EUROPEAN CENTRAL BANK

BANKING SUPERVISION

ECB report on good practices for climate and nature-related risk stress testing

May 2026

Contents

Executive summary

Climate stress-testing exercises have emerged as a key tool for supervisors to assess the impact of climate and nature-related risks on the banking system. Banks themselves are also increasingly using climate stress testing to inform required disclosures and strategic choices as part of their climate-related risk management.

The ECB's 2022 climate risk stress test (CST) was a unique exercise in terms of its exploratory nature and learning character. The exercise acted as a catalyst for banks to develop all aspects of prudent climate stress testing. Since then, supervised entities have significantly improved their climate stress-testing capabilities, building on the experience of the 2022 ECB CST to advance their internal methodologies. By the end of 2024, all significant institutions had integrated climate risk into their stress-testing frameworks.[1] However, there is still room for improvement to ensure climate stress-testing frameworks are fully comprehensive and modelling approaches are robust.

The objective of this report is to provide banks with examples of identified good practices from the 2022 ECB CST and subsequent follow-up activities that took place between 2023 and 2025. The report aims to facilitate banks' efforts to strengthen their climate and nature-related risk[2] stress-testing capabilities, in particular in light of the supervisory expectations set out in the ECB Guide on climate-related and environmental risks ("the Guide").[3] In particular, this report offers support in addressing Expectation 11 of the Guide, which focuses on the necessity to adequately incorporate climate and nature-related risks into banks' stress-testing frameworks. While this report focuses exclusively on stress testing, the report on good practices for climate and nature-related risk management from the 2022 thematic review and subsequent follow-up activities[4] shares observations and good practices illustrating different ways in which significant institutions can strengthen their management of climate and nature-related risks, in particular in light of the remaining supervisory expectations outlined in the Guide and the European Banking Authority (EBA) Guidelines on the management of environmental, social and governance (ESG) risks.[5] Both reports were originally published in 2022; however, the ECB has since identified further good practices as part of follow-up activities that

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1 See Elderson, F., "Banks have made good progress in managing climate and nature risks – and must continue", *The ECB Blog*, ECB, 11 July 2025.

2 Past publications referred to climate-related and environmental risks, or C&E risks. Going forward, the ECB will use the term "climate and nature-related risks". The terms "environmental risks" and "nature-related risks" should be considered as interchangeable.

3 See "Guide on climate-related and environmental risks", ECB, November 2020.

4 See "Good practices for climate and nature-related risk management – Observations from the ECB's five-year climate and nature risk programme (2020-25)", ECB, May 2026.

5 The 2022 thematic review covers all the supervisory expectations outlined in the ECB guide, apart from Expectation 11 on climate stress testing and Expectation 13 on disclosures. Paragraph 10 of "Guidelines on the management of environmental, social and governance (ESG) risks", EBA, January 2025 specifies that "[t]hese guidelines apply to institutions other than small and non-complex institutions from 11 January 2026. These guidelines apply to small and non-complex institutions at the latest from 11 January 2027".

took place between 2023 and 2025, which assessed supervised institutions' processes to identify and manage climate and nature-related risks.[6] The good practices outlined in this report assist banks and supervisors in preparing for future climate and nature-related stress-testing exercises, also considering the EBA's upcoming Guidelines on environmental scenario analysis[7] which enter into effect on 1 January 2027.

This report aims to foster dialogue with banks on approaches to managing climate-related risks as well as share examples of good practices that can support consistent and sound implementation across the industry. It is targeted at professionals tasked with assessing climate-related risks within the banking sector. The report highlights practical suggestions and examples to help banks overcome challenges and take further steps to advance their approaches, also in view of the upcoming EBA Guidelines on environmental scenario analysis. It directly addresses industry calls to disseminate good practices from the 2022 exercise and subsequent follow-up activities.

The examples of measures and practices described in this report are illustrative only and are not intended to be exhaustive. They have no legally binding effect and do not describe or establish new legal or regulatory requirements. An institution may be fully compliant with the applicable regulatory framework without implementing any of the specific examples set out in this report, provided that it has implemented other measures and practices that are more appropriate to its particular risk profile, business model and circumstances. The good practices outlined in this compendium do not set supervisory expectations or standards. They serve merely as illustrations that could help institutions make progress in C&N risks stress testing, taking into account proportionality, materiality and institution-specific circumstances.

The collection of data on greenhouse gas (GHG) emissions and energy performance certificates (EPCs) remains a challenge for banks, and the related constraints are acknowledged by the ECB. Nevertheless, some banks have been proactively addressing the scarcity of climate and nature-related data by independently developing proprietary indicators to identify corporate clients with high sensitivity to climate transition risks. This demonstrates that data limitations can be mitigated through innovative approaches. Furthermore, high-quality data on climate and nature-related risks remain essential for the robust assessment of risk exposures.

Regarding the integration of climate-related risks into modelling approaches for transition risk, the ECB identified various good practices that enable counterparty-level analysis. Overall, with regard to projections of credit risk parameters, advanced approaches demonstrated greater consistency with the scenario-specific shocks used for the 2022 ECB CST than less sophisticated methods. To ensure an adequate assessment of climate-related risks, banks need to extend the range of variables in their models to account for multiple transition channels. In the 2022 ECB CST, most banks had only begun integrating carbon

6 See "ECB sets deadlines for banks to deal with climate risks", *press release*, ECB, 2 November 2022.

7 See Guidelines on environmental scenario analysis", EBA, November.

prices and sectoral gross value added. Banks have since developed sectoral models to integrate climate aspects into existing probability of default (PD) models, focusing first on corporate exposures. Nevertheless, to account for the heterogenous impact of climate-related risks, the quantification of credit risk impact must be done at the most granular level. Since 2022 the ECB has observed that an increasing number of banks are engaging in counterparty-level modelling to capture the effects of climate risk on PDs. Furthermore, while the 2022 focus was primarily on PDs, more institutions have now also developed models to transmit climate risk to loss given default (LGD) estimates.

Compared with 2022, banks have developed more sophisticated approaches for modelling physical risk and taken initial steps towards integrating nature-related risks into stress testing. Although transition risk approaches are generally more mature across most institutions and physical risk approaches remain less widespread, some banks have progressed significantly in their physical risk modelling. However, it was observed that modelling practices predominantly focus on acute physical risk, whereas approaches for chronic physical risks are less common. Typically, banks begin by stressing exposures secured by real estate, utilising the LGD channel to account for physical risk via damages to collateral values. Advanced approaches have also emerged regarding the integration of physical risk into PDs for corporate exposures, modelling the impact on companies' financials stemming from extreme weather events. However, there are still challenges stemming from uncertainty over the future frequency and severity of these events as well as from the granularity of the available data. Given the localised nature of physical risk shocks, particularly acute shocks, granular data and modelling of damages remain essential for ensuring risk sensitivity across both real estate and corporate portfolios. Finally, some banks have also started taking initial steps to integrate nature-related risks into their stress-testing frameworks, either through exploratory scenario analyses or by incorporating specific nature-related scenarios into their climate stress-testing frameworks.

The 2026 updates to this report primarily focus on modelling approaches for integrating climate risk into stress testing, while the sections on data capabilities remain largely unchanged from 2022. In this new release, greater attention is paid to physical risk modelling and emerging approaches for integrating nature-related risks into stress testing, as these topics were not covered in depth in the original version of the report. Since this update is not based on a new climate stress-testing exercise involving data collection, Chapter 4 on climate-related data remains virtually unchanged. For a more extensive treatment of good practices related to climate and nature-related data capabilities, readers should refer to the accompanying good practices report from the 2022 thematic review and subsequent follow-up activities[8]. The sections that have been expanded compared with the original report, as well as entirely new additions, are highlighted in the summary tables below.

[8] See "Good practices for climate and nature-related risk management – Observations from the ECB's five-year climate and nature risk programme (2020-25)", ECB, May 2026.

Table 1

Observed good practices described in this report: climate stress-testing frameworks and scenarios

Section	Subsection	Number	Topic	Summary of good practices
Scope of climate stress-testing frameworks		3.1	Scope of climate stress-testing frameworks	Calibration of the climate stress-testing framework based on a materiality assessment of climate-related risks Use of other analytical tools to design the scope of the framework, such as deep dives into portfolios, sectors or geographies Inclusion of all portfolios that are materially affected by climate-related risks
Climate risk scenarios		3.2	Scenarios	Inclusion of both physical and transition risks in scenarios Use of scenarios that are in line with scientific climate change pathways Use of more than one transition risk scenario Selection of physical risk scenarios relevant for the geographies where banks have exposures Complementing of publicly available scenarios with internally developed ones Use of different time horizons and inclusion of scenarios with longer time horizons
Balance sheet approaches		3.3	Balance sheet approaches	Use of both static and dynamic balance sheet approaches When using a dynamic balance sheet, selection of a sectoral or a more granular approach

Table 2

Observed good practices described in this report: data needs and EPCs

Section	Subsection	Number	Topic	Summary of good practices
Internal data needs	Information on industry sector	4.1.1	Allocation of data to NACE sectors	Gathering of information at initial stage and local level Implementation of code systems and data warehouses aligned with NACE or with higher granularity to enable easier and unique mapping Centralisation of registries and mapping tools Implementation of checks to ensure matching with financial reporting (FINREP)
	Information on geolocation	4.1.2	Mapping of collateral to geolocation, at the highest granularity possible	Availability of geolocation data at loan level in internal systems Assignment of geo-coordinates to collateral for all asset classes, at the highest granularity possible Allocation of respective exposure share to specific collateral in line with common reporting (COREP)
Emissions data	Actual data	4.2.1	Retrieval of actual GHG emissions data	Combination of manual searches from sustainability reports and annual reports and use of data providers Reliance on additional data providers to fill in gaps Direct engagement with counterparties via submitted questionnaires
	Estimated data	4.2.2	Methodologies for proxy estimation	Inclusion of physical activity-based factors (e.g. production data) whenever possible. When not possible, use of economic activity-based factors (e.g. revenues or assets) based on comparable companies or sectoral emission intensity averages Waterfall logic with different estimation approaches (not applying a one size-fits-all methodology to all sectors) Specificities of sectors/subsectors and counterparties at a very granular level, considering differences within sectors
	Validation processes and observed limitations	4.2.3	Checks in place to evaluate accuracy of retrieved emissions data	Informed choice of data providers based on an assessment of documentation, methodology and data coverage, selecting the providers that better reflect the needs of the banks and portfolio characteristics Comparison of actual data received with other providers or by directly checking the companies' reports Challenging of estimated data both from providers and in-house proxies by cross-checking results with comparable reporting counterparties Identification and further analysis of outliers Asking data providers for details of methodologies applied
EPC data	Modelling for estimation of EPC data	4.3.2	Retrieval of actual EPC data	Collection of real EPC data insofar as possible Asking borrowers to provide EPC data at loan origination or when carrying out an annual review or modifying a loan Accessing of public registers Instructing valuers to collect EPC data as part of their collateral valuation review
			Methodologies for proxy estimation	Use of sophisticated approaches for estimation, such as statistical models and machine learning algorithms Ensuring that the sample is representative Ensuring that the data used as inputs for modelling are largely available in the bank's systems or it is feasible to collect them Ensuring that the variables used for modelling are selected to distinguish the different markets Ensuring that the model is back-tested to check its performance and accuracy, and its methodology is clearly established and documented Ensuring that there are appropriate governance arrangements in place

Table 3

Observed good practices described in this report: climate-related modelling approaches [*section updated with newly observed good practices*]

Section	Subsection	Number	Topic	Summary of good practices
Integration of climate-related risks into stress test credit risk models	Climate-related risk transmission to credit risk parameter	5.1	Variables included in banks' credit risk models augmented by climate-related risk	Inclusion of climate-related transition variables, such as carbon (CO2) price, GHG emissions (actual and emission pathways) and carbon (CO2) emissions (actual and projected pathways) Inclusion of climate-related macroeconomic variables (e.g. GVA growth, RRE price shock, CRE price shock) Inclusion of general macroeconomic variables (e.g. interest rate, unemployment rate, inflation/price index)
	Modelling approaches for transition risk **[extended section]**	5.2	Modelling approaches to integrate climate risk factors into the estimation of PDs	Development of satellite modes with inclusion of carbon price impact on PDs at a sectoral level combined with existing models to cover both direct and indirect transmission channels Adaptation of corporate key financial metrics to reflect the impact of relevant climate variables (e.g. additional cost due to carbon price increases), recalculation of PDs and inclusion of external models to develop asset class/counterparty level models if no internal methodology is developed
			Summary – counterparty-level credit risk modelling approaches / climate-related risk metrics	Counterparty-level modelling for the most affected counterparties could focus on the following company parameters to estimate the direct impact on PDs: Counterparties' profits and liabilities (including volatility of equity) Operational cost of counterparties Scenario-adjusted company financials Vulnerability metrics Stranded assets Development of climate/environmental risk classification. Assigning of an overall score which could be calculated as a weighted average of sub-scores (quantitative and qualitative assessment based on client's willingness and ability to transition to more sustainable production) for each financial indicator and linked to the respective PDs Capturing of transition risk mainly by stressing PDs or ratings of individual firms through changes in their profitability, climate transition costs and leverage, which ultimately affect the debt repayment capacity of the counterparty
			Summary – good practices to estimate climate-related risk impact on LGD	Consideration of cost pass-through at client level, such as how an entire increase in carbon tax expenses affects cash flow, which is considered in the valuation of the building Inclusion of new models on top of satellite models that reassess the recovery rate while preserving the link with the recovery rate observed internally Inclusion of a function that connects the conditionally expected LGD with the conditionally expected PD to ensure consistency Consideration of how stranded asset shocks will affect the value of non-real estate asset collateral. Mainly in key sectors Linear combination of asset location, LTV and maturity. Individual insurance coverage as a risk mitigant Integration of the transition risk of the real estate collateral into the LGD at property level, using the change in EPC class that is needed to align with the Energy Performance of Buildings Directive
	Modelling approaches for physical risk **[new section]**	5.3	Physical risk data requirements	Construction of hazard-specific risk indicators at granular level, matching the geographical granularity of exposure location data Consideration of forward-looking measures of physical risk, such as analysing hazards under several representative concentration pathways Mapping of information on clients' location to geo-coordinates at a more granular asset or building level Consideration of exposure-specific vulnerability measures when constructing physical risk maps Accounting for the role of insurance or defence mechanisms against hazards in the modelling of damages from physical risk
			Transmission channels	Consideration of both direct and indirect channels when transmitting physical risk shocks to credit risk parameters Indirect channels: modelling of damages to aggregate GDP, regional/sectoral GVA, inflation and decrease in labour productivity

Section	Subsection	Number	Topic	Summary of good practices
				Direct channels: modelling of impact on corporate financials via revenues or leverage, due to damages to production sites and shocks to companies' cash flow Direct channels: modelling of damages to collateral value
			Integration of physical risk in PD models	Integration of physical risk shocks into PDs via macroeconomic variables Exploitation of direct channels by modelling damages from physical risk hazards to clients' assets, production sites and logistic facilities Translation of damages into deteriorated financial performance of the borrower, either via revenues or leverage. Recalculation of stressed PDs from stressed financials and macro variables Calculation of PD shifts via satellite models and regression models Updating of rating models to include physical risk metrics
			Integration of physical risk / LGD models	Application of haircuts to collateral values based on probability and severity of physical risk events Modelling of damages to collateral value at a more granular asset or property level, considering the characteristics of the building and vulnerability to the specific physical risk hazard Consideration of how a reduction in collateral value affects the LTV. Translation of stressed LTV into stressed LGD
	Nature-related risks **[new section]**	5.4	First steps observed for integrating nature-related risks into stress testing	Inclusion of nature-specific scenarios in climate stress-testing frameworks, by modelling macroeconomic shocks from nature-related risks Exploratory scenario analyses to develop new methodologies to quantify nature-related risk impacts, also considering direct transmission channels Physical risk drivers: scarcity and degradation of natural resources driving price increases for water and biomass, affecting firms' cost base Transition risk drivers: environmental taxes and regulations increase operating costs for firms
	Long-term modelling approaches	5.5	Summary – good practices to adjust existing models to the long-term nature of climate-related risks	Recomputing of PDs based on the credit spreads provided in the scenario Indirect transmission of impact of increasing carbon prices via GVA shocks Extended short-term models on a year-to-year basis to provide climate-related risks for stressed PDs over a longer-term horizon External provider sectoral models to capture unbalanced shocks among different sectors or counterparties
	Modelling of risk mitigation	5.6	Summary – good practices to consider risk mitigants in bank's loss projections	Application of a portfolio exposure-weighted average insurance uptake Based on existing literature or publicly available data with a haircut as a means of conservatism Public insurance is not considered in the projections, but past acute physical risk events are used to compensate for the price shock, while private insurance is considered within the projections based on percentage of insurance coverage

1 Introduction

The ECB's 2022 climate risk stress test (CST) was instrumental in helping banks start to develop their climate risk-related stress-testing capabilities. It was part of a broader set of supervisory activities designed to assess the alignment of banks' risk management practices with the ECB's expectations, alongside the initial assessment in 2021 of banks' approaches to climate and nature-related risk management[9] and the 2022 thematic review[10]. While the 2022 ECB CST focused specifically on assessing banks' climate stress-testing capabilities, it also served as a learning exercise, prompting banks to increase efforts to improve data collection, adapt existing models to include climate-related risks and start building climate-specific frameworks. To further support this development, the 2022 thematic review concluded with feedback letters to each significant institution, detailing shortcomings relative to supervisory expectations, including those related to climate stress-testing frameworks. Consequently, the ECB set institution-specific remediation timelines to enhance risk management practices, including clearly defined intermediate milestones.

While banks have made considerable efforts to advance their climate stress-testing capabilities, the information collected during the 2022 ECB CST revealed a high degree of inconsistency and diversity across industry practices and substantial scope for improvement. Several significant institutions faced challenges in designing appropriate climate stress-testing frameworks, integrating climate risks into their modelling approaches and compiling relevant data. While most banks successfully allocated credit risk exposure and income across the relevant NACE sectors[11], they encountered significant difficulties in gathering information on energy performance certificates (EPCs) for real estate portfolios and greenhouse gas (GHG) emissions for corporate counterparties.

Since 2022 European banks have made significant strides in managing climate and nature-related risks. Their practices for identifying, monitoring and managing these risks have progressed and become more robust, as have their climate stress-testing capabilities. By the end of 2024, when the deadline[12] for significant institutions to include climate and nature-related risks in their stress testing and internal capital adequacy assessment processes passed, all significant institutions had integrated climate risk into their stress-testing frameworks – a substantial increase from only 41% in 2022.[13] However, in the related monitoring and follow-up activities throughout 2025, the ECB observed that material risk drivers, relevant

9 See "The state of climate and environmental risk management in the banking sector", ECB, November 2021.

10 See "Walking the talk – banks gearing up to manage risks from climate change and environmental degradation", ECB, November 2022.

11 NACE (from the French "nomenclature statistique des activités économiques dans la Communauté européenne") refers to the Statistical Classification of Economic Activities in the European Community, the standard industry classification system used in the European Union.

12 See "ECB sets deadlines for banks to deal with climate risks", *press release*, ECB, 2 November 2022.

13 See Elderson, F., "Banks have made good progress in managing climate and nature risks – and must continue", *The ECB Blog*, ECB, 11 July 2025.

portfolios and key transmission channels were in some cases still overlooked. Consequently, more work is required to ensure that stress-testing frameworks are fully comprehensive and that modelling approaches become increasingly robust.

The EBA Guidelines on environmental scenario analysis will apply from 1 January 2027. Grounded in Article 87a(5) of the Capital Requirements Directive[14], these Guidelines complement the EBA Guidelines on the management of environmental, social and governance (ESG) risks[15] by specifying supervisory expectations on how institutions should conduct environmental scenario analysis. Furthermore, they build upon the EBA Guidelines on institutions' stress testing[16] by detailing how climate-related risk factors should be integrated into stress-testing exercises, while also fulfilling Article 177 (2a) of the Capital Requirements Regulation[17]. They also establish criteria for scenario analysis designed to test the institution's resilience to the short-term negative impacts of environmental factors.

Originally based on information collected during the 2022 ECB CST and related follow-up activities, this report focuses on three primary areas: the features of banks' internal climate stress-testing frameworks, the availability of climate risk-related data (including strategies to overcome data gaps) and techniques for modelling climate risks within credit risk frameworks. The report focuses exclusively on credit risk, as it is the risk area where methodologies for climate risk integration are currently most mature and arguably most pertinent.

The ECB decided to update this report to reflect the progress institutions have made since 2022 and to ensure the practices described remain relevant, particularly in light of the upcoming EBA Guidelines on environmental scenario analysis. The existing and newly observed good practices outlined in this report illustrate potential avenues institutions could pursue to strengthen their stress-testing capabilities, in view of both the ECB Guide on climate-related and environmental risks ("the Guide") and the EBA Guidelines. The updates are primarily concentrated in the chapter dedicated to modelling approaches for integrating climate-related risk into stress testing. In terms of climate and nature-related risk coverage, the original version of this report focused mostly on climate transition risk. Certain newly observed good practices in this area have been added to the report and marked accordingly. The updated report now features a completely new section on modelling approaches for physical risk to reflect banks' progress in this area. Another key addition is a section on emerging approaches for integrating nature-related risks into stress testing. However, as methodologies for nature-related risk

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14 Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms, amending Directive 2002/87/EC and repealing Directive 2006/48/EC and 2006/49/EC (OJ L 176, 27.6.2013, p. 338).

15 See EBA, "Guidelines on the management of environmental, social and governance (ESG) risks", January 2025.

16 See "Guidelines on institutions' stress testing", EBA, July 2018.

17 Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and amending Regulation (EU) No 648/2012 (OJ L 176, 27.6.2013, p. 1)

stress testing and scenario analysis are still nascent, this section is relatively contained.

The examples of measures and practices described in this report are illustrative only and are not intended to be exhaustive. They have no legally binding effect and do not describe or establish new legal or regulatory requirements. An institution may be fully compliant with the applicable regulatory framework without implementing any of the specific examples set out in this report, provided it has implemented other measures and practices that are more appropriate to its particular risk profile, business model and circumstances.

