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Contents

Abstract

Climate change entails risks to the global economy and impacts financial stability. Beyond managing related risks, the financial sector can also contribute to the transition toward a net-zero economy. Guided by the ECB's climate and nature plan[1], this paper discusses the methodology and key findings of statistical indicators developed in three areas: sustainable finance, carbon emissions, and physical risk. Our work aims to enhance data transparency in climate change analysis, while informing monetary policy, financial stability and banking supervision.

The indicators we have developed focus on the euro area financial sector and are built from harmonised granular datasets. They also utilise climate information from public sources to the extent possible.

The sustainable finance metrics are built on well-established securities statistics and are at a more mature stage of development when compared with the other two climate risk indicators. While there are several data gaps that need to be addressed, the proposed statistical methodology offers a valuable framework for assessing climate risks in the European context, ensuring comparability across countries, time frames and under various climate scenarios. Meanwhile, the sustainable finance indicators track issuances and holdings of sustainable debt securities in the euro area, thus providing insights on funds for sustainable projects and reflecting progress in the transition towards a net-zero economy.

The carbon emission indicators study the financial sector's exposure to counterparties with carbon-intensive business models and the carbon intensity of the securities and loans portfolio. They are useful to assist in evaluating the sector's contribution to financing the transition to a net-zero economy and the associated risks. Several methodological improvements are detailed in this paper to make it easier to interpret the indicators over time and understand the trends: imputation strategies for emission and financial data, a novel balancing algorithm that accounts for changes in the composition of the underlying non-financial corporations over time, adjustments for inflation and exchange rates, and a time series decomposition.

Meanwhile, the physical risk indicators evaluate the impact of climate change-induced natural hazards on the performance of financial institutions' loan and securities portfolio. The metrics cover a range of acute and chronic hazards, presenting risk scores and expected losses, enabling historical baselines to be benchmarked with climate scenarios where data permit. From the financial side, the framework we present accounts for maturities of the loan portfolios and the collateral pledged, as well as national insurance practices, thus providing a comprehensive risk assessment.

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1 See https://www.ecb.europa.eu/ecb/climate/our-climate-and-nature-plan/html/index.en.html.

This paper discusses the methodology, underlying data, and findings for each set of indicators, while also flagging possible constraints and opportunities for future development.

Keywords: Statistical methodology, sustainable finance, climate change, carbon footprint, emissions, physical risk, data gaps.

JEL codes: Q51, Q54, Q59

1 Introduction and key methodological aspects of the indicators

"[C]limate-related and environmental risks warrant special attention owing to their size, global dimension and non-linearity, the irreversible nature of the damage they can cause, the resulting time criticality of action, as well as knowledge and data gaps."[2] This statement made by Isabel Schnabel, member of the Executive Board of the European Central Bank (ECB), underscores the critical importance of data on climate-related risk in guiding decision-making with the aim of navigating the transition to a carbon-neutral economy. In 2021, the Governing Council of the ECB established a comprehensive action plan to achieve a more complete integration of climate change considerations into its monetary policy strategy. The action plan includes, among others, measures to set up and expand climate change-related statistics to strengthen the analytical capabilities in this area. Following the action plan, the ECB and national central banks have collaboratively initiated the development of harmonised statistical indicators at the euro area level for climate-related analysis. The first set of indicators was released in January 2023.[3] Following the developments in climate modelling and data reporting, the indicators are expected to undergo regular updates and enhancements, incorporating refined methodologies and additional data sources as they become available. The regular expansion and release of updated climate-related indicators are outlined in the Climate and nature plan 2024-2025. This paper accompanies the second release of the climate-related indicators and aims to provide insights into the methodological challenges involved in constructing such indicators and the choices that were made in dealing with these challenges, give a comprehensive overview of the core findings that can be derived from the indicators, focusing on how the methodological choices made affect the final outcomes, and offer suggestions for further improvement. In doing so, the paper provides maximum transparency for users of these statistics, but may also be helpful to other actors, including in the financial sector, who are constructing their own measures, potentially benefitting from data sources that were not accessible to European System of Central Banks (ESCB) statisticians.

Following the priorities set by the Governing Council to best meet the data needs for monetary policy, financial stability and banking supervision purposes, this paper discusses three sets of statistical indicators. Firstly, the indicators track the trend in green finance, which can allow us to shift towards more a sustainable economy, while also quantifying the impact of climate-related risks for the financial sector. Secondly, from the risk perspective, carbon emission indicators gauge the progress in reducing emissions to meet environmental goals, while physical risk indicators evaluate the impact we are already witnessing and that can intensify further under

2 See Schnabel, I., "What is special about climate-related and environmental risks?"; introductory remarks at the legal conference organised by the European Central Bank on "The incorporation of environmental considerations in the supervision of prudential risks", Frankfurt am Main, 5 September 2023.

3 ECB press release, "ECB publishes new climate-related statistical indicators to narrow climate data gap", January 2023.

the various climate change scenarios. The indicators are constructed using a multitude of ESCB cross-country granular micro-level datasets, while ensuring factors such as confidentiality, replicability and representativeness. By using data from the ESCB or publicly accessible sources, reliance on proprietary data has been kept low, to ensure the accessibility of the composite indicators and uphold transparency regarding the underlying methodology. A notable advantage of these indicators is that their compilation adheres to a harmonised approach, enabling consistent comparisons across euro area countries. The following statistical indicators have been compiled to provide insights for monetary policy, financial stability and banking supervision.

Sustainable finance indicators

The first set of indicators cover sustainable finance and provide insights into the issuance and holding of debt instruments with "green" or "sustainable" characteristics by residents in the euro area. These indicators provide information on the proceeds raised to finance sustainable projects, including those that may help in the transition to a net-zero economy. The indicators highlight the growing size of financing and investments with a green and sustainable label in the euro area. Despite this increase, the relevance and size of sustainable debt within the overall debt securities market so far remains minor (the outstanding amount of sustainable debt securities issued or held accounted for slightly more than 6% of the outstanding amount of all debt securities issued or held in the euro area at the end of 2023).

In addition to the indicators first published in January 2023, which consider all sustainable debt securities, including also only self-labelled instruments, new indicators were released in November 2023[4]. As described in this paper, these more detailed indicators provide further information on the level of assurance, distinguishing, within the full universe of the sustainable debt securities market, only those securities that have been externally reviewed with a second party opinion. They show that euro area issuers are addressing the growing demand for an external review as to the alignment of their sustainable bonds with international standards and the expected contribution of the financed projects to quantified sustainable outcomes.

All relevant standards/frameworks are taken into account to assess the sustainability classification of the sustainable debt security. Additional aggregates based on specific standards, particularly the European green bond standard (EUGBS), will be considered in a future update to this publication.

Carbon emission indicators

Carbon emission indicators describe the carbon emissions associated with the corporate securities and loan portfolios of financial institutions to assess both the financial sector's role in the transition to a net-zero economy, as well as the

[4] See ECB Data Portal for sustainable finance indicators on issues and ECB Data Portal for sustainable finance indicators on holdings.

associated transition risks for the sector itself in terms of its exposure to carbon-intensive counterparties.

Two geographical scopes were considered when constructing the carbon emissions indicators, following distinct user demands. This means that certain indicators are restricted to local (i.e. national or euro area) emissions to allow for analyses from a financing perspective: how much of euro area non-financial corporations' (local) emissions are "financed" via loans. Meanwhile, other indicators have been created to analyse global emissions, at corporate level, in the loan and securities portfolio of financial institutions, thus allowing us to analyse global emissions of the euro area financial sector.

Constructing carbon emission indicators that can be meaningfully interpreted across counties, as well as over time, poses severe methodological and data challenges, including, first and foremost, a lack of data: coverage of emissions data (and to a lesser extent, financial information also) is low and varying. In addition, comparisons over time must adequately account for price and exchange rate effects, as well as changes in the composition of the underlying non-financial corporations over time. To address these challenges, the first step was to increase data coverage substantially by employing novel imputation methods regarding carbon emission and financial data. