EUROPEAN CENTRAL BANK

BANKING SUPERVISION

ECB report on good practices for climate stress testing

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Contents

Executive summary

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

The 2022 ECB climate 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 start or continue working on all aspects of prudent climate stress testing. While banks have made some progress on incorporating climate-related risks into their stress testing frameworks and have delivered comprehensive and innovative information despite the prevailing challenges, the results also show that we are at the start of a long journey. There is a high level of inconsistency across banks' practices, and several areas of climate stress testing have been identified where there is need for improvement.

The objective of this report is to provide banks with examples and suggestions on how to improve their climate stress testing capabilities based on identified good practices from the 2022 ECB CST and to support banks in their transitional journey. This report aims to facilitate banks' efforts to align their practices with the supervisory expectations set out in the ECB Guide on climate-related and environmental risks ("the Guide")[1]. In particular, this report offers banks support in addressing Expectation 11 of the Guide, which focuses on the necessity to adequately incorporate climate and environmental risks in banks' stress testing frameworks. The report on good practices for climate-related and environmental risk management from the 2022 thematic review[2] on the other hand addresses the rest of the supervisory expectations outlined in the Guide.[3] The good practices outlined in this report should also help banks and supervisors to prepare for future CST exercises.

The collection of data on greenhouse gas (GHG) emissions and energy performance certificates (EPCs) remains a key challenge for banks, and the related constraints are acknowledged by the ECB. However, some banks have been proactively trying to overcome the scarcity of climate-related data by independently developing their own indicators to identify corporate clients with high sensitivity to climate transition risks. This shows that data scarcity can be overcome. In addition, data on climate-related and environmental risks are and will continue to be key in assessing risk exposures.

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

2 See Good practices for climate-related and environmental risk management – Observations from the 2022 thematic review, ECB, 2022.

3 The 2022 thematic review covers all the supervisory expectations outlined in the Guide, apart from Expectation 11, on climate stress testing, and Expectation 13, on disclosures.

Even if banks were able to source requested data for non-financial corporations (NFCs), the data gap will still persist in the coming years to some extent. This is particularly true for other types of counterparties for which it will be difficult to collect and build data inventory – households, small and medium-sized enterprises (SMEs), etc. Hence the quality of estimation approaches will remain important. As seen in the 2022 ECB CST, most banks made extensive use of proxies. With regard to greenhouse gas emissions, institutions should engage in the retrieval of actual data and encourage counterparties to disclose GHG emissions. Where it is impossible to retrieve actual data, institutions should develop proxies in line with Partnership for Carbon Accounting Financials (PCAF) guidance. Regarding EPC data, institutions should retrieve these data from customers, EPC registers, valuers and reliable external third parties. When such data are not available, proxies can serve as a first step to bridge the gap, but at the same time high heterogeneity in the results of estimations from different approaches indicate a need for further reflection and additional effort to develop comprehensive and robust methodologies.

Regarding the integration of climate-related risks into current modelling approaches, the ECB identified various good practices which allow counterparty-level analysis, while most banks only focus on transition risk and transmission to probabilities of default (PDs). Overall, in the projected credit risk parameter, advanced approaches demonstrated greater consistency with the scenario-specific shocks used for the 2022 ECB CST than less advanced approaches. Banks need to extend the richness of variables used in their models to account for the multiple transition channels of climate-related risks; this will be key for adequate assessment of climate-related risks. Most banks have only started with the integration of carbon prices and sectoral gross value added. Banks have developed sectoral models aimed at integrating climate-related risk aspects into existing PD models, focusing first on corporate exposures. To account for the heterogenous impact of climate-related risks, the quantification of the credit risk impact has to be done at the most granular level. More effort is needed regarding the transmission of transition risks to losses given default (LGDs) and the integration of physical risks into estimations of credit risk parameters.

This supervisory report aims to contribute to the dialogue with banks on how to approach climate-related risks and increase the consistency of practices across the industry and is addressed to those dealing with the assessment of climate-related risks in the banking sector. The report highlights which practices are considered preferable to ensure alignment with the ECB’s expectations and offers suggestions and examples to help banks overcome challenges and meet expectations by the end of 2024 at the latest. It thus addresses calls from the industry to disseminate good practices from the exercise. It is important to note, however, that this collection of good practices does not prescribe a “one-size-fits-all” approach to climate stress testing. Each bank must find its own way, depending on its specific circumstances and business model needs.

Table 1

Observed good practices described in this report: Climate stress testing framework and scenarios

Section	Sub-section	Number	Topic	Summary of good practices
Scope of climate stress testing frameworks		4.1	Scope of CST frameworks	Design the scope of the CST framework based on a materiality assessment of climate-related risks Use of other analytical tools to design the scope of the framework, like deep dives into portfolios, sectors or geographies Inclusion of all portfolios that are materially impacted by climate-related risks
Climate risk scenarios		4.2	Scenarios	Inclusion of both physical and transition risk in the 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 Complement publicly available scenarios with internally developed ones Use of different time horizons and inclusion of scenarios with longer time horizons
Balance sheet approaches		4.3	Balance sheet approaches	Use of both static and dynamic balance sheet approaches When using a dynamic balance sheet, choice of a sectoral approach or more granular

Table 2

Observed good practices described in this report: Data needs and EPCS

Section	Sub-section	Number	Topic	Summary of good practices
Internal data needs	Information on industry sector	5.1.1	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 FINREP
	Information on geolocation	5.1.2	Mapping of collateral to flood risk bucket, at NUTS level 3	Availability of geolocation data at loan level in internal systems Assignment of NUTS3 codes to collateral for all assets classes Allocation of respective exposure share to the specific collateral in line with COREP
Emissions data	Actual data	5.2.1	Retrieval of actual GHG emissions data	Combination of manual search 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	5.2.2	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 asset) 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	5.2.3	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 Challenge estimated data both from providers and in-house proxies by cross-checking results with comparable reporting counterparties Identification and further analysis of outliers Ask data providers for details of methodologies applied
EPC data	Modelling for estimation of EPC data	5.3.2	Retrieval of actual EPC data	Collect real EPC data insofar as possible Ask borrowers to provide EPC data at loan origination or when carrying out an annual review or modifying a loan Access public registers Instruct valuers to collect EPC data as part of their collateral valuation review.
			Methodologies for proxy estimation	Use a sophisticated approach for estimation, like statistical models and machine learning algorithms Ensure that the sample is representative Ensure that the data used as inputs for modelling are largely available in the bank's systems or it is feasible to collect them Ensure that the variables used for modelling are selected to distinguish the different markets Ensure that the model is back-tested to check its performance and accuracy and its methodology is clearly established and documented Ensure that there are appropriate governance arrangements in place

Table 3

Observed good practices described in this report: Climate-related modelling approaches

Section	Sub-section	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	6.1	Variables included in banks' credit risk models augmented by climate-related risk	Climate-related transition variables - e.g. carbon (CO2) price, GHG emissions (actual and emission pathways), carbon (CO2) emissions (actual and projected pathways) Climate-related macroeconomic variables (e.g. GVA growth, RRE price shock, CRE price shock) General macroeconomic variables (e.g. interest rate, unemployment rate, inflation/ price index)
	Modelling approaches identified	6.2	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 Include adaption of corporate key financial metrics to reflect the impact of relevant climate variables (e.g. additional cost due to carbon price increases) and recalculation of PDs + 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 should 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 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. Transition risk is captured 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	Entire increase in carbon tax expenses is affecting cash flow which is considered in the valuation of the building (consider costs pass-through at client level) New models on top of satellite models which reassess the recovery rate (RR) while preserving the link with the RR observed internally Function which connects the conditionally expected LGD with the conditionally expected PD to ensure consistency Stranded assets, 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
	Long-term modelling approaches	6.3	Summary – Good practices to adjust existing models to the long-term nature of climate-related risks	Recomputing PD based on the credit spreads provided in the scenario Impact of increasing carbon prices is indirectly transmitted via GVA shocks Extended short-term models on a year-to-year basis to provide climate-related risks stressed PDs for a longer-term horizon External providers sectoral models to capture unbalanced shocks among different sectors or counterparties
	Modelling risk mitigation	6.4	Summary – Good practices to consider risk mitigants in bank's loss projections	Applying 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 not considered in the projections but compensate the price shock based on past acute physical risk events while the private insurance is considered within the projections based on percentage of insurance coverage

Introduction

The 2022 ECB climate stress test (CST) has been instrumental in helping banks to start developing their climate risk-related stress testing capabilities. It is part of a broader set of supervisory activities aimed at assessing the alignment of banks' risk management practices with the ECB's expectations, together with the initial assessment of banks' approaches to climate and environmental risk management[4] that was carried out in 2021 and the 2022 thematic review[5]. The 2022 CST was dedicated to assessing banks' climate stress testing capabilities. It was also a learning exercise in which banks were prompted to increase efforts to collect relevant data, adapt their existing models to include climate-related risks and start building climate risk-specific frameworks.

Particularly with regard to sourcing the relevant data for analysing climate-related risks, the ECB acknowledges the challenges in the current evolving regulatory disclosure landscape and recognises the innovative character of the data requirements of the 2022 ECB CST. Climate-related risk stress testing indeed requires new, more granular and more specific types of information and the lack of harmonisation among national regulatory frameworks and missing or evolving regulatory standards make the sourcing of these data a major challenge. Additional efforts by both banks and regulators are needed to fill these data gaps. Initiatives such as the upcoming Corporate Sustainability Reporting Directive[6] will help to increase availability of the necessary data.

While banks have made considerable effort to move ahead in the area of climate stress testing, the information collected during the 2022 ECB CST shows that there is a high level of inconsistency and diversity across banks' practices and substantial scope for improvement. Several significant institutions (SIs) faced challenges in designing appropriate CST frameworks, integrating climate risks into their modelling approaches and compiling the appropriate data. While most banks did not experience major issues in allocating credit risk exposure and income across the relevant industries (NACE sectors)[7], difficulties were encountered in gathering information on EPCs of real estate portfolios and on GHG emissions of counterparties.

The report takes into account the progress of individual banks. The description of good practices makes a distinction between the levels of sophistication of the practices described in order to better support banks in the journey of building more solid CST frameworks and to give them a clear view of which practices are seen as

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

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

6 See Proposal for a Corporate Sustainability Reporting Directive (CSRD), European Commission, April 2021.

7 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.

first steps and which approaches are seen as more advanced. The range of practices should also address the issue of proportionality. Some examples of poor practice are also presented to show banks what is not in line with supervisory expectations. It should be noted that the good practices in the report merely serve as an illustration and are not necessarily replicable, nor do they necessarily ensure alignment with supervisory expectations. The ECB emphasises the evolving nature of good practices and expects these to mature over time.

