoE affects banks' loan supply, lending rates and dividend payout adjustments.	Including CoE in bank lending equations in BEAST revealed no significant impact on model properties. However, to account for CoE considerations in bank lending, the lending rates equations were augmented with a measure of bank leverage, which entered them with a negative sign (i.e., the higher the bank equity, the higher the interest rates).
Micro	Consistency between asset and liability side in the BEAST model¹⁰¹	Bank funding can significantly affect bank lending.	The modelling of banks' liability side in BEAST was substantially revised and extended. While the volume of bank liabilities still largely follows the evolution of assets, the supply and cost of different funding sources as well as liquidity considerations added in the model can meaningfully affect funding structure. With a lag, funding structure affects the size and composition of assets.	Banks behaviourally adjust the duration and collateralisation of wholesale funding in response to relative prices for different types of wholesale funding, the supply of unencumbered assets, and regulatory compliance with the LCR and the NSFR in the model.
Micro	Liquidity measures and constraints like the LCR and NSFR	The LCR and NSFR put additional constraints on banks' asset and liability management.	LCR and NSFR measures were added to the model, relying on newly available supervisory information. Additionally, the model was extended with information about encumbrance and available collateral liquidity subcategories to enable endogenous modelling of the liquidity ratios introduced by the regulator.	LCR and NSFR were introduced in the liquidity management module characterising a bank's funding mix across the different categories of wholesale funding.

¹⁰¹ The focus area was described on the basis of the initial BEAST model version, where the liability side was modelled in a simplified fashion and – as inherited from the EBA stress test templates – there was no full consistency between asset and liability size and structure.

Level	Exercise	Goal/motivation	Activities/methodologies considered	Conclusions/findings
Micro	Management of defaulted assets	NPL management plays a significant role in many euro area jurisdictions.	This focus area translated into two streams of work: (i) a discussion of the implications of NPL management on banks' lending behaviour (on the back of the pilot exercise on lending for Greek banks), also including asset sales; and (ii) changes in the BEAST model aiming to introduce endogenous write-offs and the mechanisms of coverage expectations from the NPL guidance.	The limited availability of data on different NPL management approaches restricted changes in the BEAST model to the introduction of endogenous write-offs and regulatory recommendations (excluding NPL sales).

Source: ECB.

5 System-wide stress testing covering banks and non-banking financial institutions

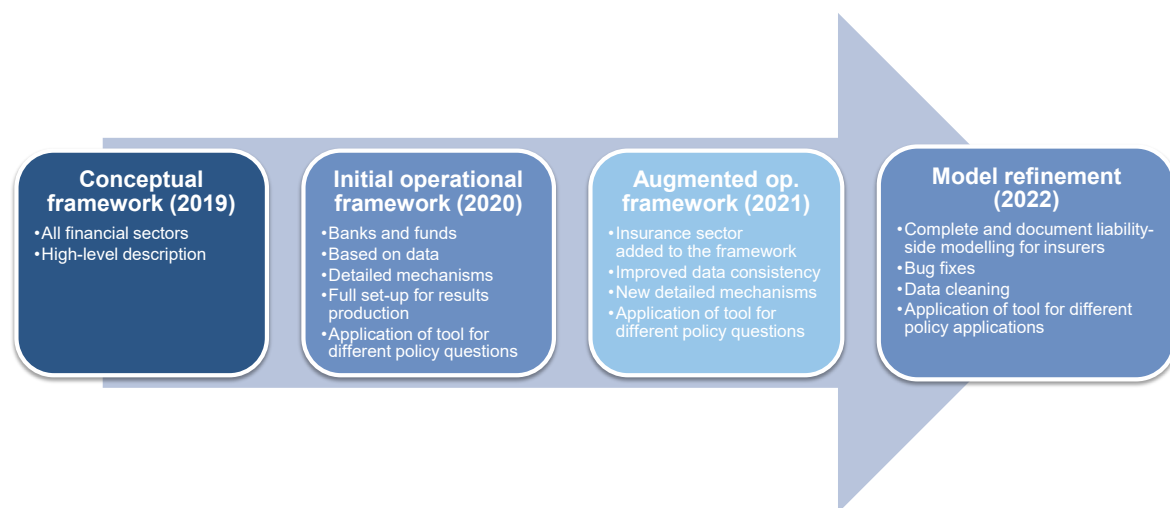
The system-wide stress testing work stream focused on developing models of interactions among banks and non-banking financial institutions, with a particular emphasis on financial contagion.

The work stream acknowledged that during the global financial crisis, interconnectedness and the network topology played pivotal roles in the propagation of contagion within the financial system.¹⁰² Moreover, the growing role of non-banking financial institutions in financing the economy underscored the need for stress-testing approaches that consider interdependencies between sectors in the financial system (Hałaj and Henry, 2017; Aymanns et al., 2018; Hałaj, 2018; Farmer et al., 2020).¹⁰³

At the heart of the work stream's framework was the “Interconnected System-wide stress test Analytics” (ISA) model. ISA was designed to monitor the effects of interconnectedness within the financial system, drawing on firm-level data. The framework integrates several large granular financial databases, input from ECB top-down stress-testing models as well as expertise and input from members, EIOPA experts and academics. A year-by-year timeline of its development is shown in Figure 14.