The good practices outlined in this compendium do not set supervisory expectations or standards. They serve merely as illustrations that could help institutions make progress in C&N risks stress testing, taking into account proportionality, materiality and institution-specific circumstances. The practices are not necessarily replicable, and they may have been amended and/or augmented with comparable practices from other institutions for illustrative purposes. The numbers shown in the figures of this report are for illustrative purposes only. The methodologies, scenarios and reference frameworks mentioned in the report may no longer be relevant or may cease to be relevant in the future. The ECB also emphasises the evolving nature of good practices and expects these to mature over time. The current update is based on information observed by the ECB up to the end of 2024 and reviewed in 2025 as part of the monitoring of thematic review follow-up deadlines.

The report accounts for the varying progress of individual institutions. Good practices are categorised by their level of sophistication to support banks in developing more robust climate stress-testing frameworks, providing a clear distinction between fundamental and more advanced approaches. This range of practices also addresses the principle of proportionality.

Information collected across all modules of the 2022 ECB CST as well as observations from subsequent follow-up activities were used to extract the good practices. For each module, specific criteria were developed and analysis performed to identify best-in-class institutions, complementing the expert views and findings gained during the execution phase of the exercise. While a representative sample of banks was selected for each module, only a small number of institutions were selected across all three modules, indicating that most banks still need to progress in one or more areas relevant for climate stress testing. The good practices observed after 2022 during the follow-up activities to the ECB CST were also extracted from a sample of supervised institutions identified as the most advanced in terms of the modelling approaches used to integrate climate risk into their stress-testing frameworks.

This report should be read in conjunction with the report on good practices from the 2022 thematic review and subsequent follow-up activities, as both serve as instruments to assist banks in the safe and prudent management of climate and nature-related risks. While the report on good practices from the 2022 thematic review and subsequent follow-up activities provides broader coverage of all supervisory expectations outlined in the Guide (addressing practices related to strategy, governance and risk management processes), this report focuses specifically on the technical challenges of designing adequate climate stress-testing frameworks.

1.1 Structure of the report

This report presents a set of good practices identified through an in-depth assessment of information provided by banks in the context of the 2022 ECB CST and subsequent follow-up activities. The report is structured as follows: **Chapter 2** outlines the criteria used to identify the good practices. **Chapter 3** examines advanced approaches to internal climate stress-testing frameworks, specifically regarding scope, scenario selection and balance sheet assumptions. **Chapter 4** describes advanced methods for collecting climate-relevant data and the development of proxies, covering sector allocation, geolocation of counterparties and collateral, GHG emissions and EPC data. **Chapter 5** illustrates good practices for integrating climate-related risks into credit risk models, detailing transmission channels and approaches for climate risk-adjusted probability of default (PD) and loss given default (LGD) estimates. This chapter comprises six topical sections: the first covers transmission channels and the second focuses on transition risk; the third and fourth sections are new additions to the updated report, dedicated to physical and to nature-related risks respectively; and the final two sections cover long-term scenarios and risk mitigants. **Chapter 6** presents concluding remarks and findings.

2 Screening approach for best-in-class identification

The 2022 ECB CST consisted of three distinct modules aimed at gathering different perspectives on banks' climate stress-testing capabilities. Module 1 was a qualitative questionnaire asking banks to provide information on the characteristics of their own internal climate stress-testing frameworks, covering both technical details about the design of the framework and some more process-related aspects. Module 2 assessed the sustainability of the income of banks and their exposures to carbon-intensive counterparties based on two climate risk metrics[18]. Module 3 focused on bottom-up loss projections for two broad categories of scenario provided by the ECB: (a) short-term transition and physical risk scenarios and (b) long-term scenarios.

For each of the three modules a sample of banks was selected and reviewed in detail to identify the most advanced approaches for the specific aspect covered by each module. For Module 1 only three blocks[19] of the questionnaire were considered in the analysis: the selection criteria were based on the block scores from the 2022 ECB CST and the best-performing banks were selected.

For Module 2 the selection of the good practices sample was based on the ability to report fee and commission income without approximation, the ability to collect actual data on scopes 1, 2 and 3 emissions[20] and the quality of estimated GHG data. For actual emissions data, the proportionality principle was applied to ensure a level playing field across the whole sample. The business model dimension was also taken into account, since each business model has its own characteristics and deals with different types of counterparty which are subject to different levels of requirements concerning the disclosure of emissions data. Regarding proxy estimates, GHG emissions data submitted by banks were compared with GHG emissions data from a benchmark source, and those banks that reported estimated values closer to the benchmark were selected.

For Module 3 the analysis was aimed at assessing whether banks sufficiently reflected scenario-implied shocks to the credit risk parameters. For the short-term disorderly transition scenario, this meant checking how projected PDs for the most carbon-intensive sectors reflected gross value added (GVA) and the carbon price shocks (e.g. direction and magnitude), while, for the flood risk scenarios, the analysis focused on the magnitude and transmission of the acute physical climate risk from loan-to-value (LTV) ratios to LGDs. Long-term modelling approaches were evaluated

[18] Metric 1 represents a measure of the sensitivity of banks' business models to GHG-intensive sectors by looking at the interest income, fee and commission income and underlying volumes from non-financial corporations in 22 NACE sectors (which have been identified by the European Commission as the most carbon-intensive). Metric 2 provides an important proxy for the extent to which banks are financing emissions and how exposed they are to emission-intensive companies.

[19] The blocks that were considered were Block 1 on general aspects of climate stress-testing frameworks, Block 4 on climate stress-testing methodology and Block 5 on climate risk scenarios.

[20] Scope 1: direct emissions from activities under the control of the company; scope 2: indirect emissions from the purchase and use of electricity, steam, heating and cooling; scope 3: other indirect emissions coming from sources not under the control of company.

in a qualitative manner, analysing both the credit risk parameters and the determinants of banks' strategic choices under the different transition pathway scenarios. For selected banks, an in-depth assessment of the explanatory notes was performed.

The selection criteria outlined above were complemented by additional analysis, taking into account both quantitative and qualitative aspects. The analysis also leveraged the supervisory expert assessment and conclusions from the quality assurance phase of the exercise. Further information on the selection criteria and on the specific analysis performed can be found in Annex A.

The 2026 update of this report is based on information collected during the follow-up activities to the 2022 ECB CST, as well as monitoring efforts to assess institutions' management of climate and nature-related risks. Given the fact that this update is not based on a climate stress-testing exercise featuring data collection, Chapter 4 on climate-related data is left virtually unchanged. For a more extensive treatment of good practices related to climate and nature-related data capabilities, the reader can refer to the good practices report from the 2022 thematic review and subsequent follow-up activities.

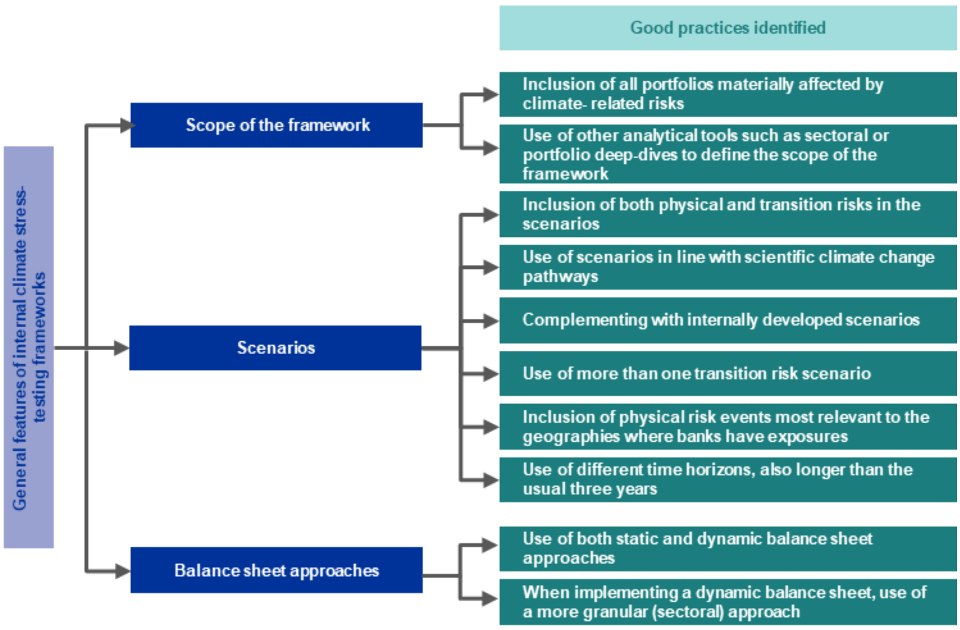
The ECB decided to focus the 2026 update on aspects related to techniques for integrating climate risk into stress-testing models for credit risk. In this light, the ECB selected a subsample of institutions that exhibited more advanced methodologies with respect to modelling approaches for climate risk and integration of climate risk into credit risk parameters. The ECB focused its selection on practices that were not covered in the previous version of this report. In this respect, greater attention was paid to practices for physical risk modelling, as this topic was not covered in depth in the original version of the report due to less mature practices at that time. In recent years, as the materiality of physical risk has increased, the banking sector has developed more sophisticated approaches to assess and measure this risk. Finally, and in line with the update of the report on good practices from the 2022 thematic review, the ECB decided to incorporate in this update the new approaches observed for integrating nature-related risks into stress testing. Recognising the nascent stage of these practices, the ECB emphasises that their inclusion aligns with its goal of sharing valuable insights with the industry, to support the development of modelling approaches for environmental risks beyond climate.

3 Climate stress-testing frameworks

When designing their internal climate stress-testing frameworks, institutions need to make some general methodological choices that affect the overall quality of the results from the stress-testing analysis. This chapter focuses on three key questions related to the general design of the climate stress-testing framework, namely how to determine the scope of the framework, which types of scenario to include and the choice of the balance sheet assumption. This chapter leverages the findings from the Module 1 questionnaire to offer banks an overview of selected sound approaches to address the three key methodological choices mentioned above.

Figure 1

Good practices in the design of internal climate stress-testing frameworks



Source: Bank submissions.

3.1 Scope of climate stress-testing frameworks

Most institutions with advanced approaches include in the scope of their internal climate stress-testing framework all the portfolios that are materially exposed to climate-related risks. Consistent with the Guide, significant institutions take into account the materiality of their exposure to climate-related and nature-related risks. In this respect, institutions use the assessment of materiality to define the scope of their CST frameworks. This ensures that the framework considers the specificities of the institution’s business model, operating environment and risk profile and is an important step to ensure sound management of climate and nature-related risks. In the good practices report from the 2022 thematic review, the assessment of materiality for climate-related risks is discussed in more detail, hence suggestions and examples outlined in both reports help banks to accurately calibrate the scope of their climate stress-testing frameworks.

The asset classes included in the 2022 ECB CST are those for which more data and methods are already available at present, but the comprehensiveness of the assessment of climate-related risks in a stress test is further supported by extending the scope of the framework to all the asset classes in the banks' balance sheets. The ECB observes that institutions are moving in this direction, taking into account the materiality of the exposures.

Most banks with advanced approaches also make use of other analytical tools to inform their decisions on the scope of their climate stress-testing framework, such as deep dives into certain portfolios or specific industries or into real estate properties to better understand how climate-related risks could affect their counterparties. Some banks make use of climate heat maps to assess the sensitivity of sectors or geographies to physical and transition risks and use this information to support the choice of scenarios and the definition of the scope of the climate stress-testing framework.

3.2 Climate risk scenarios

With respect to the choice of scenarios included in the climate stress-testing framework, institutions cover both types of climate-related risk – physical and transition risks – as part of developing a comprehensive approach. This is consistent with Expectation 11 of the Guide, under which institutions conduct scenario analysis considering how both physical and transition risks might affect their activities. On transition risk, institutions include more than one transition risk scenario as part of their analysis. This approach reflects the uncertainty of the policy environment and the fact that different types of transition imply very diverse macroeconomic impacts. Several banks align with the Network for Greening the Financial System (NGFS) categorisation of scenarios and consider one scenario for each of the three groups of transition risk scenarios identified by the NGFS: "orderly transition", "disorderly transition" and "hot house world"[21]. With respect to how physical risk is reflected in the climate stress-testing framework, banks with advanced approaches tailor their choice of physical risk scenarios to the vulnerabilities of the geographies where they have exposures. Some institutions, for example, have built very specific scenarios with the most likely types of physical risk event only for the locations most relevant to their activities. Some banks also perform preliminary assessments and analysis (e.g. climate heat maps) evaluating several types of physical risk event to identify the most relevant weather events for their activities.

Regarding the sources of the scenarios included in the climate stress-testing framework, institutions use scenarios which are in line with scientific climate change pathways, such as Intergovernmental Panel on Climate Change (IPCC) scenarios, consistent with the Guide. The NGFS was by far the most common source. Other

[21] From the fourth vintage of the NGFS long-term scenarios, the category "too little, too late" has also been added.

sources used were the IPCC, the Banque de France, the Bank of England and private providers. Several institutions used a mix of publicly available scenarios and internally developed ones. Internally developed scenarios were usually tailored to reflect the vulnerabilities to which banks are exposed, such as scenarios focusing on specific sectors or geographic areas in which the operations of clients are concentrated.

Regarding the length of scenario horizons, according to the Guide, banks consider how climate-related risks might materialise in the short, medium and long term under different scenarios. The ECB observes that banks also explore scenarios with different time horizons, including beyond the usual three-year length of traditional stress tests, to better capture different types of climate-related risk. Banks state that they mostly use short-term horizons, ranging from one to five years, for acute physical risk in order to reflect the sudden nature of extreme weather and natural events that can lead to unexpected losses in the short term. On the other hand, long horizons (more than 20 years) are often chosen for transition risk scenarios analysing policy risk, technological innovation and change in market sentiment and for chronic physical risk.

3.3 Balance sheet approaches

Banks with advanced approaches tend to consider a static and a dynamic balance sheet approach in their climate stress-testing framework, depending on the objective of the exercise. A static balance sheet approach is useful for assessing the resilience of banks to an unexpected shock in short/medium-term scenarios, while a dynamic balance sheet allows banks to assess the impact of strategic choices on their vulnerabilities, which is relevant over longer horizons. However, the quality of the results from the dynamic balance sheet exercise depends on the quality of the integration of the scenarios' climate risk factors within the banks' models, on the knowledge of counterparties' transition plans and on the approach to the dynamic allocation of exposures. This is applied by a number of banks and provides more granularity than an asset class approach, which is more high level. Some banks implement even more granular approaches at exposure level, subsector level or location level. The ECB observes that a more granular approach can provide deeper insights, although the quality of the balance sheet exercise depends on many factors, and a granular approach for allocating exposures does not necessarily guarantee the robustness of the results.

4 Data requirements for climate stress testing

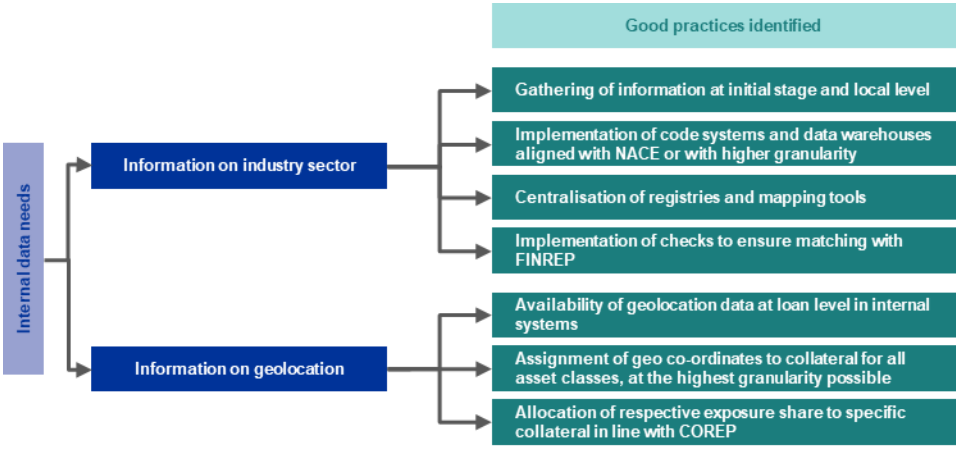
In line with Expectation 6 of the Guide, “For the purposes of internal reporting, institutions are expected to report aggregated risk data that reflect their exposures to climate-related and environmental risks with a view to enabling the management body and relevant sub-committees to make informed decisions”. To do so, they assess data needs, identify gaps and devise plans to overcome them. Data requirements for climate stress testing go beyond traditional stress-testing needs, which is why the 2022 ECB CST included several innovations. Given the novelty of the field and the need for more detailed data, the ECB observes that institutions engage closely with their clients to fill gaps and to retrieve information on counterparties’ transition plans and commitments for the purposes of internal stress-testing programmes. Institutions also perform data-gathering exercises, explore a range of data sources and foster the exchange of information.

4.1 Internal data needs

For the 2022 ECB CST, banks were asked in Module 2 to split incomes and exposures among 22 selected industries at NACE level 2, covering the high-climate-impact sectors identified by the Technical Expert Group on Sustainable Finance[22] and representing around 90% of total European scope 1 GHG emissions. In the context of Module 3 physical risk, banks also had to perform a within-country geographical disaggregation of exposures at NUTS level 3 (nomenclature of territorial units for statistics). This section describes good practices identified with respect to these areas of data needs, summarised in Figure 2.

22 See EU Technical Expert Group on Sustainable Finance, “Taxonomy: Final report of the Technical Expert Group on Sustainable Finance”, European Commission, March 2020.

Figure 2
Summary of good practices



Source: Bank submissions.

4.1.1 Information on industry sectors

In some cases the allocation of income data to NACE sectors required additional efforts, but this did not represent an issue for most banks. Institutions that gather this information at an initial stage, use code systems in line with NACE classification and store the data in centralised tools found it easier to perform such allocation.

The required decomposition of activities at NACE level 2 implies a higher degree of granularity than banks are used to disclosing in, for example, FINREP, meaning that additional efforts are needed.

Most banks already gather information on the main activities of each counterparty at an initial stage and at local level, involving staff who have direct and closer contact with clients. Codes are assigned by the front office, the risk management office or by each relationship manager, or the information is retrieved during the onboarding process. For validation purposes, additional checks are also performed by consulting the public registry. Another good practice is the use or implementation of code systems and data warehouses already aligned or reconcilable with NACE classification, even with a higher level of granularity, so that each code can be mapped to a unique NACE code. Moreover, some banks store this kind of information in a centralised counterparty registry or make use of a centralised mapping tool, which makes it possible for all interested business areas to access it. Some banks have developed checks to ensure that data extractions match with FINREP, even if only at a higher level than the one required in the 2022 ECB CST.

Collecting information directly from counterparties ensures more accurate reporting of the three main sectors of activity of holding companies. None of the banks analysed have implemented such a process. Some banks consulted publicly available reports, such as balance sheets, and internally available data, and one resorted to an external data provider to obtain information on the structure of subsidiaries.

4.1.2 Information on geolocation

To quantify the financial risk implications of acute physical risks, highly granular data at the exposure level are required. This holds true for exposures to corporates with respect to the location of firms' activities as well as for the location of collateral and financed real estate exposure. Collateral plays an important role in mitigating losses for banks but may itself be subject to damage or loss of value.[23]

In the flood risk exercise of the 2022 ECB CST, banks were asked to classify the location of their credit exposures to their counterparties in accordance with the flood stress map provided, which disaggregated regions at NUTS level 3 into minor, low, medium and high-risk areas.

The availability of geolocation data at loan level in internal systems is important for a more accurate mapping of exposures to different risk categories. In order to assign the appropriate NUTS 3 codes to the collateral, banks used as a starting point data that were available in their internal systems for all asset classes (mainly mortgages). Due to gaps in the data retrieved from the internal data sources, further adjustments were made by institutions. If addresses were missing, the postal codes of the counterparties' collateral were used to assign the respective codes.

In addition, banks with more advanced approaches have developed their own real estate databases which contain the locational data to allocate the exposure to the NUTS 3 region. Moreover, another approach observed was the allocation of addresses to NUTS 3 regions via Eurostat. However, collecting address-level information directly in the internal systems provides a more accurate geolocation of exposures.

If a loan is covered by multiple forms of collateral, banks allocate the respective exposure share to the specific collateral in line with COREP information to have each secured exposure (including split secured exposures) unambiguously linked to the respective collateral asset and to adequately reflect its vulnerability to the climate-related risks assessed. If information regarding the location of the collateral is not available, a conservative approach is applied, whereby the full exposure is mapped to the highest risk category applicable to any property securing that exposure.

In the follow-up activities to the 2022 climate stress test, the ECB observed that banks have made some progress regarding the granularity of location data available in their internal systems. The ability to allocate exposures at NUTS level 3 is now a common practice, even though physical risk can vary significantly within the same NUTS level 3. The ECB observed different levels of advancement among supervised entities with respect to geolocation data capabilities. Banks with advanced approaches are now able to locate the collateral or their counterparties at a more

23 See ECB/ESBR Project Team on climate risk monitoring, "Climate-related risk and financial stability", ECB, July 2021.

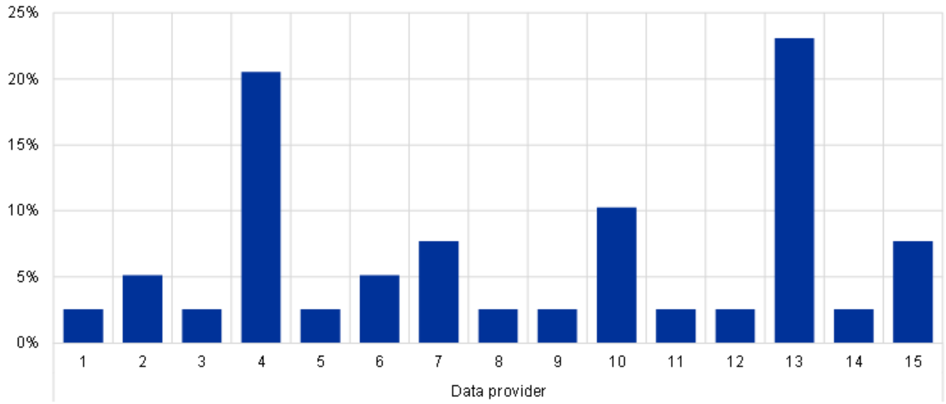
granular level than just NUTS 3, namely at asset and client level. Given the localised nature of physical climate risk shocks, the ability to localise exposures at a more granular level is a key enabler for a more risk-sensitive analysis. The reader can also refer to Section 5.3.1 on data requirements for modelling physical risk.