The report is based on the information collected in the 2022 ECB CST and hence focuses on those topics that were covered in the exercise. The focus is mainly on three topics: the features of banks' internal climate stress testing frameworks, the availability of climate risk-related data and the strategies used by banks to overcome data challenges, and the techniques used for modelling climate risks with respect to credit risk. Market risk is not considered in this report, since the methodology used in the 2022 ECB CST was very simplistic and insufficient information was collected from banks to draw meaningful conclusions. Operational and reputational risk are also not covered in the report, since they were assessed only in a qualitative way in the 2022 ECB CST and are addressed in more detail in the report on good practices from the 2022 thematic review.[8]

Information collected in all modules of the 2022 ECB CST was used to extract good practices. For each module, specific criteria were developed and analysis performed to identify best-in-class banks, 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 banks were selected across all three modules, indicating that most banks need to make progress in one or more areas relevant for climate stress testing.

This report should be read in conjunction with the report on good practices from the 2022 thematic review, as both serve as instruments to help banks in their efforts towards meeting the expectations outlined in the Guide. The report on good practices from the 2022 thematic review provides broader coverage of all the supervisory expectations[9] outlined in the Guide, addressing practices related to strategy, governance and risk management processes, whereas this report focuses specifically on climate stress testing and on the technical challenges of designing adequate CST frameworks. It is important to highlight that the Guide covers the supervisory expectations related to the disclosure and risk management of both climate-related and environmental risks, while this report only specifically addresses the inclusion of climate-related risks in banks' climate stress testing frameworks and methods. To further support banks in the development of climate-related risk management capabilities, in the context of the 2022 thematic review[10] each significant institution received a feedback letter setting out any shortcomings in its practices vis-à-vis the supervisory expectations, including those related to stress

8 See Good practices for climate-related and environmental risk management – Observations from the 2022 thematic review, ECB, 2022.

9 The 2022 thematic review covers all the supervisory expectations outlined in the Guide, apart from Expectation 11, on climate stress testing, and Expectation 13, on disclosures.

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

testing frameworks. The ECB set institution-specific remediation timelines for achieving full alignment with the expectations by the end of 2024, providing details on intermediate steps.

The ECB expects banks to further develop their CST frameworks and their data and analytical capabilities and to progress beyond the examples of good practices provided here. The fact that the scope is based on the 2022 ECB CST does not mean that areas that are not covered in this report do not need to be improved by banks, an example being climate risk stress testing with respect to asset classes other than those included in the 2022 ECB CST. In view of the evolving nature of this topic, banks will have to continuously adapt their practices.

Structure of the report

This report presents a set of useful good practices obtained during an in-depth assessment of information provided by banks in the context of the 2022 ECB CST. The report is structured as follows: Chapter 1 outlines the criteria used to identify good practices. Chapter 2 provides information on the advanced approaches to internal climate risk stress testing frameworks with respect to the scope of the frameworks, the choice of scenarios and the balance sheet assumptions used. Chapter 3 describes the advanced approaches used by banks to collect climate-relevant data and the proxy methods developed to estimate such data and covers the following data categories: the allocation of banks' income to industrial sectors, the geolocation of counterparties and of collateral from real estate portfolios, data on GHG emissions of counterparties and data on EPCs for real estate. Chapter 4 illustrates good practices identified with respect to the integration of climate-related risks into credit risk models. The chapter covers the transmission channels used in banks' models to transmit the climate shock to credit risk parameters as well as the approaches identified in climate risk-adjusted probabilities of default (PDs) and losses given default (LGDs). Modelling approaches relative to long-term scenarios are also analysed in detail, as well as the methods used to include risk mitigants. Chapter 5 presents some conclusions from the analysis conducted in this report.

1 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[11]. Module 3 focused on bottom-up loss projections for two broad categories of scenarios 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[12] 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 Scope 1, 2 and 3 emissions[13] 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 taken into account, since each business model has its own characteristics and deals with different types of counterparties which are subject to different levels of requirements concerning the disclosure of emissions data. Regarding proxy estimates, GHG emissions data submitted by banks was 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

11 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 (NFCs) in 22 NACE sectors (which have been identified by the European Commission as the most carbon-intensive ones). Metric 2 provides an important proxy for the extent to which banks are financing emissions and how exposed they are to emission-intensive companies.

12 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.

13 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.

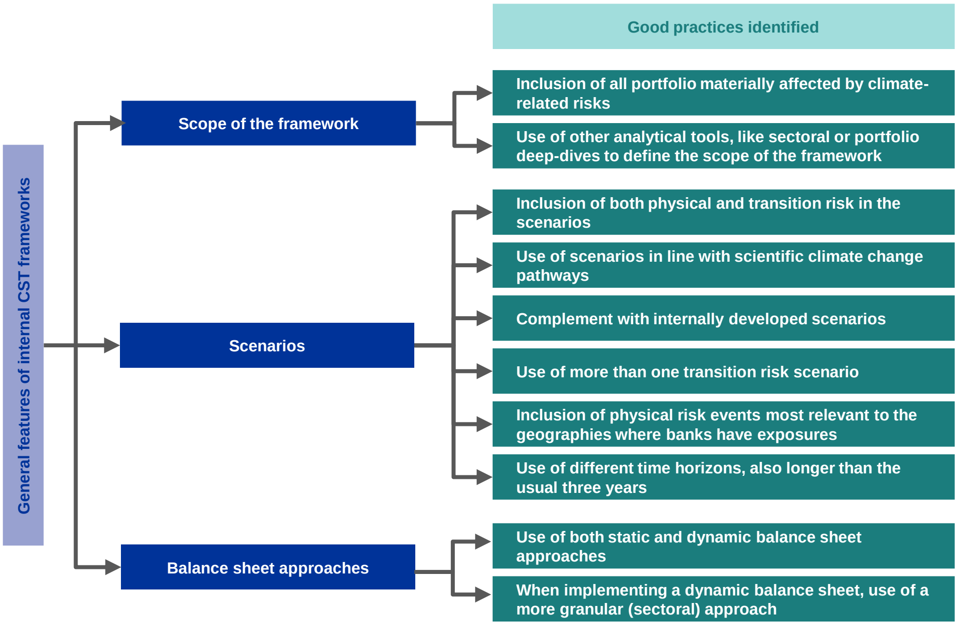
loan-to-value (LTV) ratios to LGDs. Long-term modelling approaches have been evaluated in a qualitative manner, analysing both the credit risk parameters and the determinants of banks' strategic choices under the different transition pathway scenarios. For selected banks, an in-depth assessment of the 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 on the supervisory expert assessment and conclusions from the quality assurance phase of the exercise. More detail on the selection criteria and more information on the specific analysis performed can be found in Annex A.

2 Climate risk stress testing frameworks

When designing their internal CST frameworks, institutions need to make some general methodological choices which affect the overall quality of the results from the CST analysis. This section focuses on three key questions related to the general design of the CST framework, namely how to determine the scope of the framework, which types of scenarios to include and the choice of the balance sheet assumption. This section leverages on the findings from the Module 1 questionnaire to offer banks some direction regarding the preferred approaches to address the three key methodological choices mentioned above.

Figure 1
Good practices in the design of internal CST frameworks



Source: Bank submissions.

2.1 Scope of climate stress testing frameworks

Most institutions with advanced approaches include in the scope of their internal CST framework all the portfolios that are materially exposed to climate-related risks. Banks are expected to consider climate-related risks in their materiality assessment, as stated in the Guide, hence they should use the assessment of materiality to define the scope of their CST framework. This ensures that the CST framework considers the specificities of the institution's business model, operating environment and risk profile and is an important step towards meeting supervisory expectations. 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 should help banks to accurately calibrate the scope of their CST frameworks.

The asset classes included in the 2022 SSM 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 can be enhanced by extending the scope of the CST framework to all the asset classes in the banks' balance sheet. Hence institutions are expected to move in this direction, always taking into account the materiality of the exposures.

Most banks with advanced approaches also make use of other analytical tools to inform their decision on the scope of their CST framework, like deep dives into some 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 risk and use this information to support the choice of scenarios and the definition of the scope of the CST framework.

2.2 Climate risk scenarios

With respect to the choice of scenarios included in the CST framework, the bare minimum standard should be to cover both types of climate-related risks – physical and transition risk. This is also consistent with Expectation 11 of the Guide, under which institutions are expected to conduct scenario analysis considering how both physical and transition risk might affect their activities. On transition risk, it is good practice to include more than one transition risk scenario to reflect the uncertainty of the policy environment and the fact that different types of transition will 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". With respect to how physical risk is reflected in the CST 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, built very specific scenarios with the most likely types of physical risk events only for the locations most relevant to their activities. Some banks also performed preliminary assessments and analysis (e.g. climate heat maps) evaluating several types of physical risk events to identify the most relevant weather events for their activities.

Regarding the sources of the scenarios included in the CST testing framework, the Guide recommends the use of scenarios which are in line with scientific climate change pathways, such as Intergovernmental Panel on Climate Change (IPCC) scenarios. The NGFS was by far the most common source. Other 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, like scenarios focusing on specific sectors or geographic areas in which the operations of clients are concentrated. This is considered good practice.

Regarding the length of scenario horizons, according to the Guide, banks are expected to consider how climate-related risks might materialise in the short, medium and long-term, according to different scenarios. Hence banks should consider scenarios with different time horizons, including beyond the usual three-year length of traditional stress tests, to be able to properly reflect different types of climate-related risks. Banks state that they are using mostly 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 chronical physical risk.

2.3 Balance sheet approaches

Banks with advanced approaches tend to consider a static and a dynamic balance sheet approach in their CST 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, something that is relevant to consider under 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. On the last point, a more granular approach (e.g. sectoral approach) is considered more accurate. This was applied by a number of banks and hence is preferred over an asset class approach, which is more high level. Some banks had even more granular approaches at exposure level, sub-sector level or location level. This preference for a more granular approach should be considered with the caveat that the quality of the balance sheet exercise depends on many factors, hence a granular approach for allocating exposures does not necessarily ensure the robustness of the results.

3 Data requirements for climate stress testing

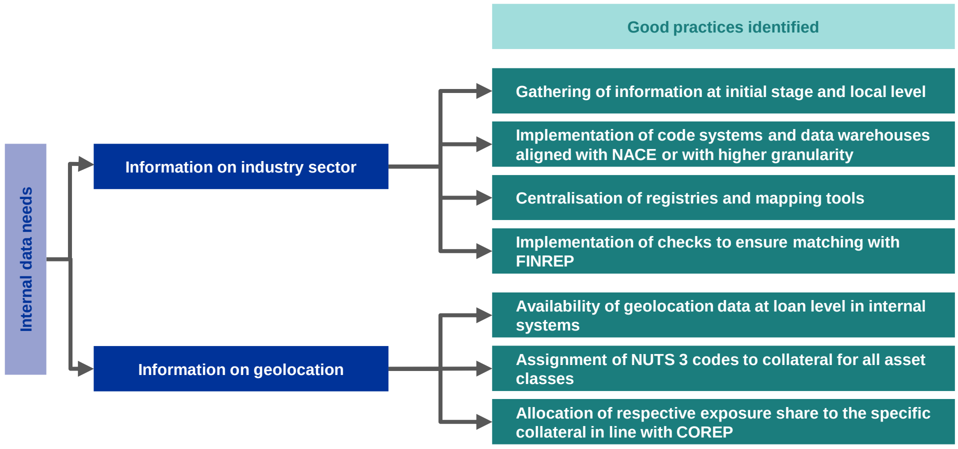
As mentioned in Expectation 6 of the Guide, to make informed decisions and to inform strategy-setting and risk management, banks are expected to report aggregated risk data that reflect their exposures to climate-related and environmental risks. To do so, it is necessary to assess data needs, identify gaps and devise plans to overcome them. Data requirements for climate stress testing go beyond traditional stress testing needs, hence the 2022 ECB CST included several innovations. Given the novelty of the field and the need for more detailed data, closer engagement with clients is necessary to fill gaps and to retrieve information on counterparties' transition plans and commitments for the purposes of internal stress testing programs. Data gathering exercises can be performed, as well as exploring a range of data sources and fostering the exchange of information.