The development of ISA involved two stages. In a first stage up until 2021, development focused on a prototype model capturing the interactions between banks and investment funds. These works relied on methodologies developed by Montagna and Kok (2016), Covi et al. (2019), Montagna et al. (2020) and Fukker and Kok (2021) as well as the investment fund stress-testing model developed by Gourdel et al. (2019). The final version of the prototype ISA model was first published in a 2021 ECB working paper and then also in Sydow et al. (2024). In 2021 and 2022 the work concentrated on incorporating the insurance sector refining existing model mechanisms, as in Fukker et al. (2022).

Figure 14
ISA development timeline



Source: ECB.

ISA's features, mechanisms and applications are described in the following subsections. These subsections first provide a high-level overview of the framework. They then cover ISA's data, structure, purpose, main mechanics, features and, lastly, applications.

¹⁰² See Franch et al. (2024) for a study on the temporal evolution of financial contagion in a network consisting of the banking, shadow banking and insurance sectors of 18 advanced economies.

¹⁰³ Despite these interconnections, the supervision of the financial sector is divided among different European Supervisory Authorities (ESAs), which include the EBA, EIOPA, ESMA and the SSM. System-wide stress-testing tools are still in their infancy.

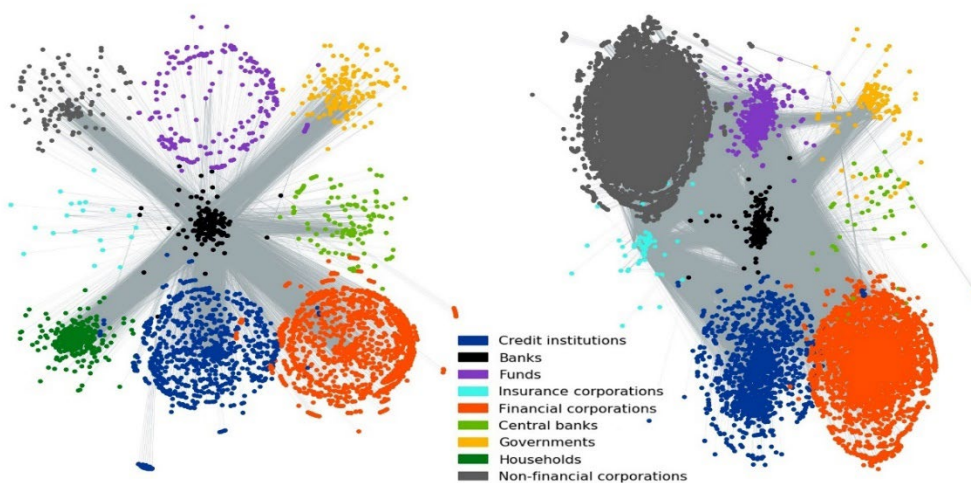
5.1 Interconnected System-wide stress test Analytics (ISA) model

ISA is a dynamic, micro-structural model for system-wide stress testing covering several financial sectors. At its core, the model attempts to provide a holistic view of the entire system's dynamics by capturing both first-round and second-round effects arising from direct and indirect exposures, and their interactions. To achieve this, the framework relies on three main mechanisms of contagion, each accounting for a different class of risk: credit, liquidity and market. More specifically, the model features liquidity and solvency interaction, a dynamic balance sheet, an advanced integration of regulatory constraints and endogenous market price formation.¹⁰⁴

The model consists of relatively independent modules. This modular approach is aligned with the objective of maximising the utilisation of existing ECB models and enhances the framework's adaptability. The modular approach accommodates a diverse array of initial shocks and scenarios and facilitates the incorporation or removal of additional sectors, countries, risks, behavioural rules and time periods.

The model includes granular firm-level data for euro area banks and investment funds, and country-level aggregated data for insurance companies. The use of granular datasets allows the balance sheets of banks, insurers and funds to be replicated to include security holdings, fund holdings and loan portfolios at counterparty or aggregate level. A representation of these loan portfolios and security holdings is shown in Figure 15. This network allows for the study of interconnections among the three financial sectors via their holdings of investment fund shares, securities issued by banks and insurers or loans to the three sectors. The modelling of the financial system at a granular entity-by-entity level for banks and investment funds and a sector-entity level for insurance companies relies on the system's multi-layer network structure reconstructed from regulatory reporting data and ISIN-level security holding information. The granular approach allows for a detailed depiction of the interaction between different layers and channels of the financial system. Moreover, the network effects play a crucial role in amplifying or absorbing the impact of systemic events.