4.2 Emissions data

With the aim of measuring the carbon intensity underlying their corporate portfolios, banks had to report in Module 2 the 15 largest non-SME corporate exposures (i.e. excluding small to medium-sized enterprises) for each of the 22 NACE sectors, as well as the counterparties' scopes 1, 2 and 3 emissions and revenue data. To report GHG emissions data, banks could collect the data themselves, resort to data providers or make use of estimations where it was not possible to retrieve actual values. Overall, according to the needs and the different coverage provided, banks relied on many different data providers, of which an anonymised non-exhaustive sample is presented in Chart 1 in order to show the wide range of providers available.

Chart 1
Data providers used by selected banks

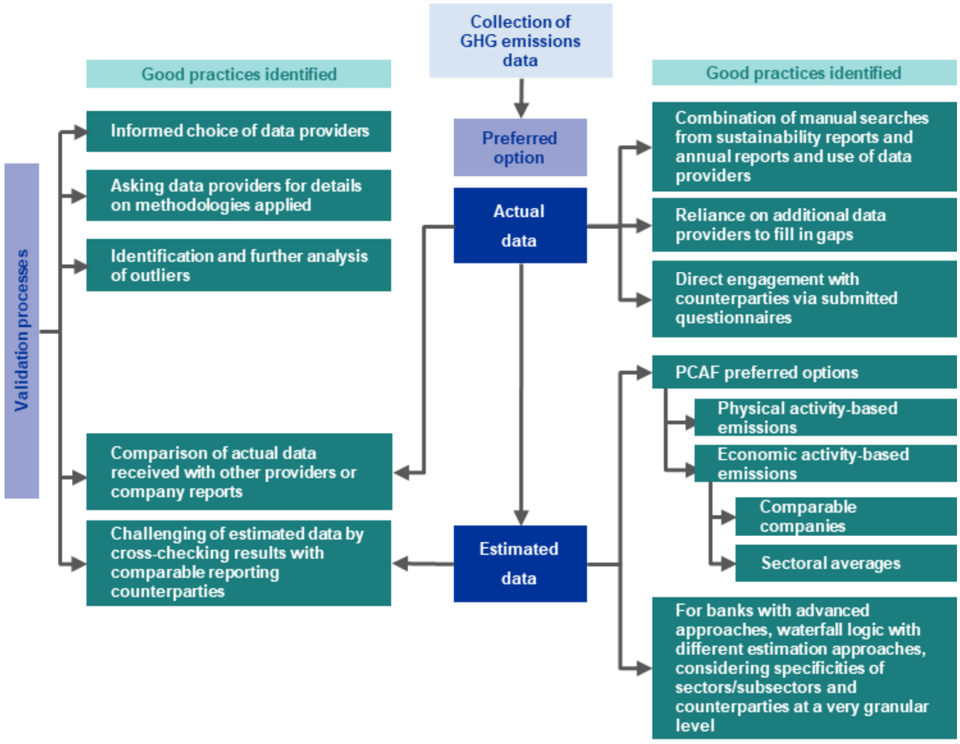
(percentages)



Source: Bank submissions.

The next sections provide more details on the approaches implemented by the banks to collect GHG emissions data (both actual and estimated) and the good practices identified, together with the validation processes, as summarised in Figure 3.

Figure 3
Summary of good practices



Source: Bank submissions.

4.2.1 Actual data

Actual data refer to data reported directly by companies in their published sustainability reports or annual reports, which are a good source of accurate emissions data, in particular when verified. Banks can obtain such information either directly from their clients' reports or from external data providers. Since the first option can be time and resource-consuming, most banks lean on data providers. It should be noted that the legal requirements to disclose emissions data vary between countries and sectors, sometimes making it difficult to access them. This aspect was mentioned by some banks as one of the difficulties encountered. Also, the fact that data are published directly by companies themselves does not necessarily mean they are reliable: if they are not verified or are not calculated according to recognised guidelines, such as the GHG Protocol, there may be little or no guarantee of accuracy. Future regulatory developments, such as the European Sustainability Reporting Standards, will be beneficial in this regard, providing transparency and defining minimum requirements.

Notwithstanding the challenges, many banks strive to collect actual emissions data and a few of them managed to retrieve and report in the 2022 ECB CST a relatively high percentage (above 70%) of actual data for scopes 1 and 2 emissions.

More than one data provider can be used to retrieve the actual data, as an additional data provider can help to complement information and fill in gaps. Furthermore, most of the selected banks searched for data themselves and did not rely solely on external data providers. In some cases, this was the first step before resorting to providers, while in other cases it happened subsequently when data were not available in the provider's database.

Along the same lines as identified in the report on good practices of the 2022 thematic review and subsequent follow-up activities, banks structured the analysis in three stages: specific task forces were set up (i) to go through public reports, (iii) to complement missing data by liaising with two data providers and (iii) to directly consult clients via individual questionnaires.

The use of actual data is a preferred option, although it required additional efforts to collect them, in particular for scopes 1 and 2 emissions. This could involve not only relying on external data providers but also engaging directly with clients. Banks are encouraging and inducing their counterparties to disclose GHG emissions and the methodologies underlying their calculations even if not explicitly required to do so by legislation, for example by collecting such data during the loan granting process or through the submission of questionnaires. Moreover, checking the compliance of actual data reported by companies with widely recognised international standards is used to address the issue of reliability.

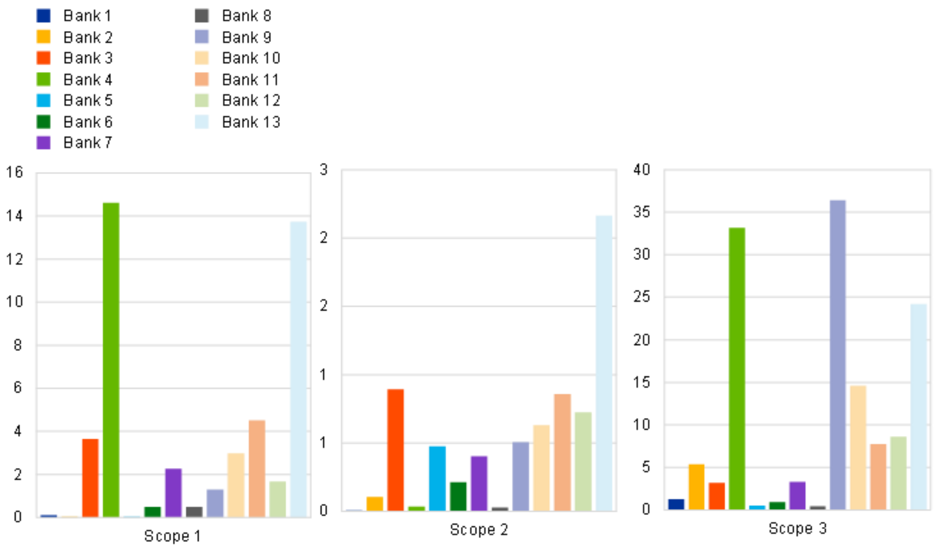
4.2.2 Estimated data

4.2.2.1 Challenges faced by banks

The 2022 ECB CST results showed that banks made extensive use of proxies to report scopes 1, 2 and 3 emissions. The availability of emissions data is indeed limited, in particular for smaller banks or those whose portfolio is mostly composed of small, non-listed counterparties that are not required to disclose their emissions, making banks heavily dependent on the goodwill of their clients when trying to engage with them in the collection process. Banks also faced difficulties in developing sound approaches due to the lack of methodological guidance, the high heterogeneity of emissions data retrieved from external providers and the lack of a common database to retrieve the climate data needed. While proxies are a first step towards closing the availability gap, huge discrepancies across emissions data (Chart 2) and the variability of approaches warrant further methodological reflection and guidance on how to improve estimation methods and increase reliability.

Chart 2
Heterogeneity of estimated emissions for the same counterparty

(GHG emissions, tCO2e millions)



Source: Bank submissions.

4.2.2.2 Emissions intensity modelling

Against the backdrop of the huge variability in approaches, the ECB performed a deep dive into the methodologies used to approximate banks' financed emissions, as detailed in their explanatory notes.

The assessment was based on the application of the first edition of the Partnership for Carbon Accounting Financials (PCAF) Global GHG Accounting and Reporting Standard for the Financial Industry[24], published in November 2020. In particular, to be consistent with the asset classes within Module 2, Metric 2 (i.e. corporate exposures to non-SME non-financial obligors), the ECB focused on the PCAF guidance for the following asset classes: corporate bonds, business loans, project finance, commercial real estate, mortgages and motor vehicle loans, which encompass those within Module 2.

Box 1
Partnership for Carbon Accounting Financials approach to the estimation of greenhouse gas emissions

The Partnership for Carbon Accounting Financials (PCAF) defines three options for calculating the financed emissions from, for example, business loans and unlisted equity, depending on the emissions data used.

24 See "The Global GHG Accounting and Reporting Standard Part A: Financed Emissions", second edition, PCAF, 2022.

While options 1 and 2 are based on company-specific reported emissions or primary physical activity data provided by the borrower or investee company or third-party data providers, option 3 is based on region or sector-specific average emissions or financial data using public data sources such as statistics or data from other third-party providers.

Options 1 and 2 are preferred over option 3 from a data quality perspective since they provide more accurate emissions results. Owing to data limitations, financial institutions may use options 1 or 2 for certain companies and option 3 for others.

Table A

General description of the data quality score table for business loans and unlisted equity

(1 = highest data quality; 5 = lowest data quality)

Data quality score	Options to estimate financed emissions		When to use each approach
1	Option 1: reported emissions	1a	Outstanding amount in the company and total company equity plus debt are known. Verified emissions of the company are available.
2		1b	Outstanding amount in the company and total company equity plus debt are known. Unverified emissions calculated by the company are available.
	Option 2: physical activity-based emissions	2a	Outstanding amount in the company and total company equity plus debt are known. Reported company emissions are not known. Emissions are calculated using primary physical activity data for the company's energy consumption and emission factors specific to that primary data. Relevant process emissions are added.
3		2b	Outstanding amount in the company and total company equity plus debt are known. Reported company emissions are not known. Emissions are calculated using primary physical activity data for the company's production and emission factors specific to that primary data.
4	Option 3: economic activity-based emissions	3a	Outstanding amount in the company, total company equity plus debt, and the company's revenue are known. Emission factors for the sector per unit of revenue are known (e.g. tCO2e per euro of revenue earned in the sector).
5		3b	Outstanding amount in the company is known. Emission factors for the sector per unit of assets (e.g. tCO2e per euro of assets in the sector) are known.
		3c	Outstanding amount in the company is known. Emission factors for the sector per unit of revenue (e.g. tCO2e per euro of revenue earned in the sector) and asset turnover ratios for the sector are known.

Source: PCAF (2020), "The Global GHG Accounting and Reporting Standard Part A: Financed Emissions", first edition.[25]

The ECB identified nine different approaches across the sample of banks assessed (Chart 3). These approaches are presented according to the main categories identified in the PCAF methodology, thus reflecting a hierarchy.

- Physical activity-based emissions: emissions are calculated using primary physical activity data for the company's energy consumption or for the company's production and emission factors specific to that primary data.
- Economic activity-based emissions: emission factors for the sector per unit of revenue, assets, revenue turnover ratio and asset turnover ratio. Different approaches were observed within the sample and are ranked below from the most to the least preferred.
    - Revenue-based emission intensity average based on comparable companies: specifically identified comparable counterparties (close nature or business) are used to calculate an average intensity for

[25] Please note that PCAF released a new version (third edition) of the Global GHG Accounting and Reporting Standard in December 2025.

  each scope, then applied to the turnover of the counterparty with missing emissions data.

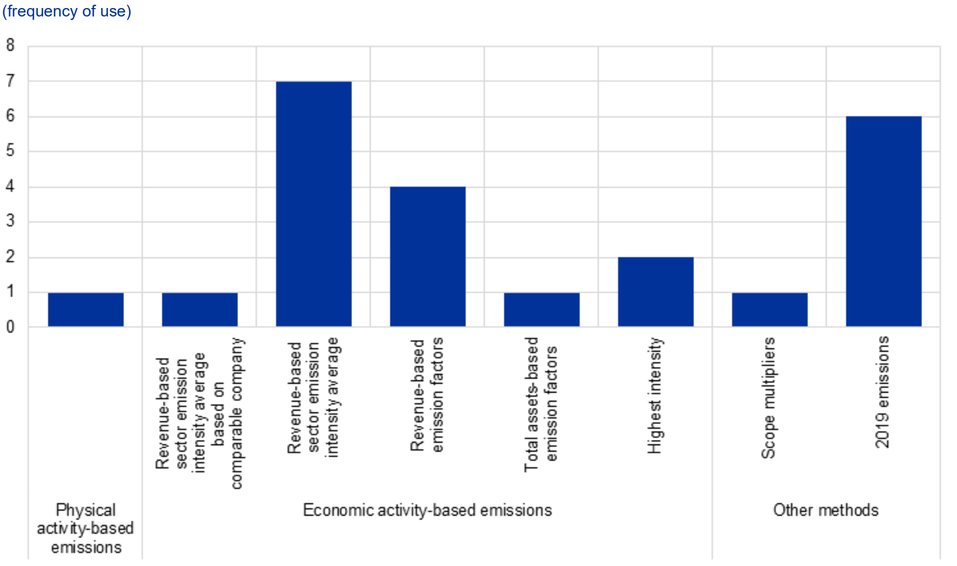
  - Revenue-based sector emission intensity average: if the sector is quite homogeneous and reporting counterparties are representative, actual emissions data from public documents of counterparties are used to calculate an average sectoral intensity, which is applied to the revenues of the counterparty with missing emissions data.
  - Revenue-based emission factors: sectoral emissions factors are applied to the revenues of counterparties with missing emissions data.
  - Total assets-based emission factors: emission factor tables (generally from environmentally extended input-output tables) are used to express the amounts of tCO_2e emissions per million euro of assets for a given sector (using NACE classifications) and country (counterparty total assets × emission factor (country / NACE code 2)). For instance, the PCAF emission factors are derived from the EXIOBASE database that estimates emissions by industry. Scope 1 emissions are directly available in the EXIOBASE database, while scopes 2 and 3 emissions are derived from input-output analysis.
  - Highest intensity: at either sectoral or group level, the highest intensity is used to derive the emissions intensity of the counterparty with missing emissions data.

- Other methods: these are not referenced in PCAF guidance but were observed in the sample.
  - Scope multipliers: mainly used when GHG intensities are obtained from Eurostat to derive scope 1 emissions. An average ratio of scope 2 to scope 1 emissions from reference counterparties with disclosed data is multiplied by scope 1 intensities derived from Eurostat data in order to determine scope 2 intensities for each counterparty with missing emissions data. However, this approach does not account for the specific characteristics to be considered for each scope and may lead to distorted estimations.
  - 2019 emissions: if information for the counterparty is only available for 2019, in the worst case, 2019 emissions data are used directly as a proxy or, in the best case, 2020 emissions are estimated by applying the incremental growth of emissions by sector from Eurostat to the counterparty's 2019 data.

Some other practices put in place by banks may lead to misreporting and underestimation: the use of comparables or calculation of averages based on broad samples of counterparties, limiting the analysis to macro sectors or to NACE level 1 and large geographical areas, may not ensure the accuracy of proxies. Since there may be differences between counterparties within the same category, an intermediary step is to assess the homogeneity of the sector and the comparability of the reporting companies before proceeding with the estimation.

Chart 3

Main methodologies used by selected banks for in-house proxies



Source: Bank submissions.

Some banks went a step further with more sophisticated approaches. These include a detailed waterfall to estimate scopes 1, 2 and 3 emissions, tailored to the specificities of the sector/subsector and counterparty and factoring in not only economic activity-based factors (revenues) but whenever possible also physical activity-based ones (production data). Most banks with advanced approaches have also implemented multiple approaches, combined several methodologies and tried to determine the best proxy depending on the context and the available data, as described in Boxes 2 to 4. Moreover, when approximating scope 3 emissions, these banks included both upstream and downstream emissions and used differentiated approaches for estimation.

Box 2

Global systemically important bank good practice approach to the estimation of greenhouse gas emissions

A global systemically important bank (G-SIB) uses different proxies.

- Sectoral proxy based on data specific to the sector or a stochastic approach[26], multiplying conversion factors by information on the type of product and production volumes (physical activity-based emissions).

[26] The bank did not provide more information, but this approach can be useful as an example of how to integrate physical activity-based data into the estimation of scopes 1, 2 and 3 emissions in a statistical manner.

- Sectoral proxy based on turnover; used if no stochastic approach was possible. If the sector is quite homogeneous and reporting companies are representative, actual data from their public documents are used to calculate an average sectoral intensity, which is applied to the counterparty with missing emissions data.

- Proxy based on comparable: reliance on specifically identified comparable counterparties with close nature or business to calculate an average intensity for each scope, which is then applied to the company.

- Propagation: the counterparty with missing data is assigned to a group and data from other companies belonging to the same group are retrieved from an external provider. The emission intensity of the reporting company with the highest turnover is then applied to the turnover of the counterparty.

- When no other option is feasible, the highest intensity of the sector is used as a last resort.

- A specific proxy has been developed for the forestry industry because of the specificities of its carbon profile and the decarbonisation potential. Emissions are set to zero by default by claiming that the sector is generally recognised as capturing carbon, leading to a negative greenhouse gas balance.

Box 3
Universal bank good practice approach to the estimation of GHG emissions

A universal bank with a multiple step approach: the first two steps are aimed at collecting actual data, while the last two steps are estimation methods.

- Step 1: Reported emissions and revenues from sustainability reports and annual reports are used. All emissions in this step are classified as actual. If no emissions from 2020 are available, data for 2019 are used. 2019 emissions are rescaled to 2020 by multiplying by the ratio of 2020 to 2019 revenue of the counterparty.

- Step 2: Data from external providers are used and classified as actual. If no emissions from 2020 are available, emissions from 2019 are rescaled as in the previous step.

If no data are available from steps 1 and 2, this implies that no reported emissions are available and meet the quality standards. In this case, the emissions need to be modelled based on step 3 and step 4.

- Step 3: Estimation at sector level, with 73 economic categories classified according to NACE sectors. For each category and each scope of emissions, a linear regression model is set up with emissions as the dependent variable and revenues as the explanatory variable, using data from external providers. Emissions for 2019 are used instead of 2020 to avoid biases caused by the economic downturn from the COVID-19 pandemic. The regression result is used to estimate the emissions of the counterparty whose data are missing, by multiplying the regression factor by the 2020 revenue. The models need to meet specific quality standards: at least 20 samples should be available, and the Pearson correlation coefficient should be higher than 0.6. This method is applied only to corporates with revenues higher than €10 million and is currently only used to estimate scopes 1 and 2 emissions.
- Step 4: Estimation based on emissions and financial data from external providers, resulting in emission intensity per euro of revenue. A waterfall logic with eight different levels is followed, combining geographic and industry/sector dimensions. For the first dimension, four levels are defined with decreasing granularity: 216 countries, eight macro regions, two markets (developed and emerging) and the whole world. For the second dimension, two levels are defined: 73 industries and 12 sectors, obtained by aggregating industries based on NACE classification. The most accurate combination is country-industry and at least 20 reported emissions must be available, otherwise the granularity decreases to the world sector level. For each combination available and each scope, the average of reported emissions is calculated and then the revenue-based emission intensity is obtained. The missing emissions are finally calculated by multiplying the company revenues by the intensity.

Some banks also rely on the methodology used by external providers for the estimation of emissions data.

Box 4
Corporate/wholesale lender using external provider approach to the estimation of greenhouse gas emissions

The approach considers the most relevant greenhouse gas emissions criteria in the companies' line of business.

- Non-reporting companies are first benchmarked against their reporting peers, identified using a proprietary classification system of eight industries, 54 sectors and 123 subsectors based on their emission profiles.
- For each subsector, the most significant metrics are identified by applying a statistical regression analysis and then considered in each specific model. Therefore, the estimation of emissions for the counterparty with missing emissions data does not account for only one financial metric (e.g. assets or revenues) but is based on a combination of several metrics (e.g. for the airline sector, revenues and number of employees are included).
- All the companies' data are quality checked and may be manually modified if needed, while models with less input are also employed as back-up options.

- Furthermore, if required, the logic is complemented with additional modelling approaches, i.e. systematic sector-specific bottom-up modelling, breakdowns of counterparties at activity level and breakdowns of holdings companies by subsidiaries and joint ventures.
- With respect to the estimation of scope 3 emissions, a combination of approaches is developed and applied according to the company and sector specificities as well as data availability. Estimations of upstream emissions are based on environmentally extended input-output models, while downstream emissions are obtained through physical activity-based, average sector-based and economic activity-based methods.

To account for the proportionality principle and ensure a level playing field across banks, the ECB identified some good practices across smaller banks. For example, most banks with advanced approaches within development and promotional lenders, diversified lenders and small domestic lenders used the revenue-based approach, applying the 2020 emission intensity of each sector at different levels of granularity (up to NACE level 4) to the turnover of the counterparties with missing emissions data.

4.2.3 Validation processes and observed limitations

Only few banks provided details on how they assure the quality of the data collected through external data providers. This could include investigating and understanding how data providers obtain the actual data and the methodologies behind the estimation processes. To ensure the reliability and the accuracy of data, establishing checks and validation processes was a critical step in the process. These checks have not been implemented by all banks, or at least not explicitly mentioned in the explanatory notes, but a few of them provided details.

Some banks performed checks by comparing the actual data received with other data providers, manually going through the annual reports or sustainability reports of randomly selected counterparties, or by first identifying outliers and subsequently performing research on counterparties' reports. When data received are estimated, some banks also tried to verify and challenge them, for example by cross-checking the results with comparable reporting counterparties, or even by asking the provider to disclose more details on the methodology behind them and checking the goodness-of-fit of models.