3.1 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 (TEG) on Sustainable Finance[14] 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.

14 See Taxonomy: Final report of the Technical Expert Group on Sustainable Finance, European Commission, March 2020.

Figure 2
Summary of good practices



Source: Bank submissions.

3.1.1 Information on industry sectors

In some cases the allocation of income data to NACE sectors required additional efforts but 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, financial reporting (FINREP), meaning that additional efforts are needed.

In terms of good practice, 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 the clients. Codes are assigned by the front office, the risk management office or by each relationship manager, or the information is already retrieved during the onboarding process. For validation purposes, additional checks were 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 them. Some banks have developed checks to ensure that data extractions matched with FINREP, even if only at a higher level than the one required in the 2022 ECB CST.

While it would have been good practice to collect information directly from the counterparties in order to report the three main sectors of activity of holding companies, none of the banks analysed has implemented such a process. Some banks consulted publicly available reports, like balance sheets, and internally available data, and one resorted to an external data provider to obtain information on the structure of subsidiaries.

3.1.2 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.[15]

In the flood risk exercise, banks were asked to classify the location of their credit exposures to their counterparties in accordance with the flood stress map provided, which disaggregates regions at NUTS level 3 into minor, low, medium and high risk areas. The ECB's expectation was that the location of the collateral should be used as the relevant address for mapping exposures to the different flood risk categories. In the case of multiple-collateral loans, the loan exposures should be split according to the value of each collateral.

Good practice entails the availability of geolocation data at loan level in internal systems. In order to assign the appropriate NUTS 3 codes for the collateral, banks use as a starting point data that are 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 are made by institutions. If addresses are missing, the postal codes of the counterparties' collateral are 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 is the allocation of addresses to NUTS 3 regions via Eurostat. However, going forward, institutions should consider collecting address-level information in their internal systems.

If a loan is covered by multiple collateral, it is good practice for banks to 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 to adequately reflect its vulnerability to the climate-related risks assessed. When 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. While this approach accounts for the maximum potential loss, not being able to determine the location of the collateral is considered poor practice.

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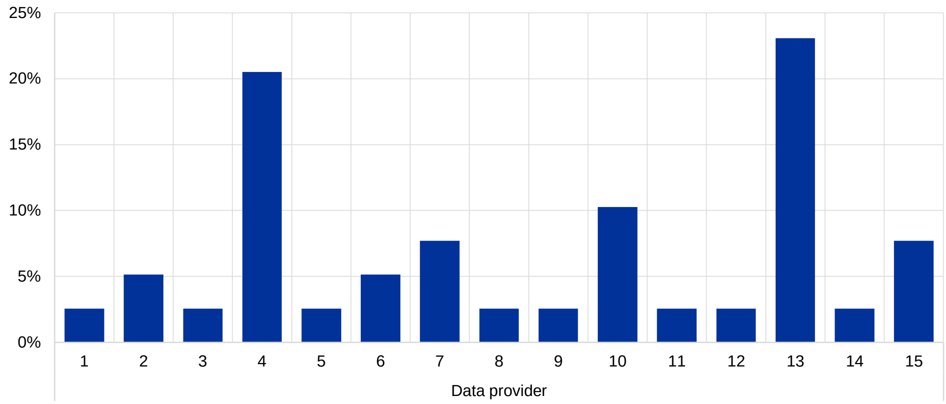
15 See ECB/ESBR Project Team on climate risk monitoring, "Climate-related risk and financial stability", ECB, July 2021.

3.2 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' Scope 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

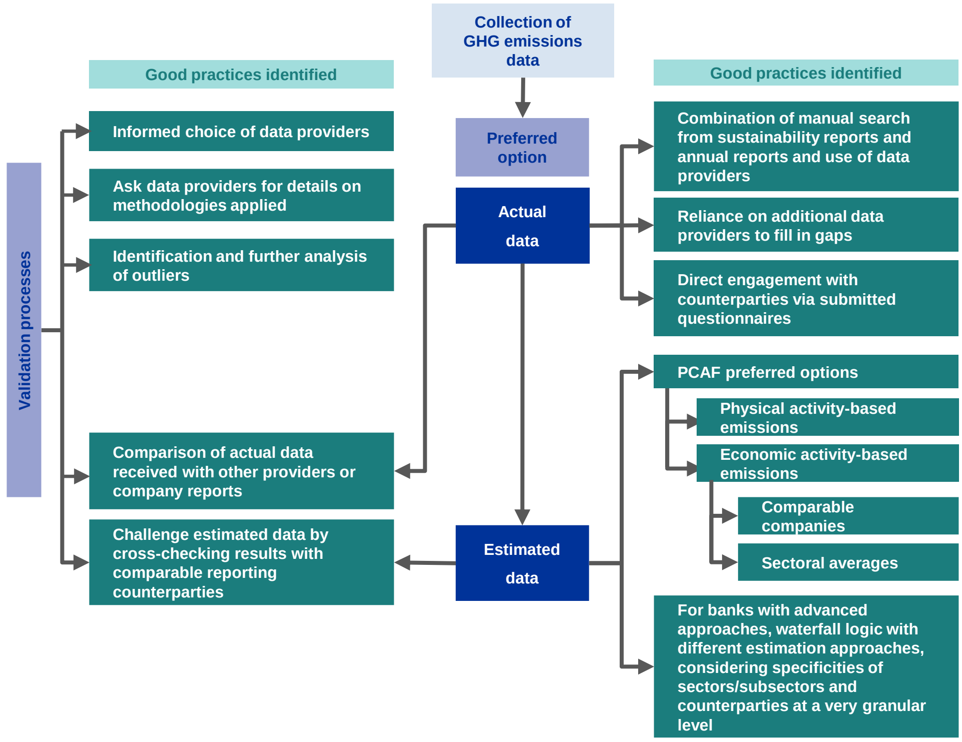
(percentages)



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.

3.2.1 Actual data

Actual data refer to data reported directly by companies in their published sustainability reports or annual reports which is considered the preferred 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, like 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 manage to retrieve and report in the 2022 ECB CST a quite high percentage (above 70%) of actual data for Scope 1 and 2 emissions.

Good practice in retrieving actual data is the use of more than one data provider: 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 the good practices of the 2022 thematic review, a bank 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.

Banks should always prefer actual data and make additional efforts to collect them whenever available, in particular for Scope 1 and 2 emissions, not only relying on external data providers but also performing such activity by themselves and engaging with customers. Institutions should encourage and induce 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 asking for and collecting such data during the loan granting process or through the submission of questionnaires. Moreover, to address the issue of reliability, institutions should check the compliance of actual data reported by companies with widely recognised international standards.

3.2.2 Estimated data

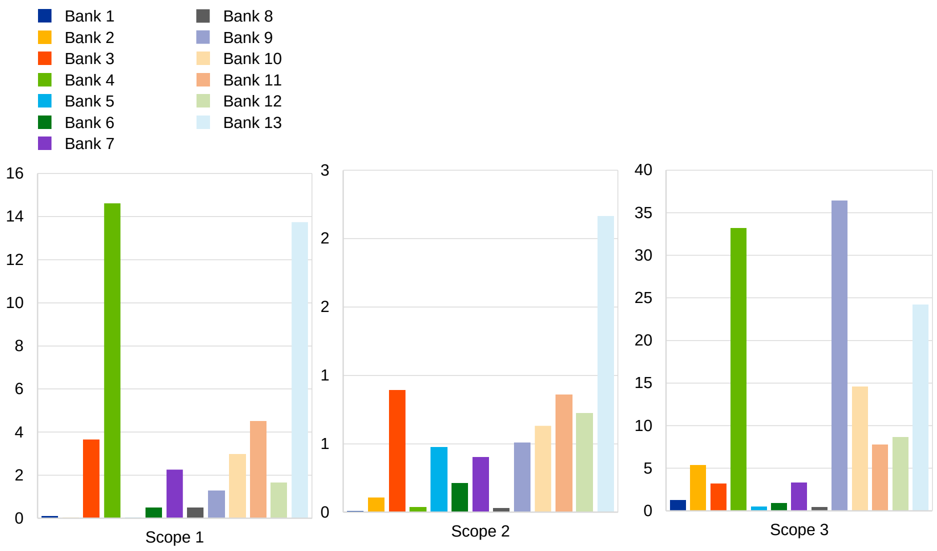
Challenges faced by the banks

The 2022 ECB CST results show that banks have made extensive use of proxies to report Scope 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 which are not subject to a requirement 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 discrepancy across emissions data (Chart 2) and great 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.

Emissions intensity modelling

Against the backdrop of the huge variability in approaches, the ECB has 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[16], published in November 2020. In particular, to be consistent with the asset classes in scope of 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 the ones in scope of Module 2.

Box 1

PCAF approach to estimation of GHG emissions

PCAF distinguishes three options to calculate the financed emissions from, for example, business loans and unlisted equity, depending on the emissions data used:

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

[16] See The Global GHG Accounting and Reporting Standard for the Financial Industry, PCAF.

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 might 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 the 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: "The Global GHG Accounting and Reporting Standard for the Financial Industry", first edition, PCAF, November 2020.

The ECB has 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 / asset turnover ratio. Different approaches are observed from the sample and ranked 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 each scope, then applied to the turnover of the counterparty with missing emissions data.

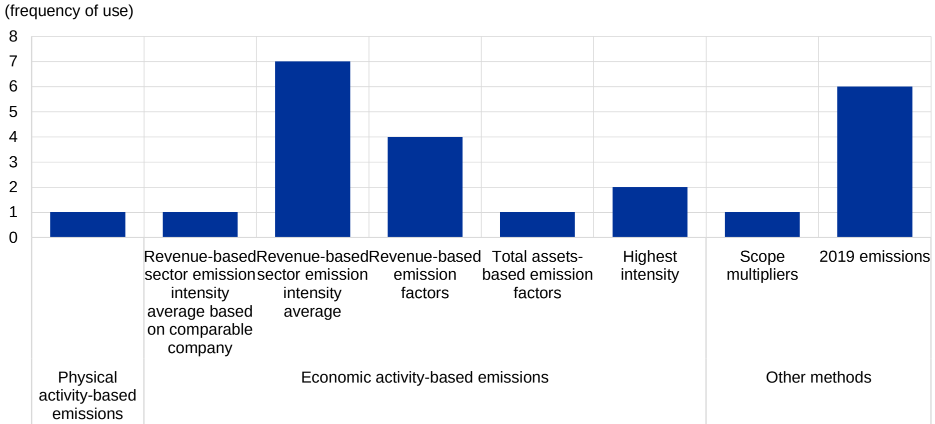
- Revenue-based sector emission intensity average: if the sector is quite homogeneous and reporting counterparties are representative, actual emissions data from public documents of counterparties are used to calculate an average sectoral intensity which is applied to the revenues of the counterparty 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 (EEIO) 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 Scope 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 and should be considered the least preferred options:
    - 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 have been evaluated as poor since they 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 the proxies. Since there can be some differences between counterparties within the same category, the homogeneity of the sector and the comparability of the reporting companies should be assessed before proceeding with the estimation.