Figure 15
ISA's exposure networks: loans (left-hand panel) and security holdings (right-hand panel)



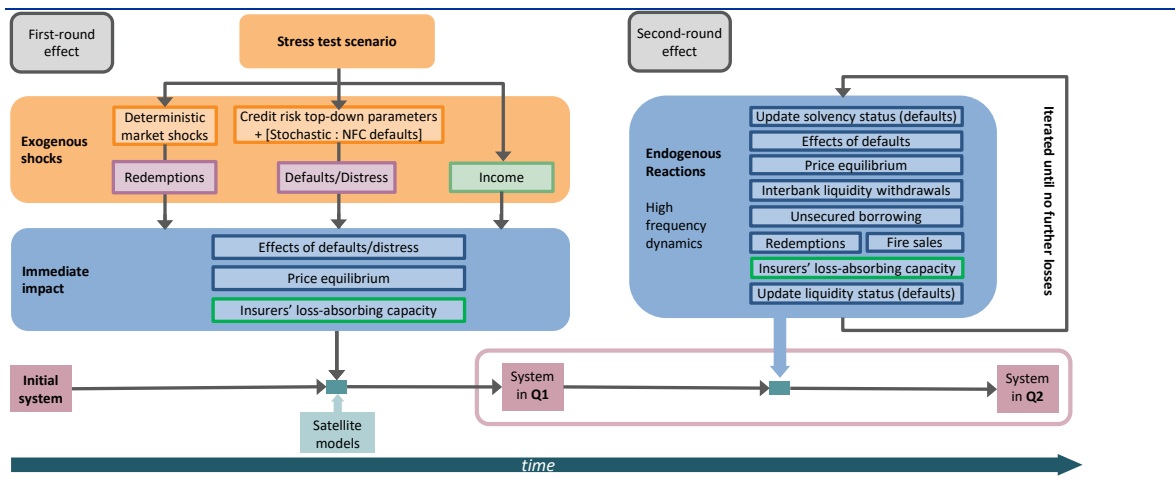
Source: ECB.

Notes: In the left-hand panel, an edge represents a loan from a bank to another entity in each sector. In the right-hand panel, an edge shows that a bank, a fund or an insurer holds assets issued by another entity in a given sector. "Credit institutions" refer to sector-specific exposures based on the information covered in the FINREP reporting templates, while "banks" represent individual institutions.

¹⁰⁴ Most importantly, ISA is a readily implementable tool that can be shared with Financial Stability Committee members possessing comparable data, ensuring consistent cross-country applications.

The main purpose of ISA is to assess the impact of adverse macro-financial scenarios on the three modelled sectors, starting from its individual financial entities. Its key features include the possibility of disentangling different sources of risk and their contribution as well as the possibility of capturing distributional effects through stochastic mechanisms. Figure 16 provides an overview of the main mechanisms included in ISA.¹⁰⁵

Figure 16
Model dynamics: ISA framework for banks, funds and insurers



Source: ECB.
Note: See also Sydow et al. (2024).

The addition of the insurance sector involved the integration of models and mechanisms pertaining to the insurance sector along with the inclusion of this sector's balance sheet data.¹⁰⁶

The insurance sector is represented by 18 country-level euro area company aggregates, which are connected to the other two sectors – banks and funds – through the securities they hold. The insurance sector draws upon a combination of aggregated balance sheet information, which includes Solvency II data collated at country level and combined with highly granular security holdings statistics. Insurance corporations are constrained by their solvency capital requirements (no liquidity constraints are considered) and engage in asset fire sales if these requirements are breached.

A further refinement of existing model mechanisms is the introduction of a granular price-at-risk measure instead of the average market price impact. This enhancement permits the assessment of tail risks associated with potential market price fluctuations under varying severity scenarios. Overlapping portfolios and investments by financial institutions in common assets may expose these institutions to distinct amplification characteristics contingent upon scenario severity and market price sensitivity. System-level losses under a scenario at the tail of market sensitivity can be three times larger than those incurred under the same scenario but utilising average market price sensitivity (price impact parameters).

The system of banks, insurers and funds is initially shocked following existing practices in sector-level stress-testing exercises conditional on a set of macro-financial variables. These initial shocks can then trigger endogenous reactions by all covered sectors. The initial set of shocks can consist of redemptions by investment funds and increased probabilities of default for NFCs, combined with stochastic NFC defaults as well as an instantaneous stock and a bond market shock. After initial losses from these changes in our system, the following endogenous, model-driven reactions may activate: (i) short-term funding withdrawal within the banking system, (ii) reduced access of solvent but illiquid banks to short-term funding in the interbank market, (iii) redemptions from investment funds driven by liquidity needs, and (iv) fire sales of marketable securities at discounted prices.¹⁰⁷