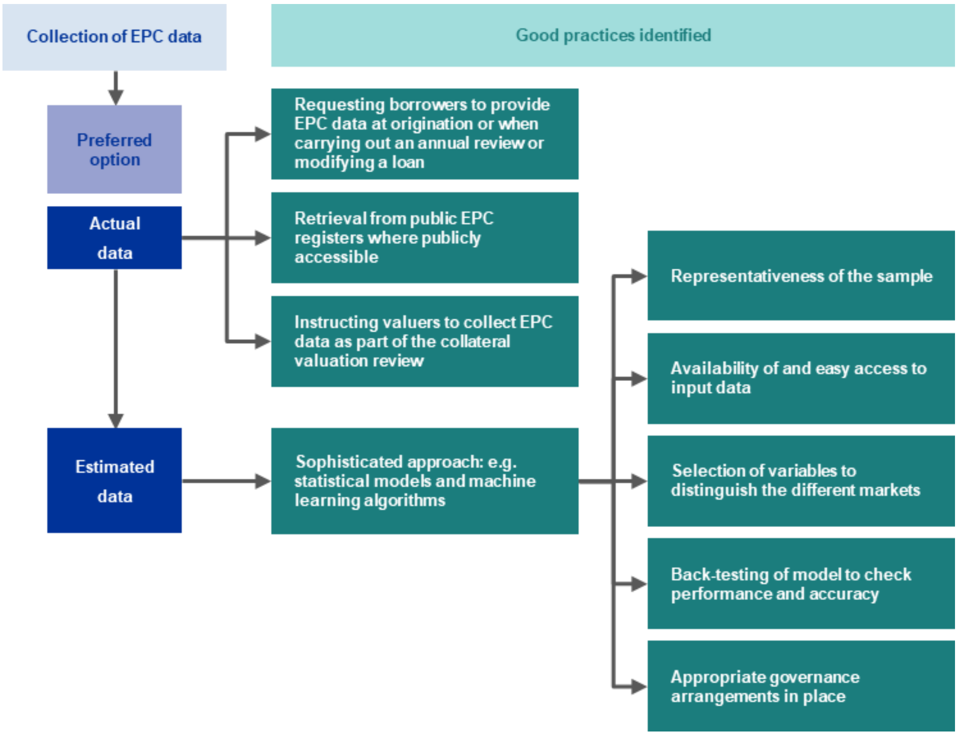
The relevance of comparing different data providers at the initial decision stage is discussed in the report on good practices for climate and nature-related risk management from the 2022 thematic review and subsequent follow-up activities. This entails banks assessing providers' documentation and informing themselves on data coverage, making an informed decision that reflects both the needs of the bank and the specificities of its clients. A couple of banks said they had reviewed documents of several providers and investigated the quality and coverage of available data. Some banks described in the explanatory notes the approach used by the selected provider, demonstrating that efforts had been made to research and understand the methodology behind data.

Assessing the quality of data is also relevant in the case of internal estimation. A bank performed a comparison of the relative scopes 1, 2 and 3 emissions estimated internally to evaluate the possibility of underestimation or overestimation. Identified outliers have been further analysed to assess whether reporting companies used to estimate the emissions were representative of the bank's portfolio.

4.3 EPC data

For Module 3 purposes, banks were requested to provide projections on the basis of sector-specific scenarios, with a breakdown of exposures by the 22 industries and of mortgages by EPCs. This section is aimed at providing an overview of the good practices identified to collect data on EPCs and the methodologies used to estimate such data when they are not available, which are summarised in Figure 4.

Figure 4
Summary of good practices



Source: Bank submissions.

4.3.1 Main challenges in the collection of real EPC data

EPCs are a key instrument to help improve the energy efficiency of buildings, and this information can be retrieved by banks from a number of sources, including (i) directly from clients, (ii) from EPC registers where publicly accessible, (iii) from valuers carrying out valuations, or (iv) from a reliable external party. However, the amount of actual EPC data collected by banks is too low, with one bank out of four having no real EPC data in their systems.

One of the main challenges for banks in collecting these data and for supervisors in assessing them is the heterogeneity of regulation across EU countries in terms of accessibility and definition. Only a few countries have publicly available EPC registers, while some countries provide only aggregate statistics, do not yet have a centralised national database or only provide information for certain regions. In terms of measurement, the indicator used to measure EPCs varies across countries or the EPC scaling varies within the same country. These issues also make the comparison of data more challenging for supervisors. As a consequence of these limitations in the EPC registers, the ECB observed, as part of ongoing targeted reviews, that EPC estimations are less robust and less accurate for banks in countries where there is no centralised database, as those banks must rely on data collected from clients only or on aggregate statistics obtained from other data sources.

It is also important to note that the challenges faced by banks are more pronounced for the existing stock of loans than for new lending, where banks have started to collect EPCs from borrowers at loan origination. Indeed, over the past decade, more and more countries have begun adopting regulation making EPCs mandatory for residential and non-residential buildings, thereby allowing banks to collect EPCs at loan origination. That said, the ECB has observed that gaps in access to real EPC data for their loan portfolios can be a challenge for some of the banks. This limits their ability to assess portfolio composition and manage the risk effectively.

To fill the data gap, most banks make use of additional data (i.e. characteristics of properties such as year of construction, type of building or floor space in square metres) to calculate a proxy. The ECB observed that the main drivers used by banks to estimate EPC data are energy consumption, type of property, floor space and year of construction. The latter in particular is used by around 72% of banks that estimate EPC data. Considering that the oldest buildings may have received an upgrade to their rating due to renovation work, it is useful to complement the year of construction variable with other more up-to-date information, for example the renovation year of different heating sources.

Regardless of how banks estimate EPC data, the main challenge still concerns the availability of these additional data. Lack of representative data makes it difficult to reach a conclusion on the performance of bank modelling: some banks estimate the inputs, while others simply do not apply the model for the missing data, leaving a high share of unknown EPCs, and some use the data of other countries to compensate. Owing to the limited amount of data and the lack of information on the oldest buildings (in particular as there is very little incentive for owners of poorer-quality buildings to provide EPC data to banks), the ECB noted that estimations are very likely to be positively skewed towards higher EPC ratings, which from a risk management perspective is not considered robust.

Because of these challenges, the progress of individual banks will in many cases continue to be constrained in terms of gathering actual EPC data. National governments and relevant EU regulators have a major role to play in mitigating heterogeneity and structural challenges in a timely manner.

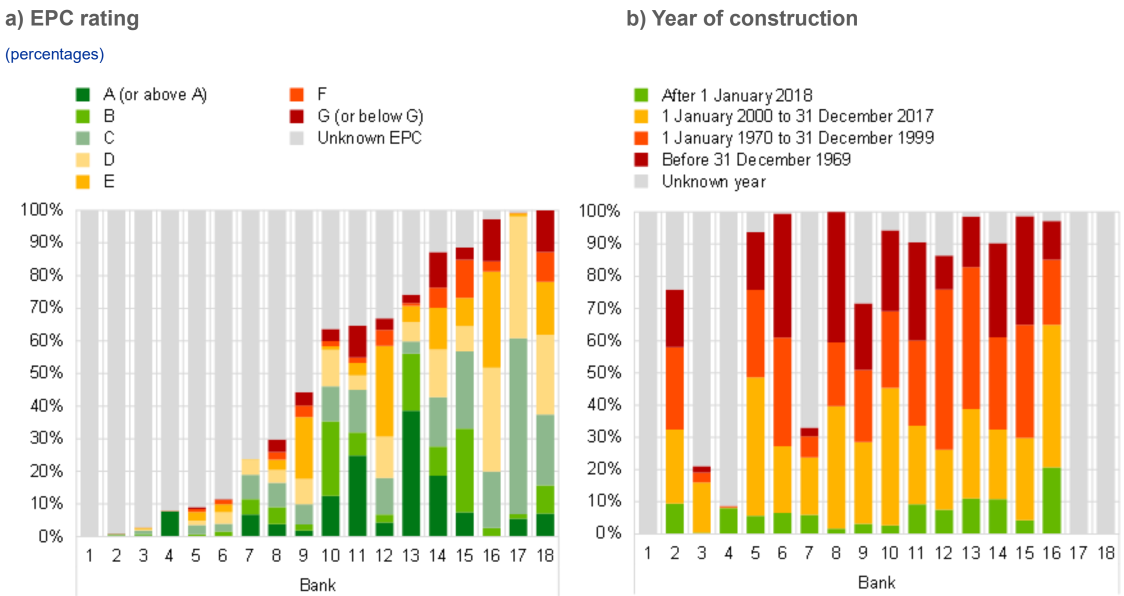
Box 5
Commercial real estate sector

The ECB performed a targeted review of the banks most exposed to the commercial real estate (CRE) sector and collected the breakdown of collateral located in the respective domestic countries by energy performance certificate (EPC) and year of construction. By comparing the share of CRE buildings with the worst ratings and the share built before 1969, the high share of unknown EPCs may be related to these older buildings, where information on certificates is not available. Moreover, the year of construction is not always internally available for banks, making the estimation with this variable, if used by itself, more challenging.

Another challenge faced by banks in providing data is that some asset classes in the CRE sector do not require an EPC or have several EPCs, for example a storage or commercial centre.

Considering the complexity of the estimation of EPC data for CRE buildings, some banks do not use proxies and just rely on real EPC data, which are still limited.

Chart A
Breakdown of CRE buildings by EPC rating and year of construction



Source: Targeted CRE review.
Notes: Based on a sample of 18 significant institutions. Each institution is assigned the same number in both panels. Reference date: 30 June 2021.

4.3.2 Modelling for estimation of EPC data for unrated exposures

For the allocation of unrated exposures (i.e. those without an actual EPC), the ECB observed two different approaches: around 20% of banks did not estimate the EPC or purchased the proxy from external data providers, while the majority developed an internal methodology to estimate the EPC. However, the methodology adopted by banks is heterogeneous and depends on several external factors, such as the accessibility of public registers and the type of information collected.

The least robust approaches observed and adopted by around a third of banks are the application of average and median values to large cohorts of buildings and the replication of EPC distribution based on aggregate statistics from external data providers or the distribution of banks' portfolios, in some cases representing only 20-40% of real EPC data. The first approach excludes the buildings with the best and worst ratings and it may positively skew the results if the underlying data do not account for buildings without a rating, which may in fact be the oldest ones. In both cases, it is key to check the representativeness of the sample in the distribution to ensure the accuracy of the results.

Another third of banks use a single-variable or a step approach, while the remaining banks use a statistical model or machine learning algorithm where more variables are taken into account as inputs, for example floor space, type of asset and socio-demographic information. However, even if these approaches are considered more robust than the others, the limited amount of data used as inputs reduces the size of the sample and its representativeness, and the results could also be positively skewed for the reasons outlined above.

Observed practices with respect to gathering real EPC data include: (i) asking borrowers to provide such data at origination or when carrying out an annual review or modifying a loan, (ii) retrieving data from public registers where publicly accessible, and (iii) instructing valuers to collect EPC data as part of their collateral valuation review. This is relevant for commercial real estate in particular, where predicted models are less accurate and data used as inputs are more difficult to collect.

For EPC data that cannot be collected, the ECB observed a few banks adopting the random forest model, the k-nearest neighbours (k-NN) algorithm or the gradient boosting decision tree (GBDT) algorithm. For the application of the model or algorithm, banks first collected all real EPC data available for their collateral to create the sample and then cleaned the sample. Subsequently the sample was split between the training set, representing around 70%-80%, and the testing set for the remaining part. The model was applied to the training set to link, for example, the real EPC data to the other variables collected, and then it was tested on the remaining 20-30% of the sample to check its accuracy and ensure the model was adequate for the estimation of EPC data. Another bank detailed the methodology and the results for the selection of the most relevant variables to be used as regressors in banks' statistical models. In this case, the regressors were excluded if the P-value was higher than 5% or the frequency (number of observations) was lower than 10%. For each univariate analysis, the performance of the regression was checked, using among others the R-squared. Then, for the regressors chosen, a correlation analysis between the independent variables was performed as well as residual analysis to review the robustness of the model.

Nevertheless, regardless of the choice of model, there are some key steps to ensure the robustness of the approach.

1. The sample is representative (in terms of size, regions represented in the sample and heterogeneity), so that the distribution is not skewed towards better EPC ratings. Moreover, it is key to consider in the modelling approach the availability of information about the oldest buildings, as they are expected to have the worst ratings unless they have been renovated in recent years.

2. The data used as inputs for the bank's modelling are largely available in the bank's systems or it is feasible to collect them. For example, if a variable used for inputs is available for 20% of the portfolio, then it is not considered representative. Moreover, if the data used as inputs need to be estimated, then the EPC estimation may be less accurate.

3. The variables used for modelling are selected in order to distinguish the two different markets, such as the type of property or the share of commercial versus residential buildings. Moreover, for both sectors, if the year of construction is used as a variable, then the year of renovation is expected to complement this information, making sure that the renovation is extensive and not just cosmetic.

4. The model is back-tested and validated to check its performance and accuracy and its methodology is clearly established and documented.

5. There are appropriate governance arrangements in place to ensure that banks regularly assess the adequacy and appropriateness of the data and modelling techniques used and the outcomes of this assessment are reviewed and discussed by an appropriate senior body within the bank.

Taking the above into consideration, it is recognised that the use of proxies by banks is sometimes necessary. However, as challenges diminish and banks make progress in addressing data gaps, it is anticipated that the use of proxies will gradually decline over time and eventually become marginal in nature.

5 Integration of climate and nature-related risks into stress test credit risk models

The assessment and quantification of climate-related risks regarding their potential impact on credit risk requires new approaches and tools to account for the peculiarities of climate-related risks. As stated in Expectation 7 of the Guide, institutions are expected to comprehensively analyse the ways in which climate-related factors drive credit risk and any other material risk to capital, paying particular attention to concentrations that climate-related risks may cause.

Approaches to climate stress testing usually take into account climate, macroeconomic, and sector and company-specific factors that may differentiate them from traditional stress-testing tools and credit risk models.

A range of direct and indirect transmission channels is needed to better capture the specific drivers of climate-related risks and to analyse the external factors and trends that shape the business conditions in which an institution operates or is likely to operate based on its main or material geographic and business exposures.

This broader analysis allows an assessment of the impact of climate-related risks on banks' business environment, as required in Expectation 1 of the Guide, but it requires a high level of granularity.

With respect to the modelling approaches applied, initial steps usually involve integrating a sectoral and regional dimension, which is complemented with counterparty granularity going forward.

All of these aspects are described in the following sections.

The first main objective of developing relevant modelling approaches is not to achieve a high degree of statistical accuracy but rather to capture the potential magnitude of climate-related risks and understand the level of preparedness of clients. According to Expectation 4 of the Guide, "Institutions are expected to explicitly include climate-related and environmental risks in their risk appetite framework".

This chapter was updated from the previous version to include newly observed good practices on transition risk and by adding two new sections on physical risk and nature-related risk.

5.1 Climate-related risk transmission to credit risk parameters

For climate stress testing a combination of climate variables (for transition and physical risk) with regular macroeconomic and financial variables is needed to quantify the impact of climate-related risks under a given scenario, as considered in

Expectation 11 of the Guide. Such variables are provided by the NGFS for the respective scenarios in their publicly available data platforms, the scope and granularity of which will also be increased with future releases. External data providers can also be used to source the respective data. The range of variables needed ultimately depends on the modelling approach, the granularity and the portfolio characteristics of the bank.

To measure the impact of climate-related risk, banks explore the inclusion of a broader range of variables. While sectoral GVA is usually a starting point, including more climate-specific variables along with the traditional stress-testing variables helps to better capture the impact. Along with the macroeconomic impact calculation, direct transmission channels contribute to a more comprehensive risk assessment. For instance, the inclusion of the carbon price is observed to be a starting point to account for the impact of climate-related risks in point-in-time credit risk parameters. To enhance accuracy, additional variables such as GHG emissions intensity, emission pathways and the development of energy sources are included. It was observed that changes in energy consumption and investment decisions were also used on a sectoral or counterparty level to capture a broader perspective of direct transmission channels. An overview of variables used for climate-related risk quantification is provided in Table 4. The incorporation of these transmission channels into existing or newly developed models is described in the next section.

Table 4

Variables included in banks' climate risk-augmented credit risk models[27]

Climate-related transition variables	Climate-related macroeconomic variables	General macroeconomic variables
Carbon (CO2) price	GVA growth	Interest rate
GHG emissions (actual and emission pathways)	RRE price shock	Unemployment rate
Carbon (CO2) emissions (actual and projected pathways)	CRE price shock	Inflation/price index
Carbon/GHG emissions intensity	Labour productivity	GDP growth
Investments in low-carbon technologies and energy efficiency		Investment
Energy consumption		Real disposable income
Energy mix		Exchange rate
Energy prices for oil/gas/coal		Sovereign bond yield
Electricity demand		
Electricity prices		
EPC labels		
EPC transition cost for F and G labels		
Water consumption (one bank)		
Disposal of hazardous waste (one bank)		
Disposal of non-hazardous waste (one bank)		
Client transition readiness		
Carbon abatement and carbon sequestration		
Sustainable aviation fuel		

Source: Bank submissions.

5.2 Modelling approaches for transition risk

While the relevant practices depend on the bank's starting point regarding the integration of climate-related risks into their models, the ultimate goal is to capture them properly for the exposure concerned. The following sections provide examples of how that can be achieved.

The ECB identified a tendency to combine existing stress-testing models with newly developed climate risk models in order to capture the sectoral/EPC-level or counterparty-specific impact of climate-related risk factors. Some of the advanced models were already developed before the 2022 ECB CST, while other banks have decided to start using a combination of internally developed models with tools from external providers.

As a first step, banks developed sectoral models aimed at integrating climate-related risk aspects into existing PD models. Direct transmission channels are captured through the inclusion of climate-related variables in either existing or newly

[27] See also the key variables for climate stress testing indicated in "UNEP FI's Comprehensive Good Practice Guide to Climate Stress Testing", United Nations Environment Programme, December 2021.

developed models. Indirect channels of transmission are also covered by the adjustment and/or development of satellite models, mostly through the inclusion of sectoral GVA. More advanced methods include counterparty-level granularity along with sectoral approaches. Banks engaging in counterparty-level modelling often start with a subset of counterparties identified as the most vulnerable (also considering the sectors) to climate-related risks.

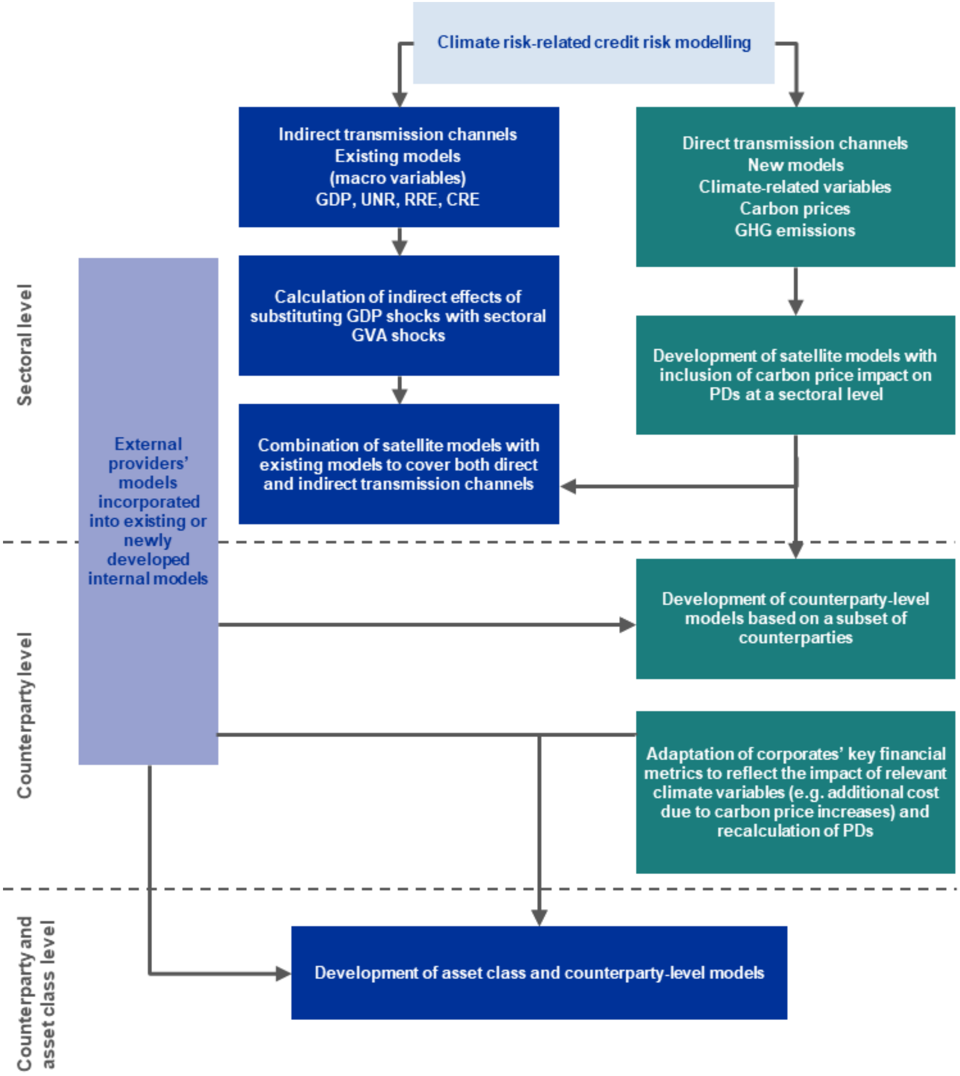
The counterparty-level modelling techniques used differ in terms of how advanced they are. Most banks use carbon prices as the main variable accounting for climate-related risks, as carbon prices are a key factor in translating transition policies into price implications. Using carbon prices at national level also accounts for the different policy ambitions among countries. A richer set of climate variables is used in more rigorous approaches. Robust modelling approaches include the use of additional variables at company level to estimate the impact on the counterparty's financial key performance indicators (KPIs), including scopes 1 and 2 emissions, energy mix and emission intensity, which act as a driver for PD estimations.