Chart 3

Main methodologies used by selected banks for in-house proxies



Source: Bank submissions.

As good practice and in line with the PCAF guidance, emission intensities should, whenever possible, be calculated using physical activity-based emissions, while the second preferred option would be economic activity-based emissions, based either on revenues, which is preferred, or on the assets of comparable companies or the sector.

Some banks with advanced approaches went a step further with more sophisticated approaches. These encompass a detailed waterfall to estimate Scope 1, 2 and 3 emissions, tailored to the specificities of the sector/sub-sector 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

G-SIB good practice approach to the estimation of GHG emissions

A global systemically important bank (G-SIB) with the use of different proxies:

- Sectoral proxy based on data specific to the sector or a stochastic approach[17], multiplying conversion factors by information on the type of products and production volumes (physical activity-based emissions).

[17] The bank did not provide more information, but that approach can be useful as an example of how to integrate physical activity-based data in the estimation of Scope 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 highest turnover is then applied to the turnover of the counterparty.
- When no other option is feasible, as last resort the highest intensity of the sector is used.
- 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 coronavirus (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 it is currently only used to estimate Scope 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 estimate GHG emissions

The approach considers the most relevant GHG 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 sub-sectors based on their emission profiles.

- For each sub-sector 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 airlines 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 EEIO 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 has 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.

3.2.3 Validation processes and observed limitations

When collecting data through external data providers, banks should perform quality assurance themselves, investigate and understand how data providers obtain the actual data and the methodologies behind the estimation processes. Banks need to put in place checks and validation processes to verify the reliability and the accuracy of data. 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.

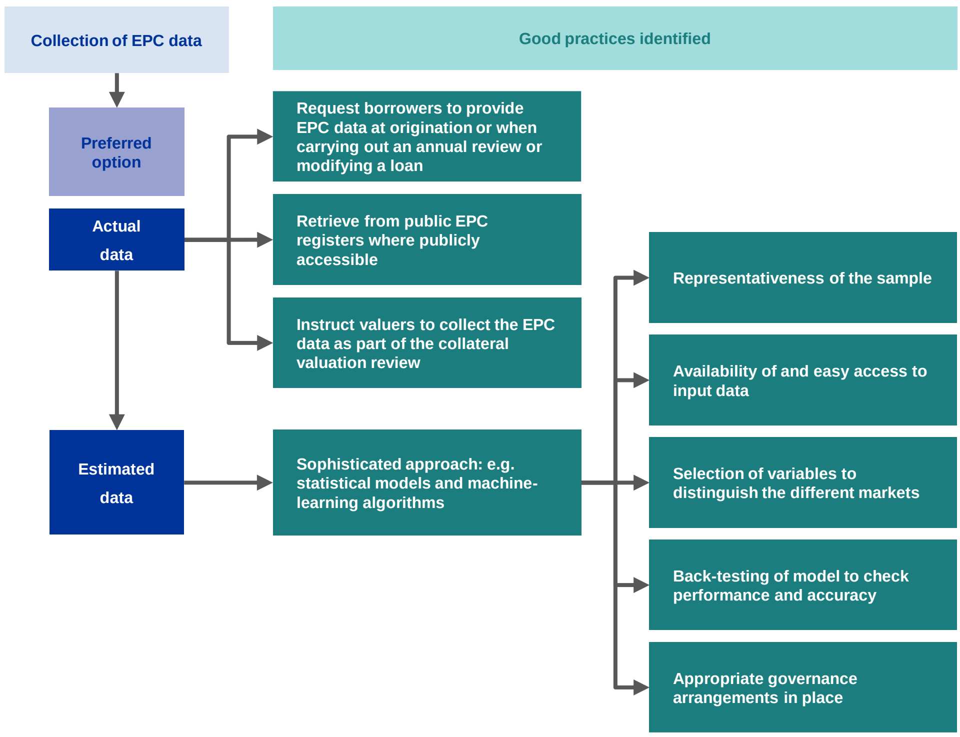
Banks should check and compare different data providers already at the initial decision stage, as further detailed in the report on good practices for climate-related and environmental risk management from the 2022 thematic review. This entails banks assessing providers' documentation and informing themselves 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.

An assessment of the quality should also be performed in the case of internal estimation of data. A bank performed a comparison of the relative Scope 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.

3.3 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 energy performance certificates (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.

3.3.1 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 could be retrieved by banks from a number of sources, for example: (i) directly from customers, (ii) from EPC registers when publicly accessible, (iii) from valuers carrying out valuations, or (iv) purchased from a reliable external party. However, the amount of actual EPC data collected by banks is too low, with one bank out of four without any 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 and some do not yet have a centralised national database or the information is available only for some regions. In terms of measurement, the indicator used to measure the EPC varies across countries or the EPC scaling varies within the same country. These issues also make the comparison and comparability of data more challenging for supervisors. As a consequence of these limitations in the EPC registers, the ECB has 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 need to rely on the data collected from customers only or on aggregate statistics provided by other data sources.

It is also important to note that in terms of the challenges faced by banks, these 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. Despite this, the ECB has severe concerns about banks not being able to get real EPC data for their stock of loans as they are then not able to understand what is inside their portfolios and mitigate the risk.

To fill the data gap, majority of banks make use of additional data (i.e. characteristics of the properties, like the year of construction, type of building, floor space in square metres) to calculate a proxy. The ECB observed that the main drivers used by banks to estimate EPC data are the energy consumption, type of property, floor space and the 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 in their rating due to some renovation work, the ECB expect banks to complement the year of construction variable with other more up-to-date information, for example the renovation year of different heating sources. The ECB cautions that banks should ensure that if they use renovation as part of their proxy model, the renovation works must be extensive and not simply cosmetic.

Regardless of how banks estimate EPC data, the main challenge for them is still about 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 some simply don’t 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.

With respect to the good practices outlined in this area, it should be considered that, 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 big role to play in making measured progress to ensure that any heterogeneity or structural challenges that exist are mitigated in a timely manner.

Box 5
Commercial real estate sector

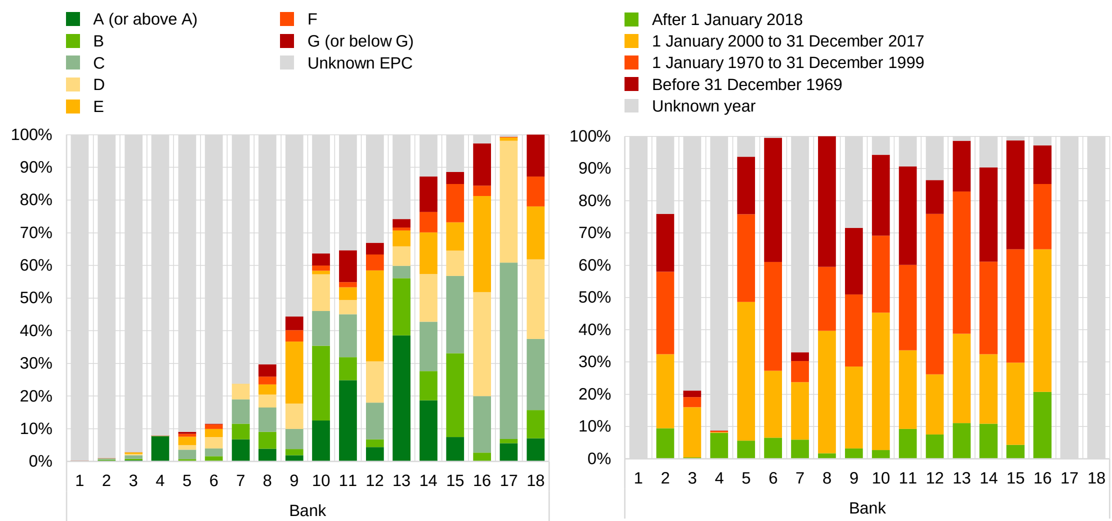
The ECB has performed a targeted review of the banks most exposed to the commercial real estate (CRE) sector and collected the breakdown of collateral located in the respective domestic countries by EPC and year of construction. By comparing the share of CRE buildings with the worst ratings and the share built before 1969, the high share of unknown EPC 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 as stand-alone, more challenging.

Another challenge faced by banks in providing data is that some asset classes in the commercial real estate 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. The ECB expects banks to collect real EPC data insofar as possible.

Chart A
Breakdown of CRE buildings by EPC rating (left panel) and year of construction (right panel)

(percentages)



Source: Commercial real estate targeted review.
Notes: Based on a sample of 18 SIs. Each institution is assigned the same number in both panels. Reference date: 30 June 2021.

3.3.2 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 do not estimate EPC or buy the proxy from external data providers, while a majority developed an internal methodology to estimate EPC. However, the methodology adopted by banks is heterogeneous and depends on several external factors, like the accessibility of public registers and the type of information collected.

The least robust approaches observed and adopted by around one 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 bank's portfolios, in some cases representing only 20%-40% real EPC data. The first approach in particular is considered poor practice because it 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 set of banks use a statistical model or machine-learning algorithm where more variables are taken into account as inputs, for example the 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 previously.

Therefore, as good practice, the ECB expects banks to collect real EPC data insofar as possible, by (i) requesting borrowers to provide such data at origination or when carrying out an annual review or modifying a loan, (ii) retrieving data from public registers when publicly accessible, and (iii) instructing the valuers to collect the EPC data as part of their collateral valuation review. This is expected in particular for commercial real estate, where predicted models are less accurate and data used as inputs are more difficult to collect.

For the EPC data that cannot be collected, the preferred good practice would be for banks to estimate, preferably using a sophisticated approach. 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 to ensure the model is adequate for the estimation of the EPC data. Another good practice observed was the detailed methodology and results presented 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, it is important that banks ensure that:

1. The sample is representative (in terms of size, regions represented in the sample, heterogeneity), so that the distribution is not skewed towards better EPC ratings. Moreover, it is key to consider in the bank's modelling the availability of information about the oldest buildings as they are expected to have the worst ratings, unless they have been renovated in the 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, like 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 are regularly assessing the adequacy and appropriateness of the data and modelling techniques being used and the outcomes of this assessment are being 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, from a supervisory perspective it is essential that when proxies are used, banks adopt risk-based practices leveraging on the good practices outlined above. In addition, as challenges reduce and banks make measured progress in resolving data gaps, the ECB expects the use of proxies to reduce over time and eventually become marginal in nature.

4 Integration of climate-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.

The approaches to climate stress testing should consider climate, macroeconomic, and sector and company-specific factors and hence differ 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, a first step that should be pursued is the integration of a sectoral and regional dimension, which should be complemented with counterparty granularity going forward. This is also consistent with Expectation 11 of the Guide which states that institutions are expected to conduct a tailored and in-depth review of their vulnerabilities through stress testing, for which institutions need to gather more granular data than for a regular stress test.

All these aspects are described in the following chapters.

The first main objective of developing relevant modelling approaches will not be 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 have in place a risk appetite framework (RAF) that considers all the material risks to which the institution is exposed.

4.1 Climate-related risk transmission to credit risk parameter

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 in 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 for which scope and granularity 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.

In order to measure adequately the impact of climate-related risk, banks should consider a broader range of variables. While sectoral GVA could be a starting point, along with the traditional stress testing variables, more climate-specific variables are needed to sufficiently capture the impact. Along with the macroeconomic impact calculation, direct transmission channels are essential for an appropriate risk assessment. Banks should start with the inclusion of the carbon price to account for the impact of climate-related risks in point-in-time (PiT) credit risk parameters. However, in order to achieve a satisfactory level of accuracy, additional variables, such as greenhouse gas emissions intensity, emission pathways and the development of energy sources should be included. In the good practices spectrum, 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 below. The incorporation of these transmission channels into the existing or newly developed models is described in the next chapter.

Table 4

Variables included in banks' climate risk-augmented credit risk models[18]

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)		

Source: Bank submissions.

18 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.

4.2 Modelling approaches identified

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

The ECB identified a tendency to combine existing stress test 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 developed models. Indirect channels of transmission are also covered through the adjustment and/or the development of satellite models, mostly by 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 ones (also considering the sectors) to climate-related risks.

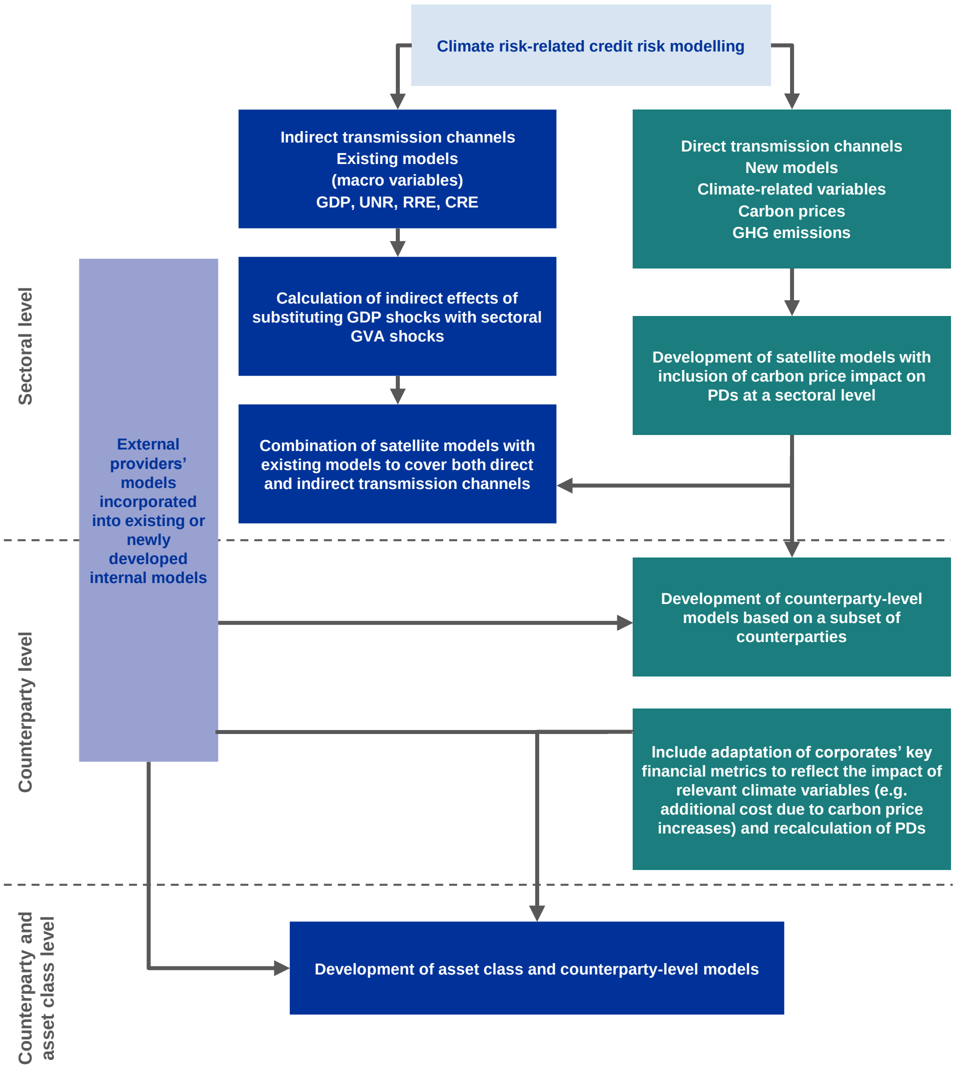
The counterparty-level modelling techniques used differ in terms of how advanced they are. Most banks use carbon prices as the main variable accounting for climate-related risks, as carbon prices are a key factor in translating transition policies into price implications. It should be noted that carbon prices should be used ideally at national level to account for the different policy ambitions among countries. In terms of good practice, a richer set of climate variables is preferable. Adequate 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 Scope 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 NFC 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 to integrate climate-related risk factors into the estimation of PDs is provided by Figure 5 below while related techniques are described in more detail in the next section.

4.2.1 Climate-related risk-adjusted probabilities of default

Figure 5

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



Sources: Bank submissions and ECB calculations.

Sectoral models

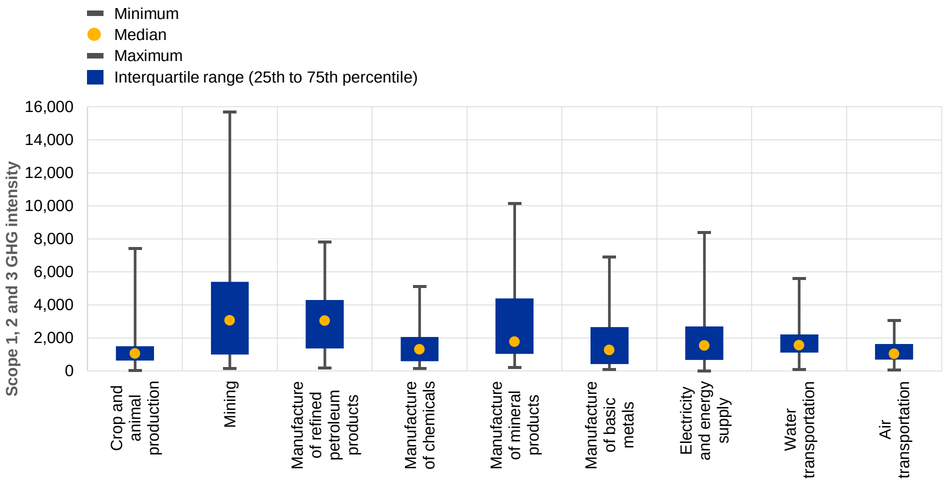
As a starting point and as an identified common practice, banks tried to capture transition risk implications at the sectoral level. Such developments are based on existing regular credit stress test infrastructure enhanced with additional components and breakdown (to sectoral level) to address the needs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

As an observed good practice, 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/customer-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 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 ECB 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.

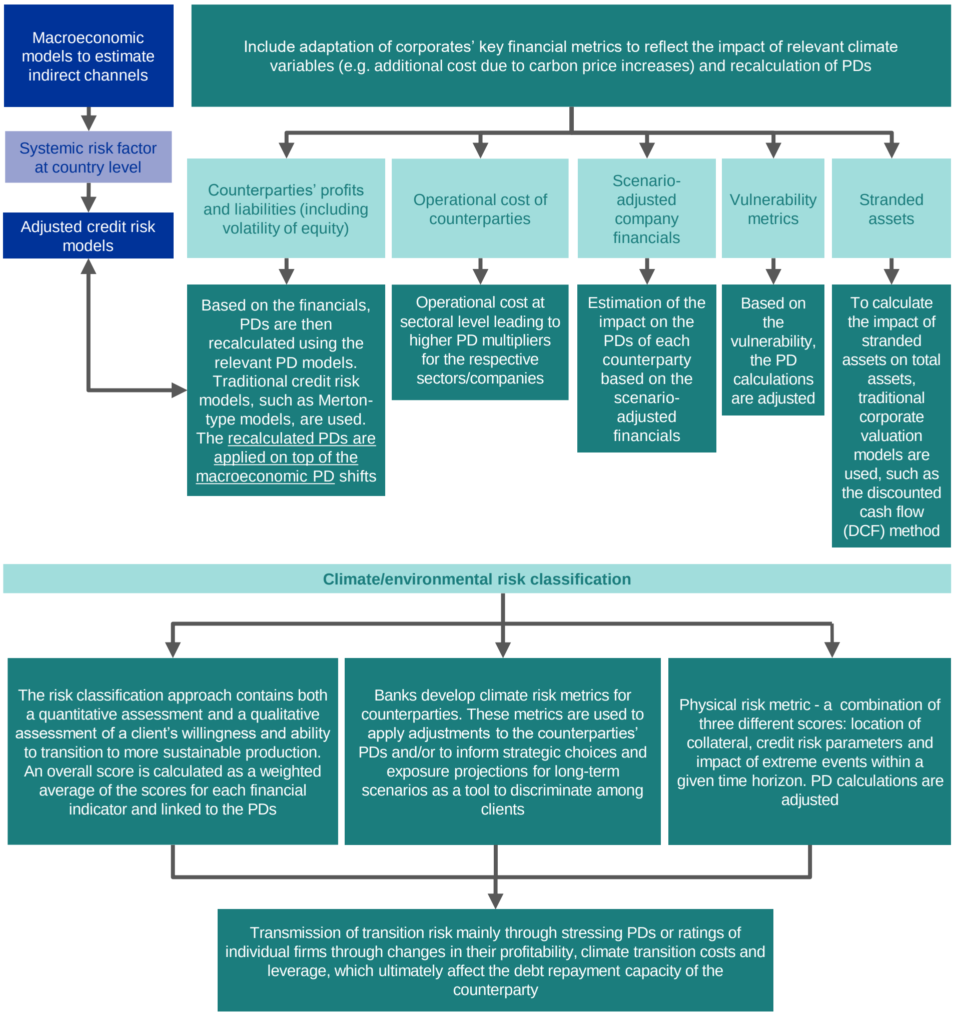
The combination of direct and indirect transmission channels differs depending on how advanced such models are based on the level of detail included. Relying on the combination of the impact of direct and indirect channels which results in the calculation of PD shifts, banks use a risk rating approach 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, banks should ensure that the models include information that matches their needs (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 (DR) and translate the projections of the climate-adjusted financial risk indicators into changes in DR and, ultimately, PD. This change is then applied on top of the PD impact estimated by the satellite model.