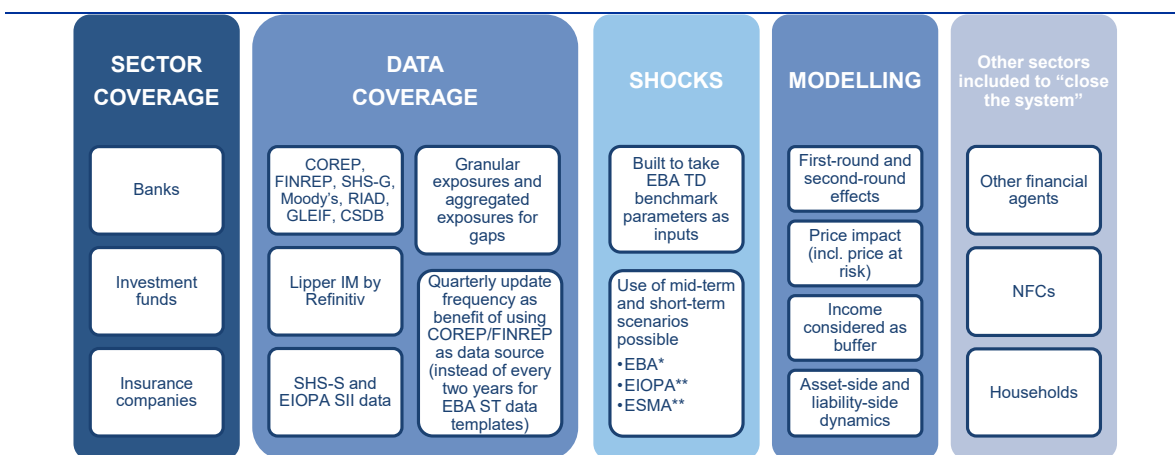
¹⁰⁵ A forthcoming ECB working paper titled "Banks and non-banks contagion: liquidity and solvency risk assessed using a network of granular bilateral exposure data" (see Sydow et al. 2024) presents several additional features implemented in ISA. Figure 16 shows in a green box the latest additions to the model.

¹⁰⁶ See Section 3.6.1 "Interconnectedness and amplification effects following a severe climate risk shock scenario through a system-wide perspective" in ECB/ESRB Project Team on climate risk monitoring report (2022).

¹⁰⁷ All these reactions are generally found to lead to additional sizeable losses within the financial system, which are not captured by stress tests that adhere to the common assumption of a static balance sheet. Applying a COVID-19 shock scenario developed for the ECB's vulnerability analysis exercise in 2020, combined with end-2019 balance sheet information as a starting point, the presence of funds together with banks in

The value added of ISA is to provide sector-specific heterogeneity and institution-specific outcomes. The granular approach takes into consideration within-sector heterogeneity, encompassing variations in balance sheets that remain unaccounted for within a modelling framework utilising aggregated data. In addition, the higher data granularity allows the model to consider better financial frictions and inefficiencies, which are otherwise difficult to model in frameworks with representative agents. ISA's micro-structural modelling approach permits the evaluation of novel metrics of systemic risk, while at the same time providing granular insights into the contribution of individual agents. The model can capture the individual contribution of each risk channel to systemic risk, as well as accommodating non-linearities and contagion effects that often surpass the capabilities of more conventional methods. ISA's main features are depicted in Figure 17.

Figure 17
Current features of ISA for all euro area countries



Source: ECB.

Notes: *EBA: three-year macro-financial scenario. **EIOPA/ESMA: instantaneous shock scenario.

The model is sensitive to different calibrations, which are currently being optimised. ISA relies on estimated parameters borrowed from satellite models or other researchers' works. These parameters include probabilities of default and loss given default, price impact quantiles, surrender shock rates and flow-performance coefficients for funds. The 2022 Macroprudential Bulletin explored ISA's sensitivity to various calibrations of price impact quantiles. In the model where price impact is higher, there are also higher system losses, primarily driven by second-round market reactions and contributions from investment funds. Ongoing efforts are underway to conduct more comprehensive sensitivity checks for the calibration of all ISA parameters.

5.2 Model applications

ISA employs a system-level perspective, centring on the financial system as a whole and consequently minimising the potential for underestimating systemic risk. The model can perform (i) a scenario analysis with an impact assessment for the whole financial system or a part of it, (ii) an evaluation of regulatory measures at institution and system level, (iii) a study of the role of the microstructure of the financial system in amplifying systematic and idiosyncratic shocks, and (iv) an estimation of measures of systemic relevance and vulnerability of different financial institutions. So far, ISA has been applied to investigate the system-wide impact of climate change, to construct investment fund-specific stress-testing frameworks and to study the systemic relevance of overlapping portfolios. These topics are discussed in more detail in the following paragraphs.

our modelled financial system is found to increase average bank capital depletion by 1 percentage point. This effect is largely due to fire sales of portfolios held by multiple institutions.

ISA supports climate risk scenario analyses. The model was used for the climate risk analyses presented in the 2021 ESRB climate report¹⁰⁸, the 2022 ECB/ESRB climate report¹⁰⁹ and the June 2022 Macroprudential Bulletin. The 2021 report looks at the impact of the Network for Greening the Financial System (NGFS) “orderly transition” and “hot house world” scenarios in the two-sector ISA model. This report finds that fire sales of common security holdings and fund share redemptions produce an additional decline in banks’ CET1 ratios of 0.9 and more than 1.2 percentage points under the two scenarios respectively. The two 2022 applications employ the three-sector ISA framework under the NGFS climate scenarios. The NGFS scenarios are translated into probabilities of default on bank loan exposures¹¹⁰ and initial asset price revaluations for the security holdings of banks, insurers and funds. These factors are subsequently amplified through contagion effects arising from bank solvency defaults and indirect contagion through overlapping portfolios. In general, ISA’s application to climate risk finds that losses from the NGFS 2050 “disorderly transition” and “no policy change” scenarios are substantially amplified in an interconnected financial system of banks, investment funds and insurers. The most substantial contribution to overall system losses is from investment funds, followed by the insurance sector and finally banks. However, even when acknowledging banks’ interconnectedness with funds and insurers, ISA generates loss estimates that are significantly larger than in a system with banks only.