Most advanced approaches observed include the asset class dimension in counterparty-specific models, characterised by different approaches and sets of variables used for each asset class, as transmission channels may vary (e.g. different methods employed for non-financial corporation than for residential mortgage exposure). The combination of counterparty and asset class-level models is developed either internally or by making use of external providers. Banks use external sector-level models along with firm-level balance sheet satellite models to obtain a holistic risk score at the corporate exposure portfolio level. Climate risk indicators/scores from external or internal approaches feed into corporate rating models to turn projections of firms' financials into projections of PDs. An overview of the modelling approaches used to integrate climate-related risk factors into the estimation of PDs is provided in Figure 5 below, while related techniques are described in more detail in the next section.

5.2.1 Climate-related risk-adjusted PDs

Figure 5

Modelling approaches to integrate climate risk factors into the estimation of PDs



Sources: Bank submissions and ECB calculations.

5.2.1.1 Sectoral models

As a starting point and as an identified common practice, banks tried to capture transition risk implications at the sectoral level. Such developments are based on existing regular credit stress test infrastructure enhanced with additional components and breakdowns (to sectoral level) to address the needs of climate-related risk modelling.

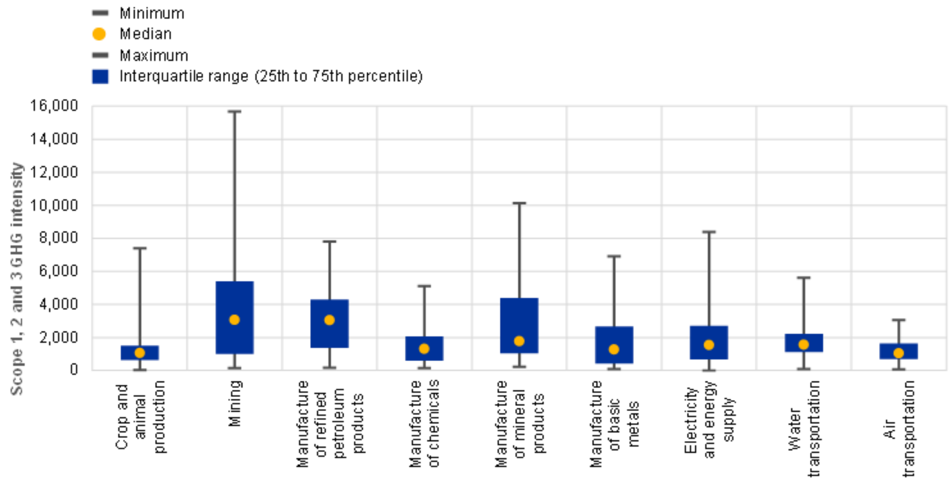
Sectoral models have been developed to ensure a higher sensitivity of the PD projections to each business sector's specificities and vulnerability to climate-related risks. Banks assess the impact of the emissions intensity and carbon price on credit risk parameters at sectoral level by estimating PD multipliers for the carbon-intensive sectors, which are then extrapolated to the respective counterparties to capture the direct channel of climate-related risk. Banks also integrate at least one sector-specific macro variable (e.g. GVA growth) to account for the sensitivity of estimated PDs within each industry sector. Adjustment of the existing International Financial Reporting Standard 9 (IFRS 9) credit risk models through separate macroeconomic models is widely observed. Some banks adjust the IFRS 9 modelling approaches with increased granularity at the sectoral level, including additional macroeconomic variables for each specific NACE sector.

While adjustment of existing models can be seen as a first step towards integration of climate-related risks into respective models, the peculiarities of individual companies and intra-sector specificities are disregarded under such approaches. Inclusion of counterparty-level data and analyses are essential to capture such features, given that within the same sector there can be high variability in the degree of vulnerability to climate-related risks. For instance, within the energy sector, a company focusing on renewable energy production would not be affected in the same way as a non-renewable energy production company, and this difference would not be adequately captured with the approaches described above. Examples of such variability can be seen in Chart 4, which shows the distribution of emission intensities for a selection of sectors as a measure of vulnerability to climate risks.

Chart 4

Dispersion of emission intensities within sectors

(tCO2e per EUR million)



Sources: Bank submissions and ECB calculations.

The above-mentioned approaches are translated into different modelling techniques, depending on the existing models in place within the banks as well as on the granularity and the quality of data/proxies available.

Some banks have adapted current satellite models (country and portfolio level) to capture the projected parameters aligned with the projected macroeconomic developments (indirect channel), while the direct channel and the subsequent sector/client-based adjustments have been estimated on the basis of sectoral models developed by external providers. The aim of these sectoral models is to capture the unbalanced shocks among different sectors or counterparties while preserving the link with default rates and recovery rates internally observed in the past. The sectoral models are normally fed with companies' financial statements obtained from external databases and the models estimate key variables (such as the change in costs, revenues, profits, additional investment for energy efficiency, etc. following the scenarios). Finally, the models are calibrated taking into consideration a representative sample of companies, which is a crucial step for the further use of the calibrated models.

The combination of direct and indirect transmission channels differs depending on how advanced such models are based on the level of detail included. Relying on the combination of the impact of direct and indirect channels, which results in the calculation of PD shifts, banks use a risk rating approach for vulnerable counterparties, which is in turn used to calculate the credit risk parameters. The assignment of sectoral or counterparty-specific financial scores based on the direct transition risk can also be obtained from external models. For the selection of the external models, evaluating whether the models include information that aligns with their specific needs is a necessary step (i.e. sectoral exposures, counterparty coverage). The external models provide a climate risk-adjusted financial sustainability risk indicator ("risk index"), which is used to analyse the historic correlation with observed default rates and translate the projections of the climate-adjusted financial risk indicators into changes in default rates and, ultimately, PD. This change is then applied on top of the PD impact estimated by the satellite model.

Newly observed good practice

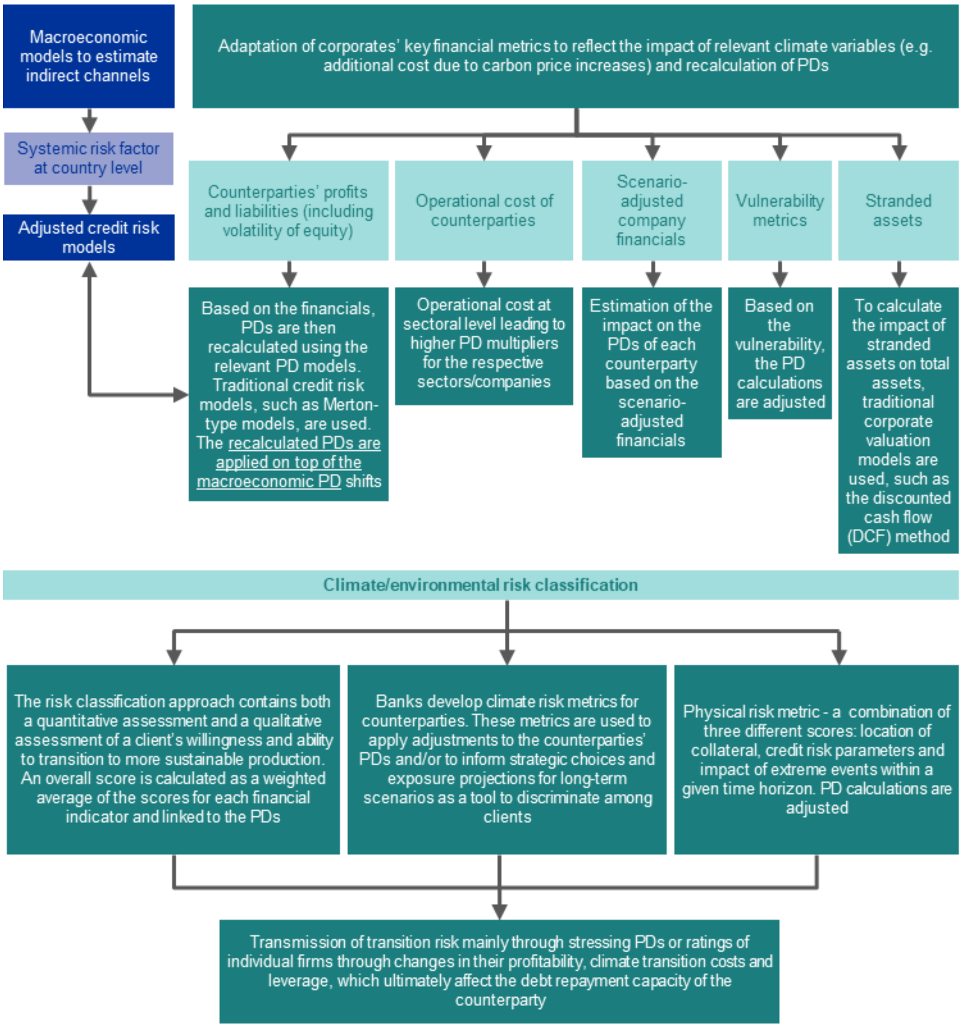
In some cases, the PD model incorporates a penalising parameter for industries that have above-average emission intensities. Another example of observed practice is including price elasticities and demand elasticities in the modelling of corporates' revenues based on qualitative assumptions, to account for potential changes in the demand and supply of goods as well as for the ability of companies to pass on a portion of the carbon cost increase to clients.

5.2.1.2 Counterparty-level modelling – counterparty financials and climate risk metrics

Regarding the methods used to estimate the impact of climate-related risks on PDs at counterparty level, a variety of approaches were observed and the main good practices are outlined in Figure 6 below and described in more detail in this section.

Figure 6

Counterparty-level credit risk modelling approaches / climate-related risk metrics



Source: Bank submissions.

Various approaches are observed with respect to the way companies' financials are affected. Some banks transmit an increase in carbon prices to corporate PDs by adjusting their operational cost at sectoral level, leading to higher multipliers for carbon-intensive sectors. Sectoral multipliers are calibrated on the basis of average PD changes observed for counterparties in those sectors for which the required data are available. As the difficulty with counterparty-level estimations lies in the need to have granular company data at hand (e.g. revenue, operating costs, GHG emissions, leverage), this first step helps to apply a shock to counterparties for which an individual impact estimation cannot be performed owing to the lack of such data.

Banks with more advanced integration of climate-related risks in their models started estimating the impact on PDs at a higher level of granularity, i.e. at the client level. These approaches can be considered good practice as such granularity is needed to account for the heterogenous nature and impact of climate-related risks. In most approaches, the scenario-adjusted company financials are used for that purpose. Modelling the transmission of climate-related risks at such a high level of granularity can be particularly insightful, especially for relevant and highly exposed counterparties, as it helps to better capture the potential impact of the materialisation of transition and physical risks on the financial health of such counterparties. The ECB observes that banks are progressively developing methods for counterparty-specific analysis and using them in their climate stress-testing frameworks.

The development of counterparty-specific analysis usually starts with vulnerable sectors, accompanied by the creation of a set of selection criteria to identify relevant and vulnerable counterparties. Such criteria include, among others, the size of the exposure to the counterparty, its emission intensity or a set of relevant climate-related risk aspects (transition plans, etc.). One bank even reported the use of Metric 2 as an indicator for the selection procedure.

Good practices include adjusting the profits in the counterparty's financial ratios to reflect the additional costs of the carbon price increase as well as the counterparty's liabilities. The PD is then recalculated through the relevant PD or rating models. The liabilities are adjusted by incorporating the costs arising from an increasing carbon price in the counterparty's liabilities (negatively affecting the market value and increasing equity volatility), calibrating the respective existing models on the basis of climate-related variables and thereby calculating the sensitivity of the PDs to relevant shocks. Traditional credit risk models, such as Merton-type models, were used to measure the relationship between those and the change in the liabilities of each company. These results are aggregated at NACE sector level and extrapolated to companies for which data are not available. Proxies based on the data received are also used to overcome the challenge of missing data on companies' financial indicators to provide greater coverage. The PD changes calculated using this approach are added to the macroeconomic PD shifts based on the results of the satellite models.

Based on the above approach to the counterparties' financial data, the estimation is also performed at asset class and sectoral/EPC level. The estimated impact on counterparties' financials is translated into a credit risk shock based on existing credit scoring scales and subsequently translated into a PD stress factor, which is then applied to the starting point parameter.

To reflect the climate-related risk potential in PDs, a good practice identified for banks with advanced approaches is the development of specific climate risk metrics for the above-mentioned counterparties. Such metrics typically consider various dimensions of transition risk, such as the carbon intensity of the business profile and type of segment the firm is active in, exposure to climate-related risks based on the sectoral and geographical revenue mix, transition plans and commitments and sector-specific elements like decarbonisation potential and strategies. These metrics have various use cases and are then used, for instance, to apply adjustments to the counterparty's PD and/or to inform strategic choices and exposure projections for long-term scenarios as a tool to distinguish between clients, allowing consistent risk treatment across the bank, which is another good practice identified.

Newly observed good practice

One bank uses a multifactor model that is designed to assess the sensitivity of assets to transition risk, by incorporating a factor that captures the impact of transitioning to a low-carbon economy.[28] The additional factor captures the sensitivity of assets considered at risk to possible declines in activity of brown sectors and green sectors, by tracking the excess return of brown companies relative to green companies. A carbon shock is taken into account in the model, which is calculated as the annual percentage change of the CO2 emission path, using integrated assessment model carbon emission pathways. The carbon shock is translated into an equity shock, leading to a rebalancing in the portfolio by allocating more to assets that have less emissions, which is modelled using constrained optimisation. Assuming a stable linear relationship between equity shocks and credit spread, credit spread changes are calculated. The bank derives the credit rating shocks from credit spread changes using a transition table. Stressed PD values are calculated as a function of credit spread shocks to assess counterparty credit risk under climate transition scenarios.

In counterparty-level analysis, more advanced approaches consider a broader set of relevant variables (carbon price, projected carbon intensity, required investments for low-carbon technologies, energy costs resulting from energy consumption, energy mix and energy prices for coal/oil/gas) to estimate the impact on counterparty-specific financial KPIs. Banks which had already developed climate risk metrics at client level transmitted transition risk mainly by stressing PDs or ratings of individual firms through changes in their profitability, climate transition costs and leverage, which ultimately affect the debt repayment capacity of the counterparty. In more detailed approaches to climate risk metrics at client level, some banks also considered companies' transition plans and commitments and validated results at individual client level.

Newly observed good practice

One bank uses transition plan quality, combined with emission intensity and financial flexibility, to additionally adjust the corporate PD and LGD. The transition plan quality is measured using a climate strategy assessment framework that utilises companies' public disclosures. Based on a scoring methodology, firms are sorted into low, medium and high segments. The approach further consists in summing the adjustments across these three climate risk factors and adding them to the final rating.

With respect to the direct impact of higher carbon costs at counterparty level via increased operating costs, banks mostly consider scopes 1 and 2 emissions, while scope 3 is mostly considered for the revenue channel (demand function) due to the greater inaccuracy associated with scope 3 emissions. While inaccuracy related to scope 3 emissions is acknowledged, it should be noted that disregarding them can lead to a significant underestimation of transition risks.

Other advanced methods also include the impact of stranded assets on corporates' financials and subsequently on PDs. More specifically, banks use the stranded asset channel for specific NACE sectors and transition risk scenarios. To calculate the impact of stranded assets on total assets, traditional corporate valuation models are used, such as the discounted cash flow (DCF) method. For example, one bank

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28 Based on Görgen, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M. and Wilkens, M., "Carbon Risk", August 2020, which investigates carbon risk in global equity prices.

outlined such an approach for the mining industry: the DCF method is applied to the full profit potential from the extraction of the oil and gas reserves over the scenario horizon under the orderly and disorderly scenarios and then compared with the profits from oil and gas extraction in the hot house world scenario where no transition risk materialises.

Some banks have developed an internal climate and nature-related risk classification approach for transition risk. The risk classification approach contains both a quantitative assessment and a qualitative assessment of a client's willingness and ability to transition to more sustainable production. For the quantitative assessment, specific companies' financial indicators are used in the manner described above. An overall score is calculated as a weighted average of the scores for each financial indicator. The relative scores are linked to the PD using an anchor stress factor at portfolio level and the respective sector-specific scores for the respective year. The anchor stress factor is calculated through empirical methods to identify the impact of macro variables on the PD.

5.2.1.3 Asset class-level modelling approach

Other observed practices to capture the impact of transition risk on PDs is the estimation of climate risk overlays or climate risk metrics which can then be applied to PDs, and which are calibrated specifically for counterparties depending on the asset class (corporate and real estate exposure). At this level of granularity banks combine internal modelling approaches with external models. External models provide stressed balance sheets that include both the "direct" effect of carbon taxes and the "indirect" effect of macroeconomic aggregates. As already mentioned in the sectoral model section, sector-level models capture the indirect effects while direct effects are measured in the firm-level models. Banks combine sector-level models along with firm-level balance sheet satellite models in order to obtain a holistic risk score. Going forward, such a risk indicator/score will feed into the (internal) corporate rating model to turn projections of firm financials into projections of PDs. This approach also adds to the combined direct and indirect channel impact described in the previous paragraph. Box 6 provides an example of the modelling of climate-related risk impact on real estate exposures.

In terms of real estate exposures, the fact that some existing IFRS 9 models already allow for EPC breakdown should be noted. Evolution of the macroeconomic variables is adjusted on the basis of the stress of the climate-related risk factors (e.g. CO_2 emissions and carbon price) at the relevant EPC level to estimate the impact on PDs.

Newly observed good practice

There are banks that have developed specific models for the most relevant exposures in their portfolio. One bank has a modelling approach for assets such as ships and aircraft, using as key factors fuel type, carbon prices and emission impact costs, which can be passed on to the final prices. The aircraft model includes additional factors such as sustainable aviation fuels[29] to reduce scope 1 emissions, while the cost of fuel accounts for kerosene price, fuel consumption and fuel efficiency (fuel efficiency represents the fuel consumed per available seat kilometres, a metric used to measure an airline's capacity). Other operating costs are projected in relation to the annual available seat kilometres. Estimated change in profit is based on assumed changes in prices, sales volume, and turnover and cost, which account for asset depreciation. At a more granular level, some banks use specific approaches to downgrade a client's debt repayment ability, thereby affecting the PDs for such portfolios. For example, a retail client can receive a stressed PD due to the changes in cost of living stemming from an increase in electricity, fuel, transportation or food prices, which affects the household's free cash flow.

Where EPCs are not available, in some cases energy price overlays are used in addition to macroeconomic overlays for retail products.

Box 6
Climate risk-related credit risk modelling approach to real estate exposures

To simulate potential impacts on real estate values under climate scenarios, one bank incorporates physical and transition climate risks into its models by applying transition risk shocks to assets with lower energy performance and physical shocks to assets with high or very high flood risk (identified via a database from a vendor). The model incorporates volatility shocks across four components: idiosyncratic and systemic, each addressing both physical and transition risks. The maximum volatility shock was derived from the historical volatility of a synthetic real estate index using a rolling eight-year observation window and based on risk indices from an external data provider. For idiosyncratic shocks, transition risk shocks target properties with poor energy performance (energy performance certificate labels F or G), scaled by the variability of transition risk across brown sectors. Systemic volatility shocks are also applied at country level by considering the proportion of population exposed to flood risk and the proportion of buildings with low EPC ratings in each country and scaled according to transition risk variation across brown sectors for each scenario and year.

One bank provided a detailed approach to estimate the impact of transition risk on PDs for real estate exposures. In a nutshell, along with the macroeconomic variables, increasing energy costs and costs related to construction improvement (i.e. renovations) have an impact on the PDs of such exposures. For households, residential heating is the main channel of impact of a transition to a low-carbon economy. An increase in the carbon price will affect the financial capacity of households. Changes in the financial capacity of households result in adjustments of internal credit ratings through both liquidity and profitability.

More specifically, the shock is transmitted through changes in the energy bills of households, which affects the cash flow of individual clients and is translated into increased PDs. Energy bills are stressed using variables such as CO_2 emissions, and the input price changes are determined by the growing cost of energy in the respective country complemented by publicly available data. A static energy mix is assumed for the short-term disorderly scenario.

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29 Sustainable aviation fuel is a non-petroleum alternative fuel based on feedstocks that reduces emissions from air transportation.

An EPC breakdown of residential properties is included as an additional dimension in the calculation of energy consumption. Less energy-efficient properties are likely to be hit more severely by an increase in energy prices. As a result, the impact of energy price increases was calibrated per EPC label.

Finally, it is worth mentioning that banks have also included in their analysis the type of use of residential properties and the way energy bills affect clients. For example, where properties are rented out by their owners, the borrower might face a lower impact in terms of cash flow changes in the short term, while borrowers who purchase properties for their own use experience higher stress in their cash flows.

5.2.2 Climate-adjusted LGD

While approaches are more common and more advanced for the transmission of climate-related risks to PD, LGD is also a key parameter for capturing the impact of climate-related risks. While some banks do not take into consideration the macroeconomic factors and real estate prices described in the scenarios, some other banks have developed capabilities to adjust their existing model, integrating at least indirect transmission channels, while some banks also consider direct transmission channels to LGD. Finally, the banks with the most advanced approaches have developed new dedicated models on top of actual satellite models to account for the direct transmission channels at the desirable level of granularity. Nevertheless, the ECB observed during the 2022 ECB CST exercise that many banks were still at an early stage in terms of factoring climate-related risks into their credit risk models to estimate LGD. In many cases, LGDs projected by banks were found to be fairly insensitive to the climate risk shocks depicted in the scenarios.

As a starting point and using the ECB-provided real estate price projections, each exposure is assigned a stressed LTV value which then translates into a stressed LGD parameter via the normal LTV-to-LGD mapping algorithm. For relevant exposures, a higher level of granularity is desirable, for which banks need to capture the effect of transition risk on LGD. In particular, considering the carbon price impact on real estate values based on the EPC bucket can be a starting point. Most banks with advanced approaches account for the impact of stranded assets on the valuation of identified counterparties since the value of some non-real estate collateral could be affected.