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

Summary – 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 of 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. Such 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 should be achieved by all institutions, at least for relevant and highly exposed counterparties, in order to ensure that the potential impact of the materialisation of transition and physical risks on the financial health of such counterparties is captured adequately. Hence further efforts are needed by banks to develop methods for counterparty-specific analysis.

Going forward, the development of counterparty-specific analysis should begin with vulnerable sectors, and a set of selection criteria should be developed 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 discriminate between clients, allowing consistent risk treatment across the bank, which is another good practice identified.

While such practices mostly consider transition risk, only a few banks consider physical risk in the design of climate risk metrics. Within those, the ECB observed the development of metrics for physical risk combining different elements. In particular, such a metric can be composed through the combination of three different scores, one related to the location of the collateral, one related to the credit risk parameters and finally one based on the impact of extreme events in a given time horizon. In this context it should be noted that the ECB expects banks to also account for relevant acute physical risk within their credit risk models, subject to the materiality assessments performed by the banks. More emphasis is put on capturing acute physical risk within the credit risk modelling approaches than chronic physical risk since the latter is usually captured through the macro-variables of the existing credit risk models.

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. With respect to the direct impact of higher carbon costs at counterparty level via increased operating costs, banks mostly consider Scope 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 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 in the orderly and disorderly scenarios and then compared to 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 environmental 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 into 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.

Asset class level modelling approach

Other good 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 are combining 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 to model 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.

At a more granular level, some banks use specific approaches to downgrade a customer's debt repayment ability, thereby affecting the PDs for such portfolios.

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

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 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.

An EPC breakdown of residential properties is included as an additional dimension in the calculation of the 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 form of usage of residential properties and the way the energy bills affect the 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.

The above approach is considered advanced at the current juncture. However, improvements in the accuracy as well as the granularity of the analysis/projections are expected going forward.

4.2.2 Climate-adjusted loss given default

While approaches are more common and more advanced for the transmission of climate-related risks to PDs, LGDs should also be considered a key parameter to capture 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, the ECB observed that some banks have developed capabilities to adjust their existing model, integrating at least the indirect transmission channels, while some banks also consider direct transmission channels to LGDs. 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 exercise that many banks are still at an early stage in terms of factoring climate-related risks into their credit risk models to estimate LGDs. 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 LGDs. In particular, banks should consider the carbon price impact on real estate values based on the EPC bucket, while 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.

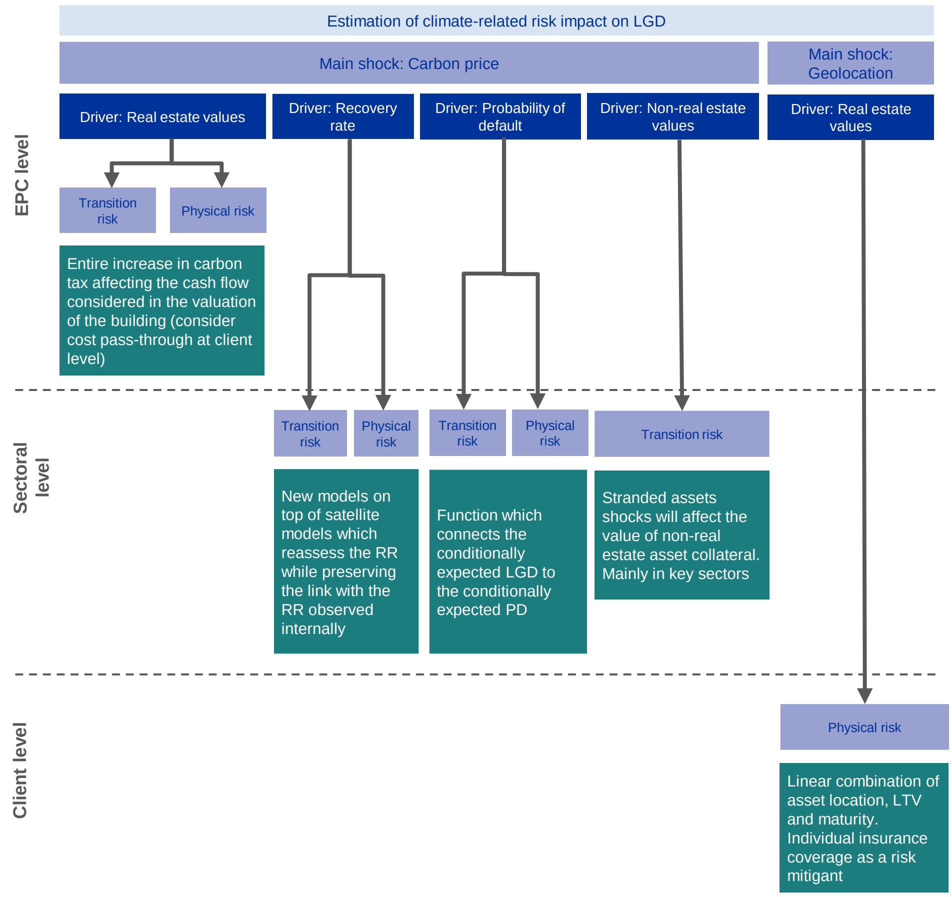
Among banks with advanced approaches, the ECB identified good practices relating to the development of a specific LGD model. Banks’ satellite models have been exploited to capture the indirect channels effects, while the impact stemming from the direct channel and the subsequent sector/customer-based adjustments were estimated, leveraging 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 PiT 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 (RRs). Moreover, to account for the adverse impact of sharply rising carbon prices as provided by the ECB in the disorderly transition scenario, 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 in the disorderly transition scenario, allowing consistent risk quantification, which is considered another good practice.

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 RRs 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 prices shocks provided by the ECB and historical realised LGD from back-test exercises. Finally, for unsecured exposure, the Frye-Jacobs formula is used to establish a correlation between estimated scenario-specific PD and LGD. While such approaches help to transmit the impact to LGDs, other good practices described in this section considering climate-specific variables seem preferable.

Regarding flood risk, some advanced banks have developed new models. For example, one bank defined a linear combination of three dimensions, which are a climate score (based on asset location), a solvency score (based on the LTV) and a maturity score (based on impact of flood risk over a time horizon), in order to consider a highly granular information to assess the impact on the exposure, while another bank with an advanced approach took into consideration the effect of private insurance coverage in the flood risk scenario. Based on country specifics, one bank assessed the percentage of insurance coverage with respect to the house price shock considering the probability of flood, stage and European Banking Authority (EBA) segment. Overall, such comprehensive approaches are considered good practices to transmit climate-related risks to LGDs.

Figure 7

Summary – Good practices to estimate climate-related risk impact on LGD



Source: Bank submissions.

4.3 Long-term modelling approaches

Banks also developed capabilities regarding long-term modelling approaches and integration of a dynamic balance sheet, consideration of banks' 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 the banks in terms of sophistication and progress. While the novelty and uncertainty surrounding long-term projections is 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 others 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 understands it as a good practice to perform the analysis at the most granular level when data are already available (e.g. large corporates) and, if not, to apply adequate extrapolation techniques (e.g. resembling the NACE/country/scenario approach) if 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, should be complemented with expert judgment at individual level, as some models do not include companies' transition plans or commitments and hence do not deliver a holistic picture. The ECB identified as a common practice that banks 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/in addition to the evolution of gross domestic product (GDP) for the whole economy for the growth/evolution of their exposures at the sectoral/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 rather short) in the 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. sectoral 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.

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

The ECB observed that some banks took simplified approaches in comparison to 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. Some 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.

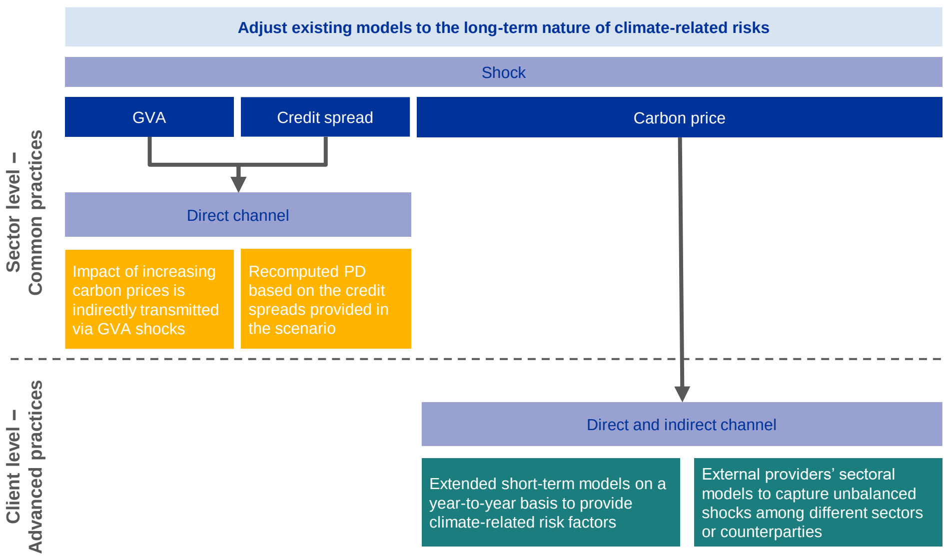
External models used by banks and already described in section 4.2.1 seem to be already equipped to project the long-term impact of climate-related risks on the credit risk parameter, in particular for corporate counterparties.

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 in 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 de-carbonisation 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 8

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



Source: Bank submissions.

4.3.2 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 has also been observed that banks are applying 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 should 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 which are based on economic pathways are adjusted to account for expectations on 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 environmental, social and governance (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 which is driven by the industry-specific GDP and would for example receive the label "maintain". For ESG relevant industries (without bank policies), banks should develop strategies depending on the level of physical and transition risk in 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 discriminate 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, 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 margin 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 mortgages 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 build 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 considers the regulatory environment for reallocation and additional assumptions, such as the appearance of green firms and the green switch process, or even enriching the long-term modelling with additional variables as a means to perform a more granular analysis (e.g. counterparty level and balance sheet reallocation).

4.4 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 the 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 lack of data. Banks should outline their assumptions on the role of private insurance/NCSs and, specifically, the insurance coverage needs to be 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.