A separate work related to the ISA model describes how stress propagates in a system of funds via two contagion layers. The 2022 ECB/ESRB report also discusses a first contagion layer, which relates to holdings by other financial institutions of investment funds and changes in the value of shares issued by open-end funds that are held by other funds. The second layer consists of overlapping portfolios in the secondary market for securities, whereby investment funds may become exposed to common shocks but may also affect one another by influencing market prices through sales and purchases. The analysis focuses on short-term scenarios, on changes in the values of traded securities and on liquidity shocks arising due to redemptions by investors. Investors in “green” funds are found to react less to losses and reward funds with more positive flows when they exhibit positive returns. Because funds exhibit a lack of differentiation relative to physical risk, the impact of market shocks driven by the information on physical risk and by the materialisation of extreme weather events appears significantly more uniform than for transition risk. Furthermore, wildfire, water stress and heat stress are tail events that damage investment funds the most. Following on from this work, Gourdel and Sydow (2023) introduce a dual view of transition and physical climate risk exposures at fund level and elaborate on the relevance of the topology of the fund network.¹¹¹ Table 15 provides an overview of ISA’s main applications.

Table 15
Summary of ISA’s system-wide stress-testing applications

	Main stress-testing policy Exercises	Description
2021	Amplification of climate scenarios in an interconnected financial system of banks and investment funds (ECB/ESRB Project Team on climate risk monitoring, 2021)	Assessment of system-wide amplification of climate risk by applying 2050 “orderly transition” and “hot house world” NGFS scenarios to ISA (two-sector model).
2021	Shock amplification in an interconnected financial system of banks and investment funds (Sydow et al., 2024)	Assessment of system-wide amplification by applying VA COVID-19 scenario to ISA (two-sector model).
2022	System-wide amplification of climate risks (Dubiel-Teleszynski et al., 2022)	Assessment of system-wide amplification of climate risk by applying the 2050 “disorderly transition” NGFS scenario to ISA (three-sector model).
2022	The macroprudential challenge of climate change (ECB/ESRB Project Team on climate risk monitoring, 2022)	Assessment of system-wide amplification of climate risk by applying the long-term “net zero” and “delayed transition” relative to “current policies” NGFS scenarios to ISA (three-sector model).
2022	Contagion from market price impact: a price-at-risk perspective (Fukker et al, 2022)	Assessment of system-wide amplification by applying different levels of redemption shocks to ISA (two-sector model) with a comparison of homogenous and heterogenous price impact parameters.

Source: ECB.

¹⁰⁸ See Box 8 “Amplification of climate scenarios in an interconnected financial system of banks and investment funds” in ECB/ESRB Project Team on climate risk monitoring (2021).

¹⁰⁹ See “Interconnectedness and amplification effects following a severe climate risk shock scenario through a system-wide perspective” in ECB/ESRB Project Team on climate risk monitoring (2022).

¹¹⁰ Probabilities of default in 2050 are derived from the ECB top-down climate stress test, while projected fund redemptions for 2050 are driven by variables such as GDP, carbon emissions, carbon and energy prices and physical risk scores.

¹¹¹ See Box 7 “Dual risk in investment fund climate stress testing” in ECB/ESRB Project Team on climate risk monitoring (2022).

6 Conclusions

Stress testing is a continually evolving field. The WGST was established in 2018 to promote advancements in top-down stress-testing methods across the European Union and via this channel also benefit European bottom-up stress-testing initiatives. Initially, the main challenges revolved around refining the approaches developed by the ESRB and the ECB for regulatory stress tests in the financial sector. However, over the four years of the WGST's existence, new challenges emerged due to events such as the COVID-19 pandemic, geopolitical conflicts and significant monetary policy changes. Policymakers began posing additional questions to stress testers that extended beyond traditional risk analysis, encompassing policy assessment and communication support. The WGST adeptly addressed most of these challenges before concluding its work at the end of 2022, leaving the stress test modelling field in Europe more advanced than ever before. Nevertheless, the work in this area will undoubtedly continue in the coming years.

There is a persistent need to enhance the robustness and universality of top-down models. This necessitates integrating new datasets as they become available, such as leveraging transaction-level data like Anacredit for credit risk modelling or EMIR for market risk modelling. It also involves reconciling different datasets, such as COREP and FINREP versus SHS-G information. Additionally, newer statistical methods, particularly for capturing non-linearities, should be incorporated into modelling approaches. Expanding models to encompass a broader or more granular range of parameters is another area for improvement. For example, enhancing the EPIC tool, which supports the market risk top-down infrastructure, can provide portfolio-level sensitivities that facilitate the benchmarking process for assessing losses from changes in asset prices. Furthermore, the three-sector ISA framework has been enhanced to include the modelling of the liability side of insurers and will later be expanded to cover central banks, hedge funds, money market funds and pension funds. The improvements allow insurers to more realistically assess how their funds will respond to exogenous shocks in bond, equity and property markets.