Among banks with advanced approaches, an observed good practice is to develop a specific LGD model. Banks’ satellite models have been exploited to capture the indirect channel effects, while the impact stemming from the direct channel and the subsequent sector/client-based adjustments are estimated, drawing on new dedicated models. These impacts on credit risk parameters have been applied at granular level to the portfolio within the scope of the exercise to obtain the projected point-in-time LGD at single facility level and to model the relevant IFRS 9 parameters, as the new models facilitate a reassessment of the calculated default rates and recovery rates. Moreover, to account for the adverse impact of sharply rising carbon prices, one bank assessed by how much the annual carbon tax expenses would increase for each property in the portfolio based on the individual CO2 emission levels. A conservative assumption was applied that the entire increase in carbon tax expenses would affect the cash flows considered in the valuation of the building (although it is likely that a significant portion of these expenses would need to be borne by the tenants). These lower property values were then used in both the LGD and PD parameters under the disorderly transition scenario, allowing consistent risk quantification, which is considered another good practice.

Another example of a direct transmission channel of transition risk at counterparty and asset level is the carbon price impact on corporates' collateral values, which can be calculated by including a penalising parameter in the LGD model equation. An emission intensity impact parameter is introduced to account for the potential increase in taxes on GHG emissions and their effect on a firm's profitability.

Finally, other banks have estimated the LGD for each borrower using a function which connects the conditionally expected LGD to the conditionally expected PD based on the assumption that the asymptotic distributions of PD and LGD are comonotonic. Another bank has stressed the recovery rates that linearly use the house price shocks provided by the ECB for the portfolio secured by commercial real estate, while for residential real estate the recovery rates are stressed by a calibrated beta using house price shocks provided by the ECB and historical realised LGDs from back-testing exercises. Finally, for unsecured exposure, the Frye-Jacobs formula is used to establish a correlation between estimated scenario-specific PDs and LGDs. While such approaches help to transmit the impact to LGD, other good practices described in this section considering climate-specific variables seem preferable.

Box 7
Climate-adjusted loss given default for real estate exposures based on energy performance certificates – newly observed good practice

One bank integrated the transition risk of real estate collateral into the loss given default at property level, using the change in energy performance certificate class that is needed to align with the Energy Performance of Buildings Directive. The revised Energy Performance of Buildings Directive[30] introduces minimum energy performance standards for residential and non-residential buildings that they need to achieve by certain deadlines.

The institution first identifies the properties that are sensitive to transition risk based on the cadastral category. To determine the energy retrofitting costs, it relies on governmental public sources to quantify the amount of CO2 emissions to be reduced and energy efficiency cost.

The input data used for this estimation are cadastral category (to identify the type of property and its use), geographical area, year of construction, surface area, insurable value (data from an external provider, which represents the expenditure necessary to fully reconstruct the building) and energy class. Estimates of energy costs per square metre and relative decrease in CO2 emissions per

30 Directive (EU) 2024/1275 of the European Parliament and of the Council of 24 April 2024 on the energy performance of buildings (OJ L, 2024/1275, 8.5.2024).

square metre are gathered from public national available sources and are available by type of property and time of construction.

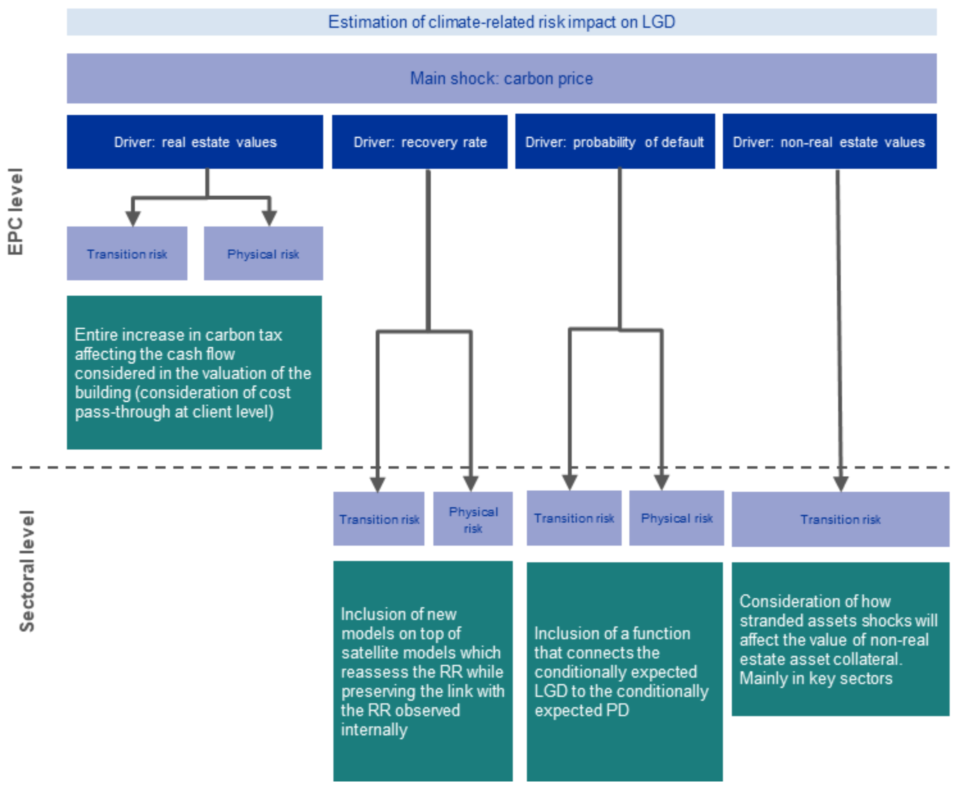
To quantify the loss expected from the transition risk, the bank first calculates for each property the amount of CO2 emissions that must be reduced in order to achieve the target value of the energy class, according to the regulation.

In the second step, the carbon emissions to be reduced are divided by the carbon emission saving and multiplied by the cost per square metre. If information on the energy class of the property is missing, the bank estimates it based on the median energy class for the buildings constructed in the same time interval.

For commercial real estate, where no direct energy consumption or emission data are available, a bank uses as a proxy the average carbon intensity from the Carbon Risk Real Estate Monitor tool[31] to assess the stranding risk of their collateral. This is considered an interim solution to overcome data availability issues, until the bank is able to source better-quality data without relying on averages.

Figure 7

Good practices to estimate climate-related risk impact on LGD



Source: Bank submissions.

31 The Carbon Risk Real Estate Monitor is a tool that provides transition pathways for different building types from more than 40 countries and all major property types.

5.3 Modelling approaches for physical risk

This section describes the main features of observed approaches for modelling physical risk across supervised entities, distinguishing between basic and advanced practices.

While most banks have started including transition risk drivers in their climate stress-testing models, approaches for integrating physical risk are still less widespread. Only about half of the institutions considering physical risk as material for their portfolio include physical risk drivers in their stress-testing framework. Also, when physical risk is considered within stress-testing models, it is often limited to a few hazards, most notably floods, and with limited transmission channels. Models and capabilities to estimate losses resulting from physical risk events still appear to be under-developed and less common than for transition risk. Moreover, approaches for physical risk stress testing face several uncertainties, such as limitations in data availability and granularity as well as limited predictability of future frequency and severity of acute events.

However, the ECB observes that some institutions are making progress in this area by developing new methodologies and increasingly sophisticated approaches.

Within physical risk, it is noted that approaches for integrating acute physical risk into stress tests are currently more common than for chronic physical risk. There might be several reasons for this, including the fact that acute physical risk phenomena are more suitable for short-term analysis given the instantaneous nature of the shock, while chronic risks often require a longer time horizon. Chronic risks are in general not treated in detail in this report, not because this risk is less relevant, but because practices are more nascent. Moreover, when chronic physical risk is considered in credit risk stress testing, it is usually captured through the macro variables of the existing credit risk models, while for acute physical risk novel modelling practices are developed. In a few cases, biodiversity risk was considered to take into account the effects of nature loss on clients' profitability and resilience.

An important choice when integrating physical risk into the stress-testing framework is which hazards to cover. An observed good practice is to create a targeted selection of hazards and include in the framework those that are, or are likely to be, material to a bank's portfolio. As indicated in the EBA Guidelines on environmental scenario analysis[32], institutions should rely on the results of the materiality assessment when designing the features of environmental scenario analysis. This principle is particularly relevant with respect to the selection of the physical risk drivers to be considered, as banks should ensure that all material climate-related hazards are covered for the stress-testing framework to be fully comprehensive. The EBA Guidelines on the management of ESG risks[33] can provide more insight for institutions carrying out their materiality assessment. The ECB observes that

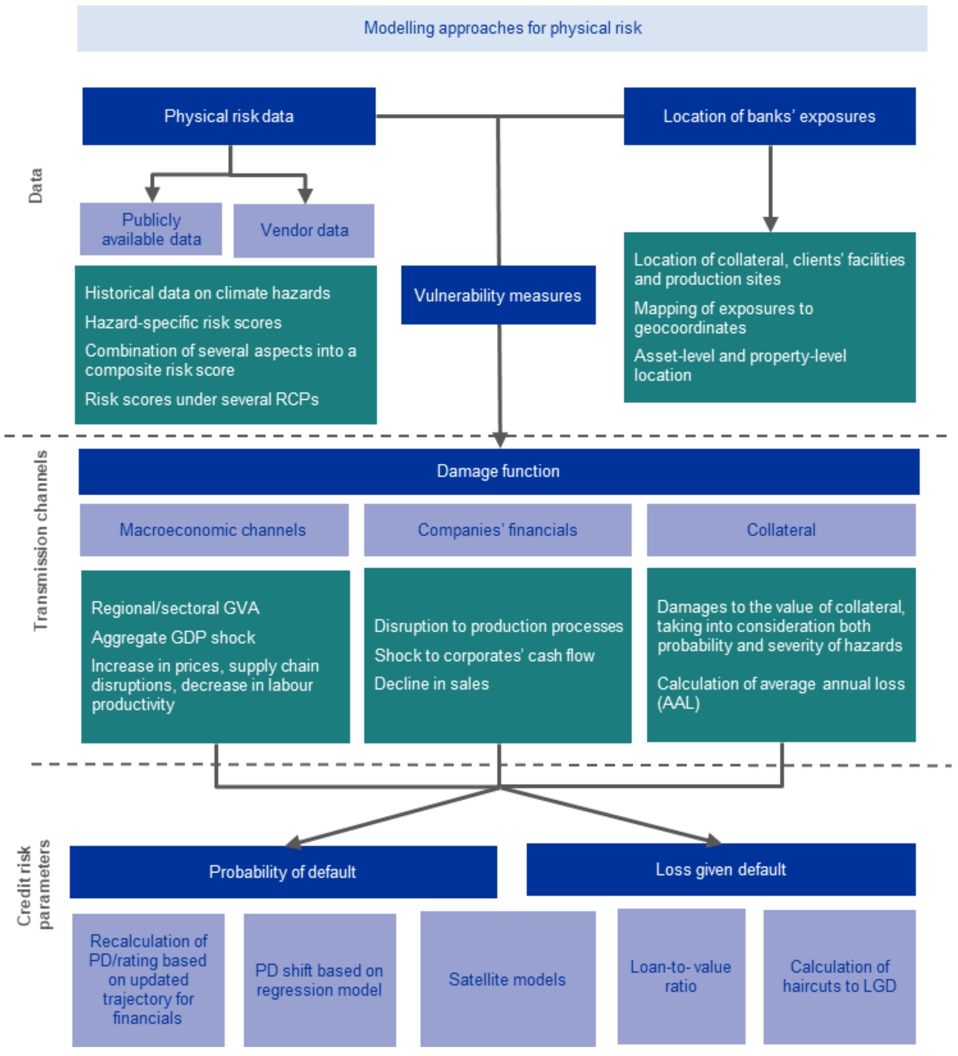
[32] See "Guidelines on environmental scenario analysis", EBA, November 2025.

[33] See "Guidelines on the management of environmental, social and governance (ESG) risks", EBA, January 2025.

currently the most common hazards considered by entities under direct ECB supervision are flood risk, wildfire risk, drought, heatwave and landslides.

The rest of the section describes the approaches used by financial institutions to integrate physical risk drivers into stress-testing frameworks. It covers data requirements, the transmission channels considered and modelling approaches for integrating physical risk into PD and LGD models. The key aspects are summarised in Figure 8.

Figure 8
Modelling approaches for physical risk



Source: ECB observations of banks' practices.

5.3.1 Data requirements

Physical risk is often described as a function of three elements: climate-related hazards, exposure and vulnerability. Data on all these three elements are needed to accurately quantify the impact of physical risks on banks' portfolios. In a recent publication[34], the NGFS also describes data requirements for physical risk analysis along these three dimensions and provides a stocktake of challenges and potential solutions.

Data on physical climate hazards can be retrieved either from publicly available data sources or from vendors. Examples of publicly available data sources used by banks are the EU Earth observation platform Copernicus[35], the European Commission Joint Research Centre, certain tools promoted by the European Environmental Agency, and national statistical datasets. The NGFS publication mentioned above provides more examples of open-source global data sources for various hazard-specific climate risk metrics. In terms of the type of data, institutions use historical information on hazard occurrence and severity (such as rain precipitation, historical flood heights and historical frequency of hazards) as well as satellite observations of Earth. Together with historical data, banks use ready-made risk indicators such as the Fire Weather Index[36] for wildfires or the Aqueduct score[37] for droughts.

Some institutions also construct new physical risk scores internally by combining data from several external sources, reflecting different dimensions of risk for the same hazard. For example, one institution derives an index for forest fire risk based on the Fire Weather Index and on other features of the region of the exposures, such as population density, distance from the city and vegetation type. These four dimensions are then used as an input to a random forest model, which calculates a unique forest fire risk index at geocoordinate level.

Institutions often transform the data sourced from public datasets and private data providers by creating maps of physical risk data at a level of granularity that matches the exposure information they have available.

As climate change increases both the probability and the severity of extreme weather events, it is fundamental that institutions consider in their models for physical risk stress testing not only historical information on hazards but also forward-looking measures, as historical data might not be representative of future risks. In this respect, a good practice performed by some institutions is to consider the extreme weather event shocks under several representative concentration pathway (RCP) scenarios. RCPs quantify possible future GHG concentrations, and different RCP scenarios portray a spectrum of possible climate futures. By considering physical risk shocks occurring under several RCPs, banks can factor in the risk that in some climate futures extreme weather events will be more severe and frequent.

For exposure data, the geolocation of collateral, client production facilities and critical infrastructures are key dimensions of physical risk. A first step is to map the location information available in internal databases (such as postal codes, addresses of

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34 See "Leveraging physical climate risk data", NGFS, September 2025.

35 Copernicus is the Earth observation component of the European Union's space programme, looking at the planet and its environment to benefit all European citizens. It offers information services that draw from satellite Earth observation and in-situ (non-space) data.

36 The Fire Weather Index is a meteorologically based index used worldwide to estimate fire danger.

37 The scores are part of the data provided by the Aqueduct Global Water Risk Atlas.

collateral and headquarters of companies) to geo-coordinates. In terms of the granularity of location data, the ECB observed different levels of advancement among supervised entities. Many institutions can allocate their exposures to NUTS 3 regions, while institutions that are more advanced are able to map their exposures to geo-coordinates at asset level and client level. For corporate clients, relevant location data include not only the address of the headquarters but also the location of other firms' establishments, including the location of production sites and critical infrastructures.

The third key element for physical risk quantification is vulnerability, which is the predisposition of clients' assets to being affected by a specific physical risk event. Vulnerability reflects the concept that different buildings, assets or agents can be affected differently by the same hazard due to their specific characteristics.

Measures of vulnerability are exposure-specific and can differ depending on the hazard. Vulnerability is a key concept when estimating the potential damage to assets from physical risk hazards, as different vulnerability considerations will lead to the selection of different damage functions. For flood risk, for example, key vulnerability metrics include the type of building and the floor. Considering vulnerability measures allows for a more realistic quantification of potential damages from acute weather events. Some banks with advanced approaches insert vulnerability metrics into the calculation of exposure-specific physical risk scores. For example, one institution constructs an internal score for drought risk combining information on water scarcity from the Aqueduct score with client-level information on water intensity and energy consumption to retrieve a client-specific drought risk score that reflects the vulnerability of individual business partners to drought risk. The drought risk score built in this way is then used to stress the PDs of clients, as explained in the following sections.

Vulnerability can be reduced by adaptive capacity, which is the capability to adjust to potential damages and possibly to contain the impact of the physical risk event. Some institutions include considerations of adaptive measures in their physical risk modelling, such as financial adaptation, by looking at insurance coverage of buildings and facilities or, in terms of physical resilience, by gathering data on defensive measures from extreme weather events. One bank, for example, takes into account local flood defences in determining flood risk scores for its analysis. Another bank considers a coefficient for underinsurance, which in this case is deemed a measure of vulnerability, as an input in the model used for quantifying damages to borrowers' assets from physical risk events. The EBA Guidelines on environmental scenario analysis also suggest considering existing and potential future insurance gaps when analysing the mitigation effects of public and private insurance coverage.

In terms of data requirements, the ECB observes that some institutions are quite advanced and are able to retrieve physical risk hazard information at a very granular level and to map this information to the location of exposures at asset and client level.

5.3.2 Transmission channels

The ECB observes that when integrating physical risk drivers into their stress-testing models, banks consider both direct and indirect transmission channels.

Banks consider indirect transmission channels such as sectoral and regional GVA and gross domestic product (GDP), as well as aggregate macroeconomic variables. Relevant macroeconomic transmission channels, as also highlighted in the EBA Guidelines on environmental scenario analysis, include inflation, disruptions to supply chains and labour productivity shocks. In order to incorporate physical risk impact into the scenario pathways for macroeconomic variables, banks need to use damage functions that map the physical risk shocks to a deterioration in the macro-financial environment. Banks often rely on damage functions available from the academic literature, draw on methodologies used for NGFS scenarios or call upon consultancy companies. Some institutions also estimate the impact of acute physical risk events on the regional economy, differentiating among sectors. One bank, for example, models the impact of flood risk on sectoral output in affected regions, reflecting the different impacts that a flood can have on different industries.

Given the localised nature of acute physical risk shocks, direct transmission channels are particularly relevant, as first-round impacts on assets from extreme weather events affect borrowers in heterogeneous ways based on their location and type of assets.

In terms of direct channels, physical risk shocks are translated into damages to companies' assets, such as production sites, inventories and critical infrastructures, or to collateral. With respect to techniques for modelling damages to clients' assets, banks rely on consultancy companies or develop models internally based on publicly available data and research. Some institutions apply techniques used in the insurance sector, such as catastrophe modelling, to quantify damages from extreme weather events.

The quantified damages to assets are translated into financial impacts for the affected borrowers and then integrated into PD and LGD. The ECB observes that, among banks that include physical risk drivers in their credit risk stress-testing framework, it is currently more common to integrate physical risk into LGD models, while fewer institutions adjust PD models.

One future advancement with respect to indirect transmission channels is the consideration of second-round effects of acute physical risk shocks and feedback loops. The first vintage of NGFS short-term scenarios[38] offers an example of how scenarios could include economic and financial spillover from extreme weather events, also in regions not directly impacted by the hazard but with significant economic linkages.

38 See "NGFS Short-term Climate Scenarios for central banks and supervisors", May 2025.

5.3.3 Probability of default

For the corporate portfolio, institutions use a mix of direct and indirect transmission channels to integrate physical risk effects into PD models. A first step is the integration of physical risk shocks into PD models via macroeconomic variables.

Institutions with advanced approaches exploit direct channels by modelling damages from physical risk hazards to clients' assets, production sites and logistic facilities. These damages are then translated into a deteriorated financial performance of the borrower, either via revenues or leverage.

Depending on the sector, the type of borrower and the physical risk hazard, different modelling strategies are used. For example, one bank simulates the length of business interruption associated with a flood risk event and derives the expected drop in sales for the client due to this disruption. Different impacts in terms of sales declines are assumed for clients in different industries, as impacts on business activities due to damage to the production site may vary. The sales decline is then translated into a PD shift by applying a regression model. Another institution models the impact of acute physical risk on agriculture sector clients as a shock to companies' cash flow due to the impact of hazards on crop production. Another approach observed is to model an increase in costs for corporate counterparties due to damages to tangible assets, which translate into decreased profitability.

The stressed financials of borrowers are used to recalculate stressed PDs due to physical risk shocks with several techniques. Some banks use Merton-type models to compute stressed PDs, incorporating the financial impact of physical risk on companies' assets. Other banks incorporate stressed company financials as inputs into their rating models. Other use satellite models to calculate PD shifts based on physical risk scores.

Some institutions are developing physical risk metrics combining different elements. In particular, such a metric can be composed through the combination of three different scores, one related to the location of collateral, one related to credit risk parameters and one based on the impact of extreme events over a given time horizon. These metrics are then directly incorporated into rating models to obtain stressed PDs.

The ECB observed that some banks also consider the impact of a deterioration in the collateral value on the balance sheet of the client as a stress factor for recalculating PD ratings.

For mortgages, several institutions do not consider the effect of acute physical risk on PDs and only model the LGD impact. Other institutions consider the impact of physical risk on PD for mortgages via macroeconomic factors.

For retail clients, one bank calculates PD shifts via macro drivers using a retail migration model.

5.3.4 Loss given default

The ECB observed that most institutions which include physical risk in their stress-testing framework make use of the LGD channel to calculate credit risk losses from acute physical risk events. To estimate the impact of physical risk on LGD, banks use both indirect and direct channels. In terms of indirect channels, banks consider the effect of acute physical risk events on regional or sectoral GVA, or on other aggregate macro variables (such as GDP or inflation) and incorporate the effect into the LGD via satellite models.

For exposures secured by real estate and mortgages, the key direct channel used to integrate physical risk into LGDs is the value of collateral.

Basic practices consist of applying haircuts to real estate prices at regional level (NUTS 3 or less granular), proportional to the level of physical risk of the region and expected damage (based on both the probability and severity of the hazard). Banks with more advanced approaches consider damages to collateral value at a more granular asset or property level. Some also distinguish between building types and take into account the characteristics of properties (such as the floor, floor surface or conservation state of the building) and vulnerability to the specific physical risk hazard.

One bank indicates that the collateral in its portfolio is largely covered by insurance against flood risk, therefore the real estate price shock of the physical risk scenario is driven by a market revaluation of real estate prices rather than the economic loss due to the destruction of collateral. The market repricing of real estate values is due to the anticipation of increased frequency and severity of floods in the future and increasing insurance risk premia.