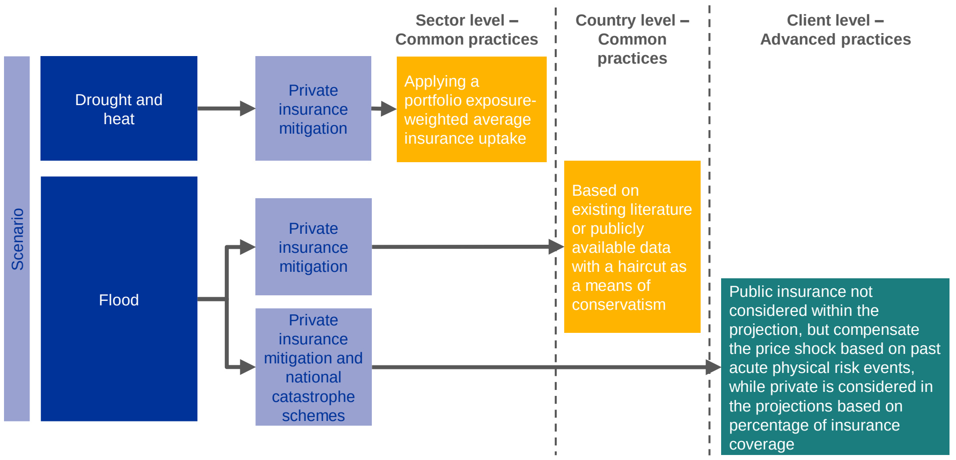
As a common practice in the flood scenario, banks provide projections without the NCS effects following the methodological note. The schemes are quite heterogenous between countries, but in order to estimate the impact of NCS, few banks assessed past acute physical risk events for the coverage provided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

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 have leveraged on external data providers to analyse in detail the private insurance coverage at flood risk area level. Thus, the insurance coverage has been 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 on the basis of the percentage of insurance coverage, providing the sufficient granularity for their analysis, as they were able to collect such data at loan level.

Banks should increase their efforts to gather relevant information at the most granular level possible and to build a consistent methodology to estimate the effects of such risk mitigants into their modelling.

Figure 9

Summary – Good practices to consider risk mitigants in bank's loss projections



Source: Bank submissions.

Conclusion

The ECB's 2022 climate stress test was a useful learning exercise for banks and supervisors and helped identify good practices which should serve the industry in advancing in their climate stress testing capabilities and further aligning with supervisory expectations. It acted as a catalyst to strengthen banks' efforts to develop climate stress test frameworks in line with the expectations set out in the ECB Guide on climate-related and environmental risks. The exercise showed that banks have made considerable progress in their climate stress testing capabilities, despite its innovative and pioneering features. At the same time, it also revealed numerous deficiencies, data gaps and inconsistencies between institutions in terms of data sources, estimation methodologies and quantification of the impact of climate-related risks on their exposures. Conversely, institutions with exposures in areas vulnerable to physical risks or to counterparties with high transition risks, as well as institutions located in countries for which national climate stress testing exercises have already been conducted, are among the most advanced groups of institutions in this regard.

The ECB finds that institutions that are more advanced in their data sourcing approaches and estimation methodologies for climate data are also more advanced with respect to quantifying the impact of climate-related risk on their exposures. This finding is supported by the significant overlap of institutions with advanced approaches identified in these two areas, indicating that they are also more aware of relevant challenges and are already making efforts to overcome them. In many cases, credit risk parameters projected by banks were found to be insensitive to the climate risk shocks depicted in the scenarios. Observed good practices mainly focus on transition risk and the transmission to probability of default, while only a few institutions have already developed approaches to quantify the impact of transition risk on loss given default. It seems that there has been less progress with respect to the integration of physical risk into credit risk models and hence this is another key area identified by the ECB in which banks need to step up their efforts.

Climate and environmental risks will remain key priorities of the ECB and other European authorities and banks are expected to be able to properly manage their climate and environmental risks by the end of 2024. Hence banks have to continue their efforts to significantly improve their climate stress testing framework and analytical capabilities to assess climate-related risks. This is necessary to reduce the risks of mispricing lending decisions, misallocating resources and overpricing collateral and to allow adequate quantification of climate-related risks under various outcomes and materialisation of events. Over time, climate and environmental risks should be treated like any other risk faced by banks and fully integrated into prudential risk categories (credit, market and operational risks, business model and strategy) and, more broadly, into capital and recovery planning.

Customer relationships will remain key to continuing to close data gaps over the next years. It is important that banks engage with their customers in order to also foster the necessary change in the real economy. The assessment of customers' transition plans is key to managing climate-related and environmental risks. As observed in the review of good practices, some banks are moving in this direction, but it has to be common practice for the whole industry with climate-relevant exposures. Going forward, future supervisory initiatives might entail more qualitative analysis of banks' transition planning using scientific pathways (e.g. using NGFS scenarios) to assess the alignment of their portfolios with the Paris Agreement on climate change.

The ECB observed that banks have developed capabilities to achieve long-term loss projections but at different speeds. Given the long-term nature of climate-related risks and the transition plans of banks and their clients to adjust to different pathways, expanding the projection horizon beyond those used in traditional stress testing exercises will remain a key feature going forward. Hence, as part of their internal CST frameworks and internal climate stress testing activities, the ECB expects institutions to extend their modelling capabilities to a longer time horizon to be able to quantify long-term climate-related risks and to review results against their climate strategy and risk appetite.

Supervisory climate stress testing will remain a key tool to assess the vulnerability of banks to climate-related risks but also the progress banks make over the next two years. Hence the ECB expects banks to step up their efforts in all the areas covered in this report. While this report focuses on modelling approaches for those asset classes in scope of the 2022 ECB CST, the ECB expects institutions to develop methodologies for all asset classes in which institutions have significant exposures vulnerable to climate-related risks. Regarding the development of respective methodologies and meaningful climate scenarios from the supervisory side, collaboration with the industry will be critical going forward. As significant improvements are expected in terms of data availability and quality as well as in terms of modelling capabilities, more stringent quality assurance can be expected in future exercises.

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 1.

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, fee and commission income from, as well as 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 Scope 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 customers within the scope of the exercise may have found it easier to engage directly with customers 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 performed was based on observed changes in PD in 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) in the different long-term scenarios were evaluated. Finally, the description of the credit risk parameters for every 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.

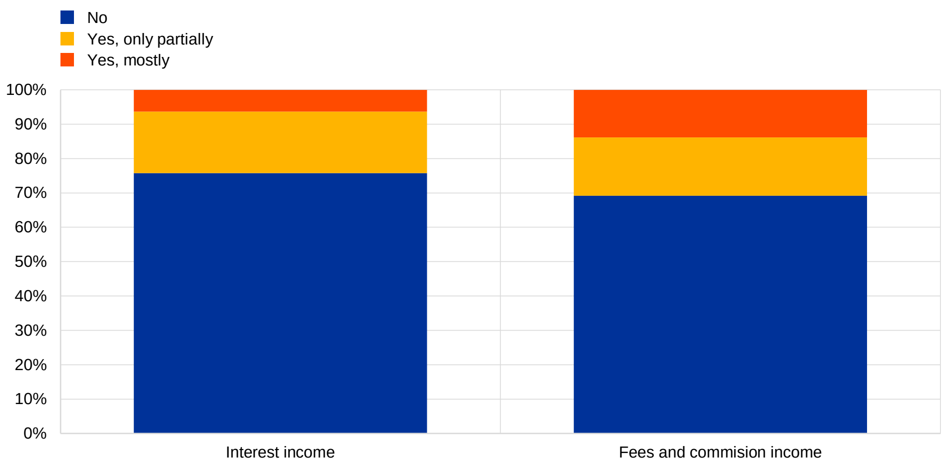
A.2 Insights on topical analysis of participating institutions

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)



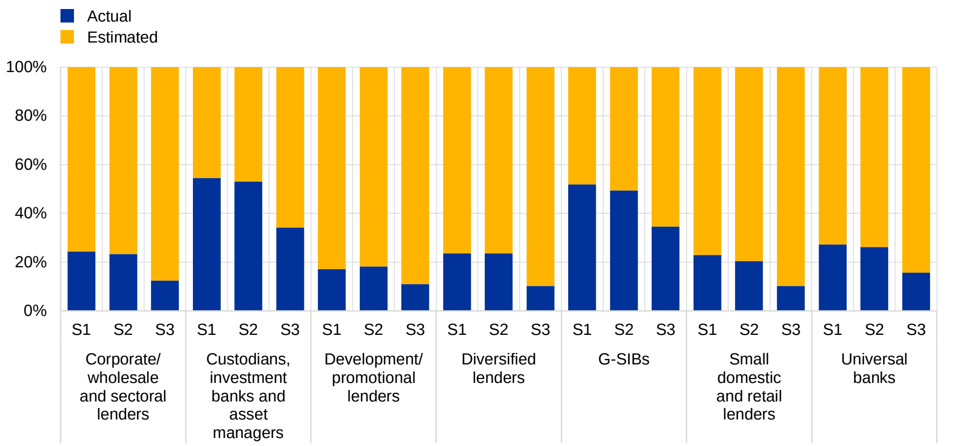
Sources: Bank submissions and ECB calculations.

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, G-SIBs and universal banks reported the highest percentages of actual data (Chart A2).

Chart A2

Actual versus estimated emissions by business model

(percentage shares)



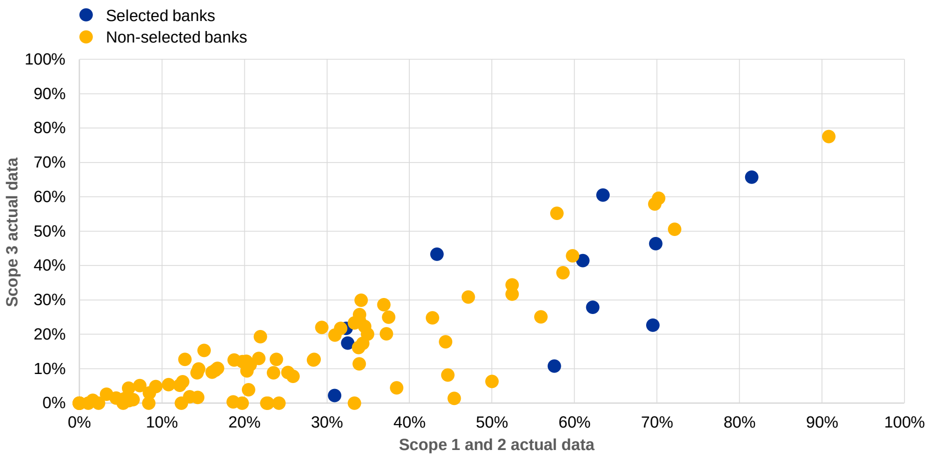
Sources: Bank submissions and ECB calculations.