Enhancing top-down model validation efforts is another crucial aspect of the future agenda. Model validation is already well-developed for credit risk IFSR 9 parameters and the BEAST model. It includes comparing projections with banks' own forecasts (ex post) and back-testing against past exercises (ex ante). For the BEAST model, it involves evaluating pseudo out-of-sample forecasting properties, long-term properties and impulse response functions. Although the validation framework for top-down market risk and profitability models is still less advanced, their results are regularly compared with banks' own forecasts. The ideal validation framework for top-down models should incorporate both ex ante and ex post elements and be sufficiently automated to facilitate timely model adjustments along with the conclusions of validations. For macroprudential models, specific elements such as long-term property testing, validation tests using different calibrations and broadly defined impulse responses may also be included.

There are also aspects that, although primarily focused on enhancing the stress-testing process, benefit top-down modelling. Coordinated efforts to ensure higher-quality stress test submissions from banks in bottom-up exercises, and an improved and efficient outlier detection process in the early stages of each stress test would have a positive impact on the quality and back-testing validation of top-down stress test models.

Furthermore, new policy questions have emerged from the changing environment, including climate and cyber risks. These new risks necessitate testing the resilience of the banking system and potentially implementing mitigating policies. Recent experience indicates the need for models capable of generating multiple scenarios and evaluating their impact. Such models enable the analysis of tail events that often remain obscured, providing a more comprehensive assessment of uncertainty across multiple dimensions compared with the traditional single-scenario approach.

The WGST's work, alongside numerous models, represents an extraordinary level of cooperation between European central banks and supervisory authorities in the realm of stress testing. Stress-testing methods often face the challenge of being perceived as “black boxes” due to their complexity and rapid evolution. This perception is further reinforced by disclosure limitations aimed at preventing manipulation by the institutions undergoing stress tests. In this complex field, the WGST played a crucial role in demystifying the “black box” through its forum and this publication. It fostered the exchange of data and experiences, building trust and a shared understanding of common objectives among stakeholders.

7 References

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8 Appendix

8.1 Credit risk: expected default rates

The expected default rate (or point-in-time probability of default) model is tailored to provide projections that are both country-specific and portfolio-specific. The projections are conditional on scenarios and individual banks' starting points for:

- geographies c including 27 EU countries and 17 non-EU geographies;
- portfolio segments (asset classes) including non-financial corporate loans collateralised and not collateralised by real estate, mortgages, consumer credit and financials.

The projections are calculated following the steps below:

- a) Projection of country-specific and portfolio-specific paths of probability of default: For country c and portfolio segment s , the country and portfolio starting points $PD_{c,s}^{T_0,TD}$ (from the free data collection at country level) and probability of default multiples ($PDmult_{c,s}^{t,TD}$) are applied to derive the top-down projected paths:

$$PD_{c,s}^{t,TD} = PD_{c,s}^{T_0,TD} * PDmult_{c,s}^{t,TD} \quad (61)$$

The superscript t denotes the projection time (in years) spanning the stress horizon (e.g., if $T_0 = 2022$, then $t \in \{2023, 2024, 2025\}$).

- b) Conversion of country-level aggregate probabilities of default to distance-to-default measures: The country-specific and portfolio-specific paths of probability of default are translated into a distance-to-default measure (DD):¹¹²

$$\begin{aligned} DD_{c,s}^{t,TD} &= \Phi^{-1}(PD_{c,s}^{t,TD}) & (62) \\ DD_{c,s}^{T_0,TD} &= \Phi^{-1}(PD_{c,s}^{T_0,TD}) & (63) \end{aligned}$$

where $\Phi^{-1}(\cdot)$ is the inverse standard normal cumulative distribution function.

- c) Application of distance-to-default measures to bank-specific starting points: The absolute changes in distance to default $\Delta DD_{c,s}^{t,TD} = DD_{c,s}^{t,TD} - DD_{c,s}^{T_0,TD}$ are applied to the bank-specific and portfolio-specific starting point to obtain the desired projection path for the bank and portfolio segment (c, s) as:

$$PD_{c,s}^{t, bank} = \Phi(\Phi^{-1}(PD_{c,s}^{T_0, bank}) + \Delta DD_{c,s}^{t,TD}) \quad (64)$$

where $PD_{c,s}^{T_0, bank}$ is the starting point provided by the bank.

There is no starting point adjustment for the sovereign banking book. The outcome of points (a) and (b) is applied uniformly for all banks. It is justified by the postulate that there should be no heterogeneity in the evaluation of sovereign risk between banks at any point in time.

¹¹² The KMV model, developed by Kealhofer, McQuown and Vasicek in 1974, is an extension of Merton's model and represents a structural approach to calculate distance to default. This is a key indicator in credit risk, estimating the likelihood that a borrower will be unable to meet its debt obligations. The empirical translation of distance to default into expected default frequency is proposed by Crosbie and Bohn (2003) and Kealhofer (2003).