Most institutions use the stressed collateral value to recalculate the LTV ratio. The resulting LTV ratio is used to derive a stressed LGD via standard LTV-LGD mapping.

For corporate exposures, some banks consider both the impact on company financials and on collateral values as inputs for the recalculation of LGD.

Regarding flood risk, some advanced banks have developed new models. For example, one bank has defined a linear combination of three dimensions, which are a climate score (based on asset location), a solvency score (based on the LTV ratio) and a maturity score (based on the impact of flood risk over a time horizon), in order to assess the impact on the exposure with highly granular information.

5.4 Nature-related risks

The ECB observes that some institutions have taken the first steps towards including nature-related (i.e. non-climate environmental) risk drivers in their stress-testing exercises. This section provides an overview of the emerging practices observed to incorporate nature-related risks into scenario analysis and stress testing. A more comprehensive treatment of nature-related risk management practices is provided in the good practices for climate and nature-related risk management report, which should be read in conjunction with this document.

The ECB observes that the first steps for considering nature-related risk drivers in stress testing are often in the form of exploratory scenario analyses, which banks use to gather insights on transmission channels and potential impacts of nature-related risks on their portfolios. Institutions see these exploratory exercises as a way to start developing methodologies and modelling approaches to quantify impacts from nature risks in a stress test setting, with the goal of integrating nature-related risk drivers into the stress-testing framework once approaches are more mature.

One bank performed an exploratory scenario analysis considering both nature-related physical and transition risk drivers. The scope of the analysis is initially limited to selected sectors and to a sample of counterparties, driven by materiality and data availability considerations. The physical risk scenario assumes that scarcity and degradation of natural resources cause an increase in the prices of water and other commodities (biomass). Corporate clients are affected in their cost base by these price increases in a proportionate manner with respect to their consumption of water and/or commodities. Meanwhile, the transition risk scenario assumes an environmental tax that forces companies to pay for the negative effects they have on the environment (water pollution, non-GHG air pollution, land pollution, etc.), both for own operations and the supply chain. The environmental tax increases production costs for corporate clients proportionally to their negative impact on nature (nature charges). Under both scenarios, the higher costs translate into reduced profitability for corporate clients and into stressed financials.

Another bank conducted an exploratory portfolio analysis by constructing a transition risk scenario based on environmental regulation in its main country of operations. The transition risk scenario considers a reduction in national permits for nitrogen pollution, water pollution and land use, and the introduction of an environmental tax proportional to the impact of companies on water pollution. The bank assesses which clients and sectors might be affected by permit reductions, considering the location of companies and production sites, the ability of companies to change location as well as certain impact dimensions with respect to nitrogen pollution, water pollution and land use. Through this methodology the bank is able to quantify exposure at default. The bank plans to extend this methodology to develop models for nature-related risk stress testing.

One bank includes in its climate stress-testing framework a separate nature-related transition risk scenario. The scenario focuses on regulatory changes that aim to reduce environmental pollution and biodiversity loss based on the Kunming-Montreal Global Biodiversity Framework[39]. These regulations are expected to reduce output and to affect the financial performance of sensitive industries. This is reflected in the scenario through GVA projections over a three-year horizon for each sector. Nine

[39] The Kunming-Montreal Global Biodiversity Framework was adopted at the 15th meeting of the Conference of Parties (COP 15) and sets goals for 2050 and targets for 2030 to protect and restore nature.

sectors from the bank's portfolio were identified as being vulnerable to nature-related transition risk.

A few banks also included some nature-related risk drivers in their climate stress-testing framework, alongside climate risk drivers. They adapted NGFS scenarios to include nature-related drivers such as agricultural climate regulation and tighter restrictions on nitrogen emissions. These nature-related risk drivers are modelled as updated trajectories for sectoral GVA and GDP, reduced revenues for the agriculture sector and supply chain disruptions.

Overall, stress-testing capabilities for nature-related risks are nascent and practices are heterogeneous and in a development phase. The absence of reference scenarios and consensual methodologies to quantify the impacts of nature-related risks in a stress test contributes to the heterogeneity of approaches, as institutions need to experiment and develop these tools internally. The ECB anticipates that banks will continue to develop their short-term nature-related risk capabilities, building on the progress already made with climate-related risks. This anticipation is based on broader observations that banks increasingly view nature-related risks as material, are investing in enhancing their nature-related risk management and are benefiting from improving availability of nature-related data.

5.5 Long-term modelling approaches

Banks also developed capabilities regarding long-term modelling approaches, including integration of a dynamic balance sheet, consideration of transition plans in their strategic choices for the dynamic exercise and breakdowns at sectoral or counterparty level. The ECB noted that such practices vary among banks in terms of sophistication and progress. While the novelty and uncertainty surrounding long-term projections are acknowledged, going forward the ECB will continue assessing the ability of banks to substantiate strategic choices and estimating the impact on the credit risk profile of exposures under different transition pathways. Hence, institutions are expected to understand the impact of climate-related risks on the business environment in which they operate in the short, medium and long term to make informed strategic and business decisions according to Expectation 1 of the Guide.

In terms of observed good practices, the level of sophistication is quite different. Some models are still under construction, some run the transition risk long-term models and the dynamic balance sheet in parallel, while others have integrated the dynamic balance sheet into the transition risk long-term models, allowing for integrated assessment. For the latter, the ECB deems as good practice analysis at the most granular level, if data are already available (e.g. large corporates). If not, banks should ideally apply adequate extrapolation techniques (e.g. resembling the NACE/country/scenario approach) where possible. Otherwise, only the scenario-dependent sectoral developments are accounted for. Finally, as a sanity check and also as good practice, the output provided by the model, at least for large companies, is complemented with expert judgement at individual level, as some models do not include companies' transition plans or commitments and might not deliver a holistic picture. A common practice identified by the ECB is for banks to project exposure evolution depending on the scenario and internal strategy and adjust their models to estimate respective credit risk parameters, which is considered a critical feature to allow adequate climate-related risk assessment in the long term.

A majority of banks consider, as a minimum, sectoral pathways (GVA evolution) instead of or in addition to the evolution of GDP for the whole economy for the growth or evolution of their exposures at the sectoral or geographic level, so the models have been reconstructed to have at least one sectoral variable. These banks do not perform counterparty analysis but estimate the impact of transition risk at sectoral level, where the impact of increasing carbon prices is transmitted via GVA shocks. Such practices are seen as good starting points but, as mentioned previously, disregard the heterogenous nature of climate-related risks.

A good practice identified among banks with more advanced approaches is the reflection of portfolio and counterparty characteristics (e.g. less complexity if the average duration of loans is relatively short) in long-term modelling, integrating also their strategy and commitments with respect to different transition pathways, and performing such analysis at the required level of granularity (e.g. sector and EPC bucket), also taking into consideration counterparty-specific perspectives (e.g. based on counterparty-specific climate risk indicators). All aspects are explained in more detail in the next sections.

5.5.1 Adjustment of stress test credit risk models to the long-term horizon

The ECB observed that some banks took simplified approaches compared with the short-term model and recomputed the exposure-weighted PD at NACE level using the credit spreads provided by the ECB for each scenario and kept constant the LGD for the projection period. Other banks took the same approach used for the short-term transition risk but fed the calculation with 30-year projections (i.e. static balance sheet) and adjusted the final outcome by an overlay.

Banks with more advanced approaches extended short-term credit risk models for the longer time horizon on a year-to-year basis and were able to provide climate-related risk stress factors and projected credit risk metrics at an annual frequency at sectoral and EPC level. Such approaches require significant work to extend and interpolate scenario variables to the input frequency required by respective models.

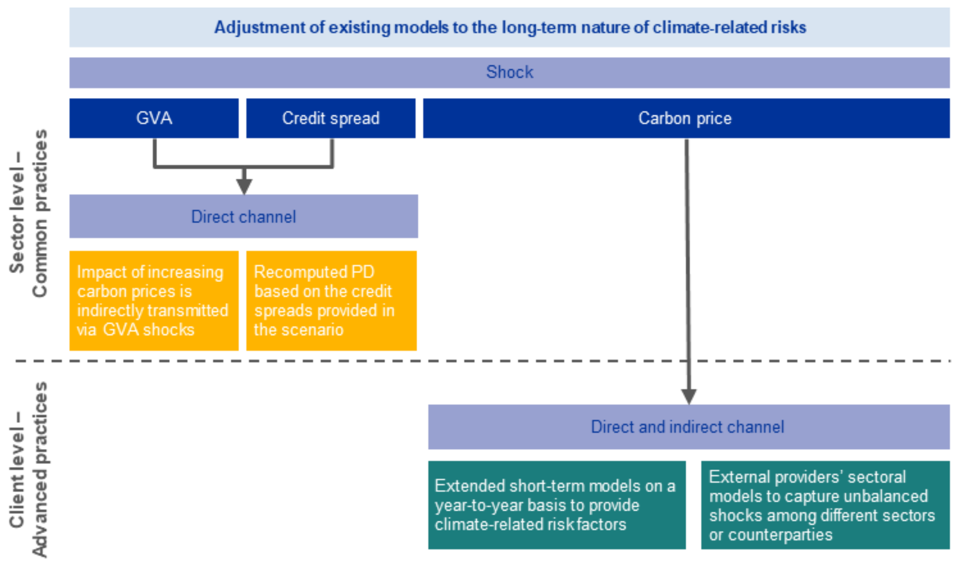
External models used by banks and already described in Section 5.2.1 seem to be already equipped to project the long-term impact of climate-related risks on the credit risk parameter, in particular for corporate counterparties.

In a nutshell, banks with advanced approaches can derive risk parameters for the full time horizon based on the starting point portfolio and the scenario-dependent rating deterioration as well as the exposure reallocation and growth.

Extrapolation of stress test transition risk modelling through projection of financial data and emissions data at counterparty level was also used under the long-term scenarios. The financial data are updated by increasing clients' costs for their emissions, while the emissions are based on expected future pathways. In conjunction with the internal climate measurement, which evaluates the alignment of the counterparties with the decarbonisation pathway, this captures the idiosyncratic risk at counterparty level. Banks have also derived sector-specific assumptions by using available data from the NGFS output file in addition to the pathways provided by the ECB. If the two sets of data (ECB and NGFS) are still not enough to run the internal financial models, one bank has also developed capabilities in terms of general equilibrium modelling to enrich available pathways based on the interactions between producers and consumers, which provides scenario-dependent (GHG price, GHG emissions and GDP pathways provided by the ECB) sectoral revenues, intermediate consumptions and sectoral value-added growth rates.

Figure 9

Good practices to adjust existing models to the long-term nature of climate-related risks



Source: Bank submissions.

5.5.2 Integration of bank strategy (commitments)

The ECB observed that banks with less advanced approaches basically do not consider the difference between scenarios in their strategic responses. It was also observed that banks apply expert judgement to their long-term projected exposures (e.g. based on GVA projections provided in the scenarios combined with banks' public commitments and government regulation) to reflect their strategic actions. Most banks with advanced approaches define different reallocation strategies (e.g. invest, maintain, divest) based on the sector specifics and scenario narrative using key scenario variables (carbon price, GVA and other climate risk factors such as GHG emissions pathways) and an assessment of the riskiness of portfolios. Thus, if the dynamic balance sheet is applied, good practices indicate that the underlying assumptions used for allocation strategies reflect a combination of various elements, such as the financing position of a bank in a specific sector, risk impact of climate policies at counterparty level and banks' and/or clients' strategic transition plans. Hence, exposure projections based on economic pathways are adjusted to account for expectations of how sectors will be affected by different transition pathways and whether the bank wants to continue financing its clients in those sectors.

For a more explicit integration of reallocation strategies, some banks distinguish, for instance, between ESG-neutral and ESG-relevant industries to indicate the vulnerability of the respective portfolio: ESG-neutral sectors may follow the inertial dynamics of the economic sector that is driven by the industry-specific GDP and would, for example, receive the label "maintain". For ESG-relevant industries (without bank policies), strategies depend on the level of physical and transition risks under the different scenarios. According to Expectation 6 of the Guide, institutions are expected to report aggregated risk data or internal metrics that measure the vulnerability of financed corporate exposure in highly affected sectors to climate risks, which is also used to consider all relevant stages of the credit-granting process based on Expectation 8 of the Guide. The following paragraph describes assessment approaches to support such strategic choices.

Additional indicators or dedicated tools to perform a vulnerability analysis of the exposure to climate change-related risks can also support the integration of strategic choices in line with transition pathways for long-term projections. A good practice identified among banks with advanced approaches is the development of an internal metric to measure the vulnerability of financed corporate exposure in highly affected sectors to climate risks. Such indicators reflect, for instance, the level of transition and physical risk across the time horizon and the scenario-dependent transition pathway and are also used to distinguish between clients and determine the banks' willingness to finance clients in the green transition. Such indicators reflect various kinds of information, but common aspects are the company's awareness of climate change-related risks and opportunities, the credibility of transition plans, the carbon intensity of the business profile and the sector-specific decarbonisation potential. In some cases, they are also used within the credit allocation and/or pricing process, which improves consistent risk assessment of climate-related risk across various business lines. This then helps to align banks' balance sheets with published decarbonisation objectives while preserving risk-adjusted profitability and credit margins across sectors.

Another relevant good practice identified by the ECB is to consider top-down and bottom-up elements (sectoral GVA, need for investment at sectoral level) in the long-term projections, which allows banks to ensure consistency with scenario narratives and to integrate sector-specific views. The bottom-up estimates are portfolio/sector-specific, making use of internal inputs (e.g. for the mortgage portfolios: historical and expected inflow and outflow, historical and expected migration between EPC labels, market share assumption on existing and newly built real estate and government policies) and the specifics of climate scenarios assessed. The top-down estimate is based on macroeconomic variables and broader trends in bank lending and serves as a sanity check for the bottom-up estimates.

In order to develop a thorough understanding of climate risk implications for portfolios, the ECB also identified banks which first perform long-term projections based on a static balance sheet and subsequently perform projections under a dynamic balance sheet, deriving strategic choices and portfolio allocation assumptions based on the results and conclusions from the first step. This can be considered another good practice in order to take informed decisions based on the vulnerability of a portfolio to transition and physical risks.

Another good practice is to consider the regulatory environment for reallocation and additional assumptions, such as the appearance of green firms and the green switch process, or even to enrich the long-term modelling with additional variables as a means to perform a more granular analysis (e.g. counterparty-level and balance sheet reallocation).

5.6 Modelling risk mitigation

Even though the use of private insurance/national compensation schemes (NCSs) as risk mitigation techniques was accepted and foreseen in Expectation 7 of its guide, the ECB observed that most banks did not incorporate them into their projections, as such information is not broadly available. This occurs particularly under the drought and heat scenario owing to the lack of data. The 2022 ECB CST methodology required banks to outline their assumptions on the role of private insurance/NCSs and to ensure that insurance coverage was clearly linked to the hazard outlined in the scenario. The ECB observed that few banks developed capabilities to consider the effect of private insurance in their projections in the area of flood risk, but for half of those banks the insurance covers a large amount of the collateral loss. Regarding the drought and heat scenario, neither NCSs nor private insurance are considered, as banks could not collect relevant data to take into account the positive effect of the risk mitigation.

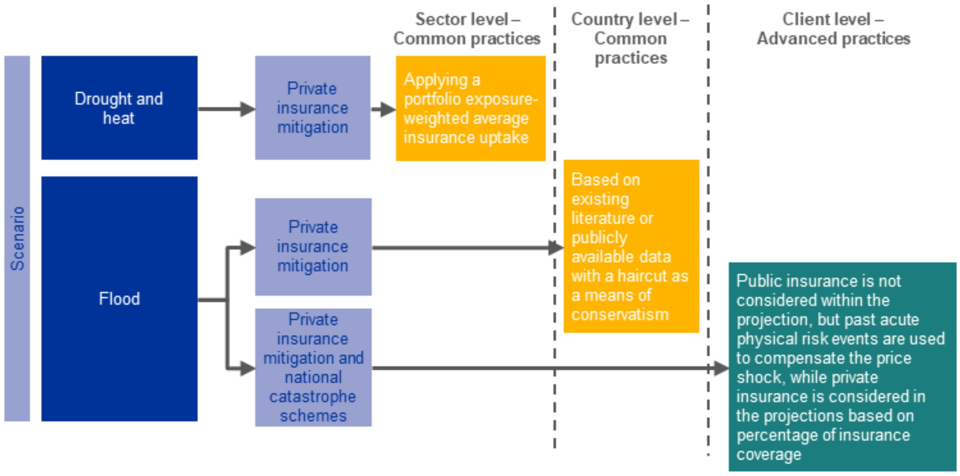
As a common practice under the flood scenario, banks provide projections without the NCS effects following the methodological note. The schemes are quite heterogenous between countries, but in order to estimate the impact of NCSs, few banks assessed past acute physical risk events for the coverage provided by such schemes. Coverage assumptions are then applied to reduce the real estate price shock, yielding less severely stressed LTV ratios and hence LGDs. In terms of transmitting the shock to the risk parameter, a common practice is to consider the market value of the collateral as a main driver of the LGD projection via the LTV ratio.

Where no data were available, some banks used average coverage ratios (based on publicly available data) with a significant haircut as a constant discount factor to the house price shock, but this must be considered rather poor practice. As a minimum, some banks relied on external data providers to analyse in detail the private insurance coverage at flood risk area level. Thus, the insurance coverage was applied as a mitigating factor to the real estate shock, resulting in a reduction in LGD. Some banks with advanced approaches adjusted the house price shock based on the percentage of insurance coverage, providing sufficient granularity for their analysis as they were able to collect such data at loan level.

The accuracy of modelling risk mitigation will benefit from enhanced efforts to gather relevant insurance information at the most granular level possible and from building a consistent methodology to estimate the effects of such risk mitigants in banks' modelling approaches.

Figure 10

Good practices to consider risk mitigants in banks' loss projections



Source: Bank submissions.

6 Conclusion

This report presents a collection of good practices observed by the ECB over five years of supervisory activities concerning the integration of climate and nature-related risks into stress-testing frameworks. The initial version of the report reflected the innovative yet emerging approaches identified in the context of the ECB's first supervisory climate risk stress in 2022. Since then, through a series of follow-up activities and supervisory interactions up to 2025, the ECB has observed a significant evolution in industry practices, in terms of both sophistication and risk coverage. While good practices observed during the 2022 ECB CST focused primarily on transition risk and its transmission to PDs, follow-up activities have shown that more institutions have now developed approaches to also quantify impacts on LGDs. Furthermore, the period following the 2022 ECB CST has seen marked progress in modelling physical climate risk and its transmission to credit risk parameters. Nevertheless, climate risk modelling remains an emerging field, with stress-testing frameworks generally capturing only a subset of relevant climate risk drivers. The current frontier in climate and nature-related stress testing is now defined by innovative approaches to incorporate nature-related risks. While the absence of reference scenarios and consensus on quantification methodologies for nature-related risks presents notable challenges, initiatives such as the dissemination of good practices can play an important role in overcoming these obstacles and fostering progress.

While the ECB acknowledges the progress banks have made in stress testing climate and nature-related risks, it also recognises the increasing materiality of these risks, which necessitates further improvements. The economic and financial consequences of climate change and nature degradation are already evident and continue to intensify. While acute physical risks are already materialising, observations from the supervisory activities carried out over recent years suggest that these risks are not yet comprehensively integrated into all banks' stress-testing frameworks, and observed practices are often limited to a sub-group of risk categories, regions and portfolios. To address this gap, the newly introduced section on physical risk modelling in this report provides practical examples and good practices that banks can use to enhance their analytical capabilities.

Strengthening the comprehensiveness of climate stress-testing frameworks is essential to ensure that material risks are adequately captured. This, in turn, will help mitigate the risks of mispricing lending decisions, misallocating resources and overvaluing collateral, while enabling more accurate climate risk quantification across various scenarios. As required by national laws implementing Article 74 of the Capital Requirements Directive, institutions are required to have, among other things, effective processes to identify, manage, monitor and report the risks they are or might be exposed to, including ESG risks in the short, medium and long term. Accordingly, material climate and nature-related risks must be ultimately treated with the same rigour as other risks faced by banks and must be fully integrated into prudential risk categories (credit, market and operational risks, and business model and strategy) as well as into capital and recovery planning.

Supervisory climate stress testing will remain a key tool for assessing the vulnerability of banks to climate-related risks. The ECB, in collaboration with the EBA and national central banks and supervisory authorities in the EU, is developing a framework to incorporate climate risks into regulatory stress testing. Both transition and physical risks will be integrated into the EU-wide stress test, in line with the Joint Guidelines on ESG stress testing[40] recently published by the European Supervisory Authorities and applicable from 1 January 2027. The ECB will continue to utilise its supervisory stress tests to identify vulnerabilities and assess banks' resilience to financial and economic shocks, including those stemming from climate and nature-related risks. This compendium of good practices is also intended to support institutions in enhancing their modelling capabilities.

40 See "Joint Guidelines to ensure that consistency, long-term considerations and common standards for assessment methodologies are integrated into the stress testing of environmental, social and governance risks pursuant to Article 100(4) of Directive 2013/36/EU and Article 304c(3) of Directive 2009/138/EC", EBA, ESMA and EIOPA, January 2026.

Annex

Annex A: Approach to selection and related insights on topical analysis of participating institutions

A.1 Detailed selection criteria

This section gives more details on the selection criteria for Module 2 and Module 3 that were summarised in Chapter 2.

For Module 2, banks were selected based on the quality of the data reported under both metrics. For Metric 1, banks were asked to report their interest income as well as their fee and commission income from, and their exposure to, non-financial corporations split across the 22 NACE 2 sectors within the scope of the exercise in line with the definition of income given by the FINREP financial reporting framework. Best-in-class institutions were selected among banks that did not make use of approximation to report such data, excluding those with major data quality issues and taking into account expert assessment performed during the exercise to restrict the sample.