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)



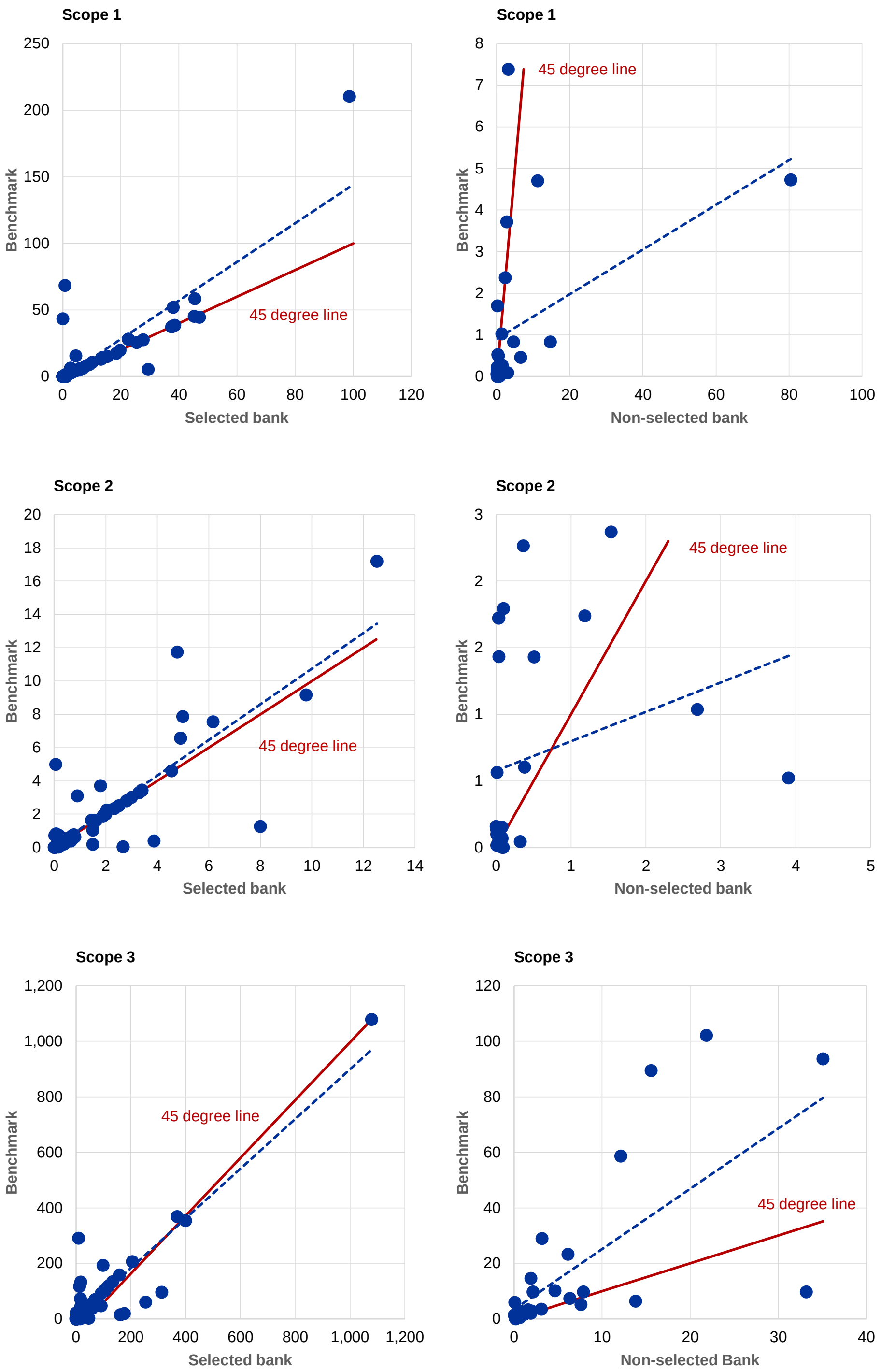
Sources: Bank submissions and ECB calculations.

For the estimation of missing emissions data and comparison with the benchmark source, Register of Institutions and Affiliates Data (RIAD) 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 (S1, S2 and S3), 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, tCO_2e millions)



Sources: Bank submissions and benchmark data.
The axes show the emissions data in tCO_2e 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.

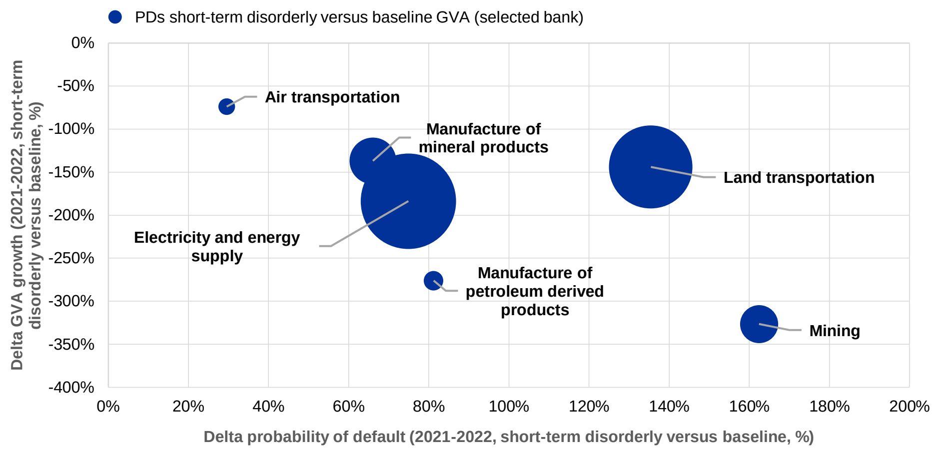
Owing to the limited coverage achieved with this approach, expert assessment of the quality assurance of the banks' submissions was also considered to identify the most advanced banks, while respecting the characteristics of each business model. Hence the final sample resulted from the combination of 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)[19]

(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.

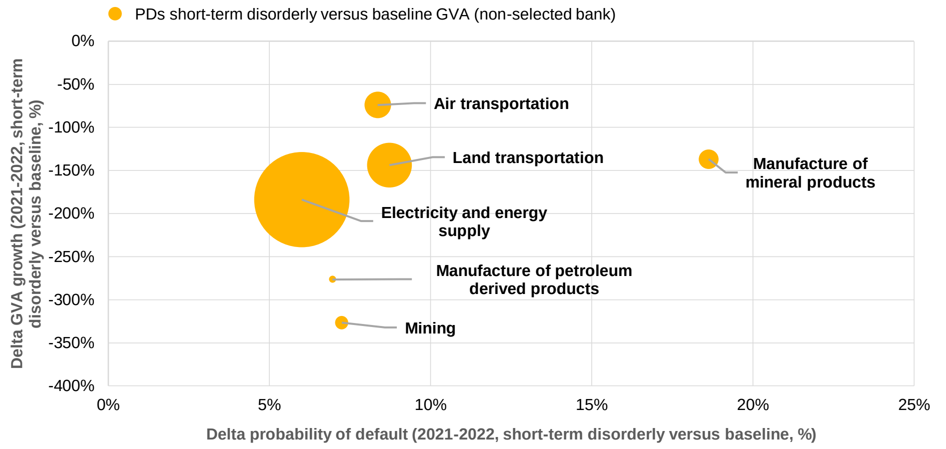
Chart A5 indicates sensible PD estimations for the respective GVA growth (from 20% to 160%) and consistency with the emissions intensity of sectors. The linearity criterion is also fulfilled since PD increases when GVA decreases.

19 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 of sectoral PDs observed at around 160%.

Chart A6

Non-selected banks' sectoral changes in PD and GVA growth (short-term disorderly versus baseline)[20]

(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.

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.

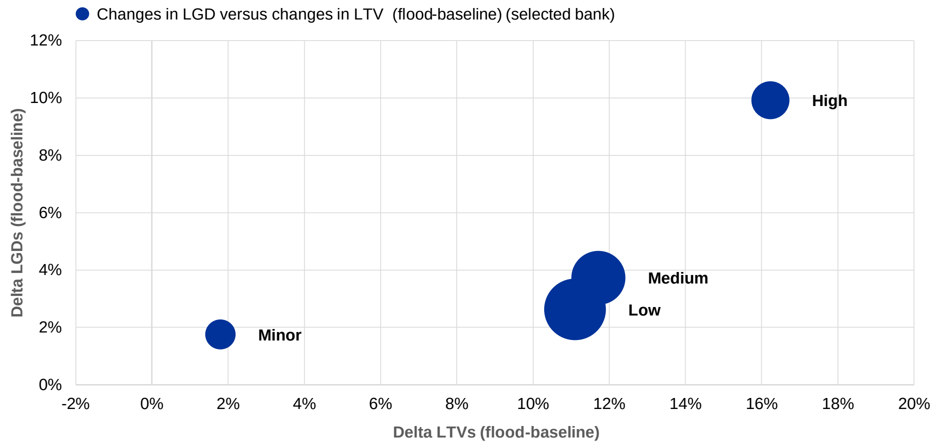
For the flood risk scenario, the selection of banks was based on the transmission of the respective physical risk to LGDs. To extract the respective results, bubble charts were compiled showing changes in LGD along with the changes in LTV for the respective exposures. Charts A7 and A8 illustrate the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

20 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.

Chart A7

Selected banks' changes in LGD and LTV by risk region (flood risk scenario versus baseline)[21]

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

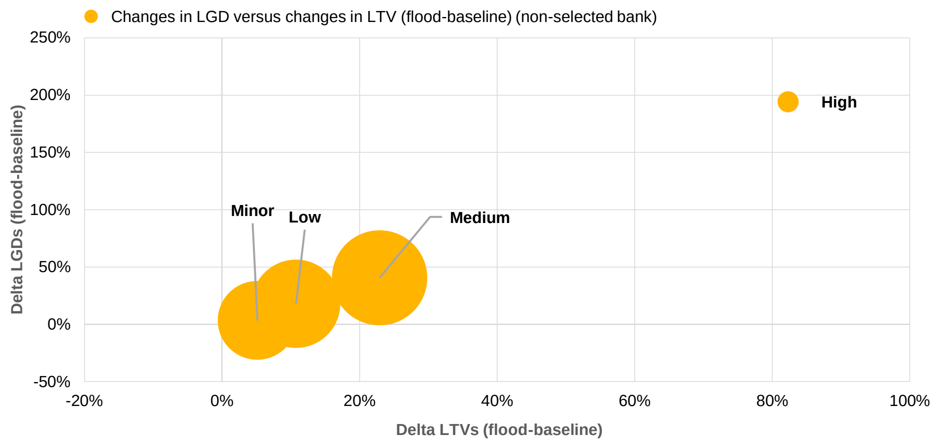


Sources: Bank submissions and ECB calculations.
Note: LGDs are weighted based on total exposures.

Chart A8

Non-selected banks' changes in LGD and LTV by risk region (flood risk scenario versus baseline)[22]

(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

[21] The chart indicates that the order of magnitude in terms of increases in LTV 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.

[22] The chart indicates that the order of magnitude in terms of increases in LTV 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 stress test
DCF	Discounted cash flow
DR	Default rate
EBA	European Banking Authority
TEG	Technical Expert Group on Sustainable Finance
ECB	European Central Bank
EEIO	Environmentally extended input-output
EPC	Energy performance certificates
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
ISS	Institutional shareholder services
IT	Information technology
k-NN	K-nearest neighbours
KPIs	Key performance indicators
LGD	Loss given default
LTV	Loan-to-value
NACE	European Classification of Economic Activities in the European Community
NCS	National compensation schemes
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
PiT	Point-in-time
RIAD	Register of Institutions and Affiliates Data
RR	Recovery rate
RRE	Residential real estate
SIs	Significant institutions
SME	Small and medium sized enterprises
ST	Stress test
UNEP FI	United Nations Environment Programme Finance Initiative
UNR	Unemployment rate

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

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