8.2 Top-down tools

This annex summarises the tools entering the top-down infrastructure and supporting the use of top-down models. These tools play a relevant role during the quality assurance process of the EU-wide stress tests, comprehensive assessments and other top-down exercises. Each of the following analytical tools is discussed in turn: business logic (embedded within Stress Test Accounts Reporting, STAR), “IFRS9er” (including the “Pocket IFRS9er”), the ECB Path Generator, “Niler”, “SHS-G” and “EPIC” tools, and model assessment questionnaires. The overall ECB top-down analytical infrastructure is deemed fit-for-purpose, relatively automated and encompassing a broad range of quality assurance aspects.

8.2.1 IFRS9er

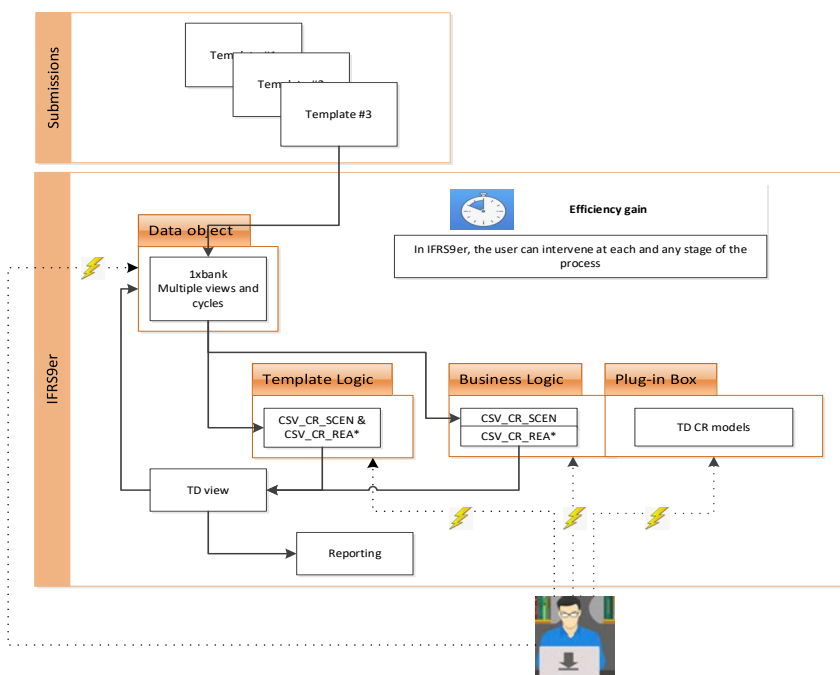
The IFRS9er is a Matlab-based tool that generates top-down credit risk projections. It is the main credit risk tool that produces the capital impact stemming from loan losses and risk exposure amounts. It performs simulations and provides comparative statistics as well as hybrid views on flag impact. Additionally, it has been used for further aggregations of stress test results and sensitivity analyses. Several ad hoc requests for specific analysis (e.g., revised impact for asset classes and geographies, automated production of graphs, etc.) have been accommodated in the developed tools throughout the quality assurance phases.

The IFRS9er tool is based on the EU-wide stress test data and ITS supervisory reporting. Data objects allow the usage of both starting points and projections, consisting of risk parameters and flow projections. The process components can be divided into the following modules:

1. scenario;
2. top-down models for (i) IFRS 9 parameters and (ii) risk exposure amount parameters;
3. business logic, which corresponds to equations flowing risk parameters into balance sheets linked to the capital depletion of banks.

The IFRS9er can be considered a platform that connects the top-down models and allows a sequenced computation to measure the credit risk impacts (Figure 18). Its object-oriented structure allows for decoupling from running top-down models, producing benchmarks and data versioning, and offers increased speed and scale. Accordingly, the platform allows models to be run with different inputs. Additionally, a smaller and user-friendly version of IFRS9er has been developed, “Pocket IFRS9er”. It allows users to independently access a series of original IFRS9er functionalities to perform sensitivity analyses and provide a peer benchmark view for the portfolio-level parameters.

Figure 18
Graphical representation of IFRS9er architecture



Source: ECB.
Note: CSV_CR_SCEN and CSV_CR_REA stand for the EBA templates that the main information for the calculation of credit risk impairments and risk exposure amounts are provided for respectively.

8.2.2 Credit risk path generator tool

The ECB Excel-based Path Generator replicates the methodology and calculations of the top-down credit risk models in an Excel file. The ECB Path Generator is a valuable, user-friendly tool shared externally with banks (without internal models) to facilitate additional analytical steps in relation to the top-down credit risk benchmarks.

8.2.3 Nller tool

The Nller is a Matlab-based tool that generates net interest income projections conditional on a macroeconomic scenario. The logic of the Nller is analogous to that of the IFRS9er. The main building blocks of this calculation engine are the macroeconomic scenario, the top-down projections for NII margins and the business logic equations linking the projected parameters to the relevant balance sheet and profit and loss variables such as total NII, profit and CET1 capital. Granular starting point parameters for margins, reference rates and exposures are retrieved from bank’s stress test templates.

Users can change scenarios, top-down parameter projections and business logic equations. The flexibility of the tool with respect to the scenario and the top-down projections allows the user to answer policy-relevant questions outside the scope of the stress test, such as the impact of an increase in interest rates on bank's profitability or the impact of various assumptions on the reference rate pass-through for loans and deposits rates. One useful feature of the NII tool is that the impact of the top-down projections on NII can be disentangled from the impact of the methodological constraints prescribed by the stress test methodology. It also generates a decomposition of NII into the main drivers, such as the reference rate, the margin or the increase in non-performing exposures. This tool is still being continuously developed and improved.

8.2.4 SHS-G tool

The SHS-G tool is built upon the database of Securities Holding Statistics by Reporting Banking Group (SHS-G) and aims to compute the impact of a scenario on a bank's granular portfolio of direct market exposures (equities, fund shares and bonds). The tool allows the partial revaluation of each portfolio item with respect to all the scenario variables that have a direct, first-round effect on its fair value, according to the corresponding sensitivities. It can provide a general impact in terms of profits and losses on the fair value of the full portfolio, given the single-item revaluation process, and disentangles risk drivers according to several possible levels of granularity (e.g., based on the type of instrument or the scenario variables). The data preparation process is built upon the following databases.

1. SHS-G: Provides information on securities held by euro area banks at security level. It covers the exposures of all significant banking groups under direct ECB supervision, including holdings of subsidiaries and branches outside the euro area. The perimeter of the database includes debt securities, listed shares and investment fund units/shares.
2. CSDB: The Centralised Securities Database (CSDB) provides information about instruments, issuers and prices for debt securities at ISIN-by-ISIN level. This database is used to enrich SHS-G information and compute item sensitivities.
3. Iboxx: Provides information on fixed income, modified duration and convexity.

The SHS-G tool-based analysis performs a partial revaluation of banks' exposures reported in the SHS-G database. For each ISIN in the database, losses are estimated under a stress test scenario by considering four risk areas: interest rate risk, credit risk, equity risk and FX risk. To fully capture the heterogeneity among instruments, shocks are applied at the highest level of granularity (single contract level) by considering the characteristic of the ISIN available via CSDB and Iboxx.

The losses related to interest rate and credit risk factors take into account the modified duration and convexity of the contract, while losses related to the market price of equity or foreign exchange are a linear function of initial shocks. For the interest rate risk, a shock is applied for each currency and set of residual maturities. To achieve this, each item is assigned to a maturity bucket and the corresponding modified duration and convexity are computed, based on CSDB and Iboxx data. Similarly, for credit risk, the counterparty sector (sovereign, financial companies, non-financial companies), its credit worthiness¹¹³ and the contract's residual maturity are considered. Finally, the impact for a given security is calculated at ISIN level as:

$$impact_{\{interest\ rate, credit\}} = market\ value \cdot (modified\ duration \cdot shock + 0.5 \cdot convexity \cdot shock^2) \quad (65)$$

$$impact_{\{equity, fx\}} = market\ value \cdot shock \quad (66)$$

¹¹³ The credit worthiness is expressed in EBA credit quality steps.

8.2.5 EPIC tool

The EPIC tool¹¹⁴ is built upon the EMIR¹¹⁵ derivatives database and aims to reprice items in the entity's derivatives portfolio, also providing their sensitivities to each corresponding risk factor.

Eventually, the computation of sensitivities also allows the revaluation of items' fair value according to one or multiple scenarios. The tool is in continuous development to accommodate challenges posed by:

- the database (i.e., misreporting issues, scope of the reporting framework);
- the scope (i.e., pricing of more complex and exotic instruments);
- the performance (i.e., increasing the efficiency of the tool considering the extensive data available).

Currently, the EPIC tool allows for the analysis of interest rate derivatives (interest rate swaps, forward rate agreements) and contracts with underlying equity/commodities (European options, futures). Although these items already cover a major portion of banks' derivative portfolios, instruments that are still not in the scope need to be considered (CDS contracts, exotic options, inflation-linked derivatives, foreign exchange derivatives, etc.).

The EPIC tool provides various outputs based on the revaluation of single items. It calculates a measure of liquidity risk on the derivative portfolio by estimating variation margins dependent on scenario realisations, provides the option of distinguishing different risk drivers and aggregates the impact according to different levels of granularity (e.g., based on the type of instrument, the underlying asset class or the scenario variables). The risk drivers considered in this context are risk-free rates, government and corporate bond yields, stock market values and exchange rates. Through the same rationale as the SHS-G tool, the EPIC methodology is ultimately meant to frequently update portfolio sensitivities and partially reevaluate portfolio items.

The relevance of the EPIC tool goes beyond the stress-testing exercise, as it is also an instrument for the daily monitoring of portfolio strategies and emerging risks. Due to the high frequency of EMIR data (daily reporting) and their high granularity (especially by instrument and underlying asset class), EPIC allows a 360° overview of banks' derivative portfolio composition.

8.2.6 Model questionnaires

The model assessment questionnaires include the supplementary technical information provided by banks on their models. The use of model assessment questionnaires by top-down teams is key to supporting the quality assurance process. Less conservative bank projections are often justified by bank model deficiencies, therefore enabling the top-down credit team to substantiate the ECB challenger view.

¹¹⁴ EMIR repricing tool.

¹¹⁵ European Market Infrastructure Regulation.

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