Metric 2 banks were asked to report the scopes 1, 2 and 3 GHG emissions of their 15 most relevant counterparties for the above-mentioned 22 NACE 2 sectors, as well as their respective exposures. In selecting the best-in-class banks, a distinction was made between actual data and proxies, always applying the proportionality principle to ensure a level playing field. For actual data, both the business model dimension and the number of reported counterparties need to be considered, because institutions with fewer clients within the scope of the exercise may have found it easier to engage directly with clients and collect actual data. The approach therefore consisted of selecting for each business model the banks that were able to report the highest share of actual data, conditional on the number of counterparties being higher than the group median. With regard to proxies, a comparison was performed between GHG data submitted by the banks and collected from a benchmark source. This meant that the banks selected were those that had reported estimated values closer to those reported by the benchmark. The benchmark source was chosen owing to its high coverage and the quality of the underlying methodology. However, since this approach would limit the analysis to those banks with counterparties in common with the chosen source, expert assessments were also considered, expanding the subset of selected banks in order to achieve a holistic view. The best-in-class banks reflected all business models so that smaller banks can also be given a clear path for improvement.

For Module 3, with respect to the short-term transition risk scenario, the analysis and selection were based on observed changes in PD under the respective scenario. This allowed for assessment of whether banks sufficiently reflected the scenario-implied GVA and the carbon price shocks (e.g. direction and magnitude) in their projected PDs for the most carbon-intensive sectors, also accounting for their exposures in the respective sectors. For the flood risk scenario, the magnitude and transmission of the acute physical climate risk from LTVs to LGDs and respective LGD deltas were used as the main criteria for selecting the sample of banks.

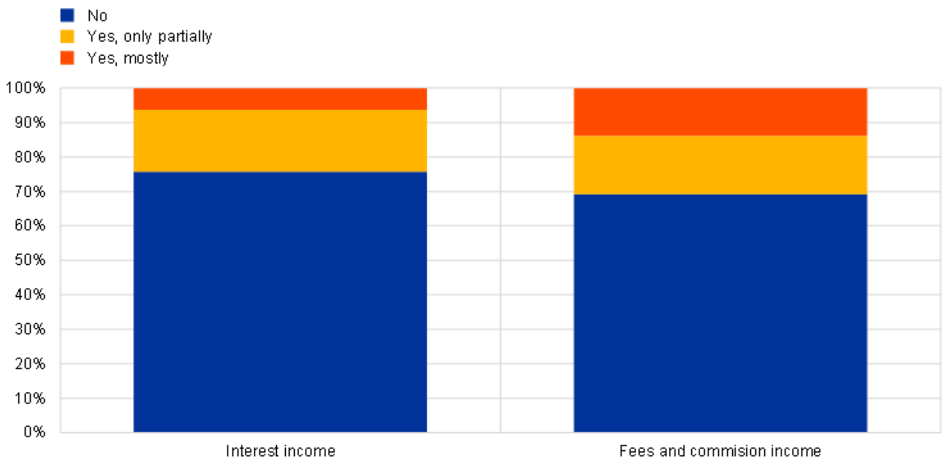
Banks were asked to submit their answers in a qualitative questionnaire regarding their strategic decisions on the long-term scenarios. In order to identify banks with robust approaches to providing meaningful forward-looking balance sheet assumptions, the level of detail provided on the main determinants of a bank's strategic choices under various transition pathways (e.g. entailing assumptions at NACE sector and EPC rating levels) under the different long-term scenarios were evaluated. Finally, the description of the credit risk parameters for each scenario (orderly, disorderly, hot house world) and the respective modelling approaches were assessed. The analysis also leveraged the supervisory expert assessment and conclusions from the quality assurance phase of the exercise.

A.2 Insights on topical analysis of participating institutions

Chart A1 shows that for Module 2, Metric 1, most banks in the sample managed to break down both interest income and fee and commission income by NACE 2 sector without resorting to approximation. The final selection of banks was then extracted from those that did not make use of approximation for both types of income, also reflecting the analysis performed during the execution phase of the exercise.

Chart A1
Use of approximation to allocate income

(percentage shares)



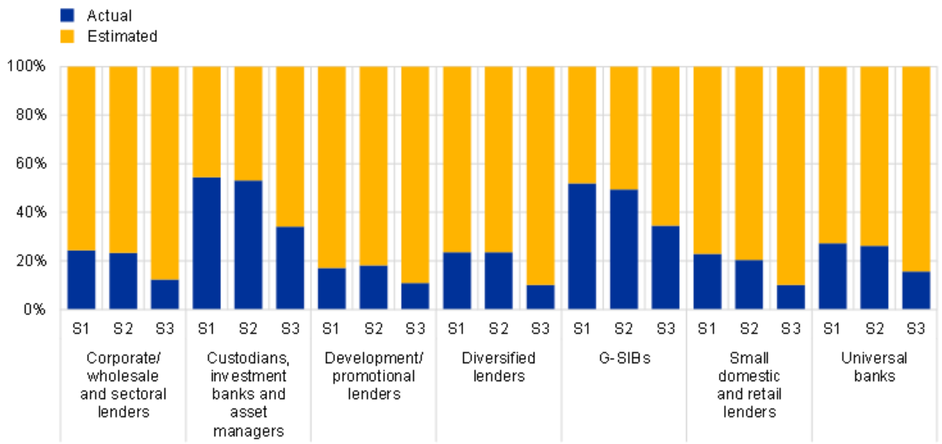
Sources: Bank submissions and ECB calculations.

With respect to actual GHG data for Metric 2, the analysis at business model level shows that the share of actual data that banks within each category managed to collect varied. Business models like custodians, investment banks and asset managers, global systemically important banks and universal banks reported the highest percentages of actual data (Chart A2).

Chart A2

Actual versus estimated emissions by business model

(percentage shares)



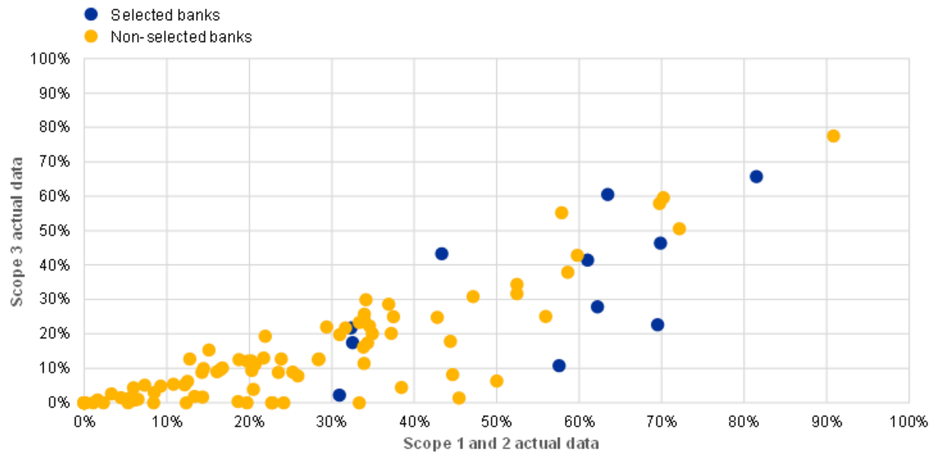
Sources: Bank submissions and ECB calculations.

There is also some variability within each business model both in terms of the shares of actual and estimated data and the number of reported counterparties. To consider this aspect, the median number of counterparties was computed for each business model, and the final selection of banks was restricted to those within each category with higher percentages of actual data and a sample of reported clients larger than the median. The final set of selected banks is shown in Chart A3 in terms of share of actual data.

Chart A3

Percentages of actual data among selected and non-selected banks

(percentage shares)



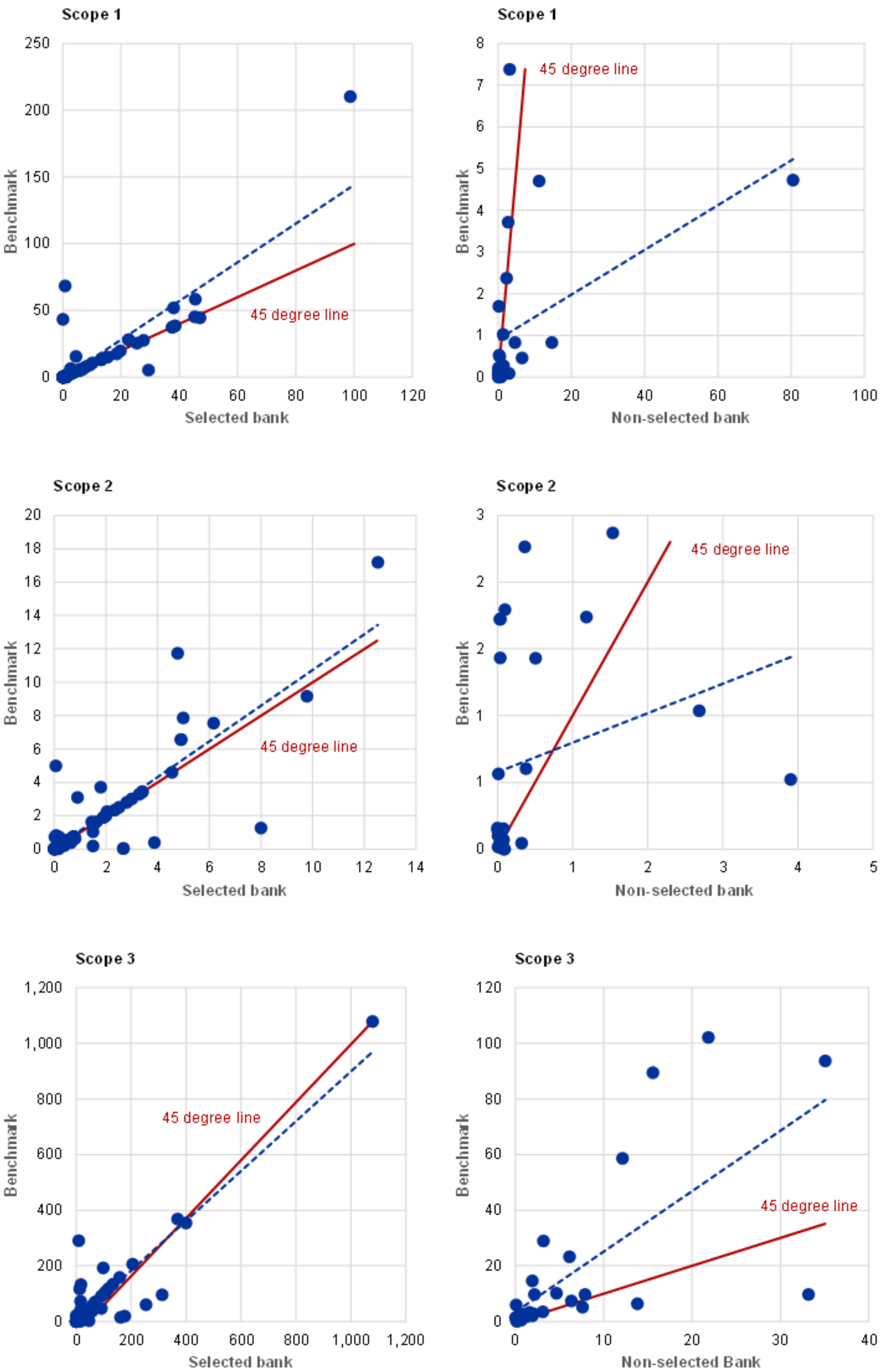
Sources: Bank submissions and ECB calculations.

For the estimation of missing emissions data and comparison with the benchmark source, Register of Institutions and Affiliates Data codes were assigned in order to match counterparties. From the mapped sample, the banks selected were those that reported the highest number of counterparties with estimated data closer to the values of the benchmark. Chart A4 gives an example of this selection, whereby, for each scope (scopes 1, 2 and 3), the scatter plots show the differences in data reporting of a selected bank compared with a non-selected bank with respect to the chosen source, indicating the higher quality of estimated data for selected banks. In an additional step, values reported by the selected banks were compared with those reported by all the banks for the same counterparty. In general, the values of the selected banks that are close or equal to the benchmark end up in the median of the distribution of all banks.

Chart A4

Comparison of GHG emissions data reported by selected and non-selected banks with respect to the benchmark

(GHG emissions, tCO2e millions)



Sources: Bank submissions and benchmark data.
Note: The axes show the emissions data in tCO2e millions reported by the bank (x-axis) and the benchmark (y-axis), while each point represents a common counterparty; the closer each of them is to the 45 degree line, the more similar the bank's reported emissions value is to the benchmark and therefore the more accurate the estimation.

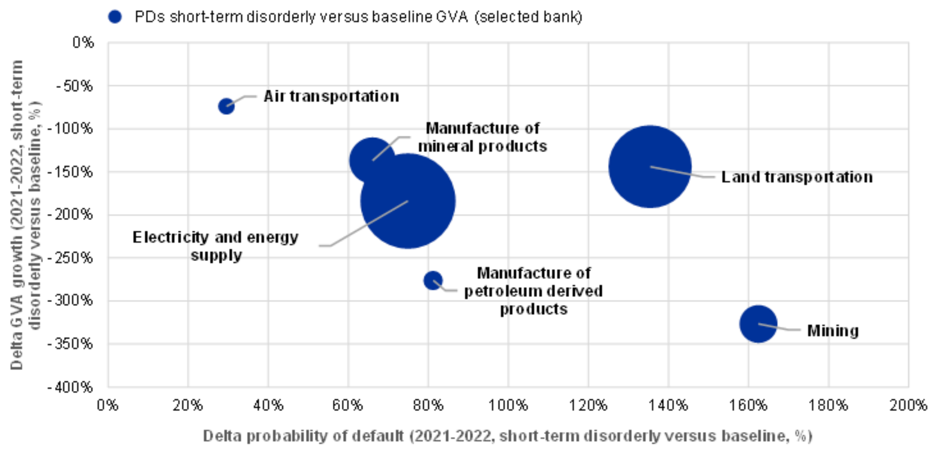
Owing to the limited coverage achieved with this approach, expert assessment of the quality assurance of the banks' submissions was also considered to identify the most advanced banks, while respecting the characteristics of each business model. Hence, the final sample resulted from the combination of these analyses.

In order to select the best-in-class banks in terms of climate-related risk modelling capabilities, a quantitative analysis was performed of changes in PD at the level of each short-term scenario to check the consistency of projected PDs with the magnitude of shocks. In terms of GVA shocks, as indicated in Chart A5, a slight linearity with PD changes is expected. Charts A5 and A6 show this in detail for the selected and non-selected banks respectively.

Chart A5

Selected banks' sectoral changes in PD and GVA growth (short-term disorderly versus baseline)

(x-axis: PD increase 2021-2023; y-axis: GVA growth 2021-2023; bubble size indicates the exposure magnitude for each sector)



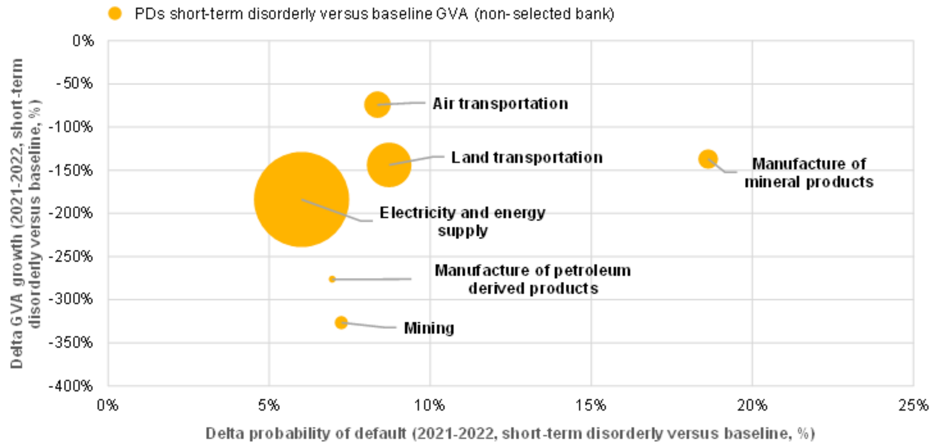
Sources: Bank submissions and ECB calculations.
Notes: The chart indicates that the order of magnitude in terms of sectoral GVA shocks is reflected in the increases in PD. For example, GVA in the mining sector drops the most with a decrease of almost 350%, which is reflected in the largest increase in sectoral PDs observed at around 160%.

Chart A5 indicates sensible PD estimations for the respective GVA growth (from 20% to 160%) and consistency with the emissions intensity of sectors. The linearity criterion is also fulfilled since PD increases when GVA decreases.

Chart A6

Non-selected banks' sectoral changes in PD and GVA growth (short-term disorderly versus baseline)

(x-axis: PD increase 2021-2023; y-axis: GVA growth 2021-2023; bubble size indicates the exposure magnitude for each specific sector)



Sources: Bank submissions and ECB calculations.
Notes: The chart indicates that the order of magnitude in terms of sectoral GVA shocks is not adequately reflected in the increases in PD. For example, GVA in the mining sector drops the most with a decrease of almost 350%, while the respective increase in sectoral PDs only amounts to around 8%, even less than in other sectors that are prone to less severe GVA shocks.

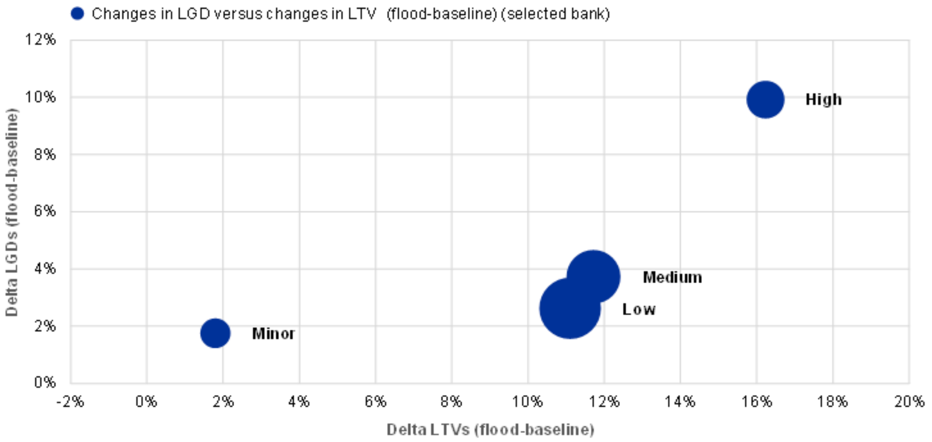
By contrast, Chart A6 shows an example of a non-selected bank. In this case, very low PD estimates are observed for the respective GVA growth. In addition, the magnitude of the PD increase is not consistent with the GVA decrease and the emissions intensity of the respective sectors.

For the flood risk scenario, the selection of banks was based on the transmission of the respective physical risk to LGDs. To extract the respective results, bubble charts were compiled showing changes in LGD along with the changes in LTV for the respective exposures. Charts A7 and A8 illustrate the difference observed in the adequacy of the modelling of LGDs and LTVs for selected and non-selected banks.

Chart A7

Selected banks' changes in LGD and LTV by risk region (flood risk scenario versus baseline)

(x-axis: LTV increase 2021-2022; y-axis: LGD increase 2021-2022; bubble size indicates the exposure magnitude for each specific risk region)

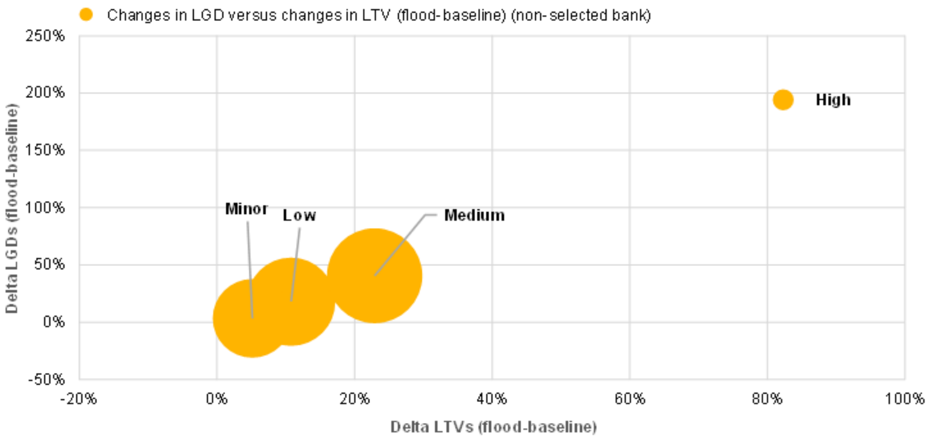


Sources: Bank submissions and ECB calculations.
Note: LGDs are weighted based on total exposures. The chart indicates that the order of magnitude in terms of increases in LTV ratios is also reflected in the respective changes in LGD, drawing a clear distinction between the risk areas that were prone to different shocks in house prices.

Chart A8

Non-selected banks' changes in LGD and LTV by risk region (flood risk scenario versus baseline)

(x-axis: LTV increase 2021-2022; y-axis: LGD increase 2021-2022; bubble size indicates the exposure magnitude for each risk region)



Sources: Bank submissions and ECB calculations.
Note: LGDs are weighted based on total exposures. The chart indicates that the order of magnitude in terms of increases in LTV ratios is not adequately reflected in the respective changes in LGD and that there is no clear distinction between the risk areas and respective differences in house price shocks.

Annex B: List of acronyms

COREP	common reporting
CRE	commercial real estate
CST	climate risk stress test
DCF	discounted cash flow
DR	default rate
EBA	European Banking Authority
ECB	European Central Bank
EEIO	environmentally extended input-output
EPC	energy performance certificate
ESG	environmental, social and governance
EU	European Union
FINREP	financial reporting
GBDT	gradient boosting decision tree
GDP	gross domestic product
GHG	greenhouse gas
G-SIB	global systemically important bank
GVA	gross value added
IFRS	International Financial Reporting Standard
IPCC	Intergovernmental Panel on Climate Change
k-NN	k-nearest neighbours
KPI	key performance indicator
LGD	loss given default
LTV	loan-to-value
NACE	European Classification of Economic Activities in the European Community
NCS	national compensation scheme
NFC	non-financial corporation
NGFS	Network for Greening the Financial System
NUTS	nomenclature of territorial units for statistics
PCAF	Partnership for Carbon Accounting Financials
PD	probability of default
RIAD	Register of Institutions and Affiliates Data
RRE	residential real estate
SMEs	small and medium-sized enterprises

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For specific terminology please refer to the ECB glossary (available in English only).

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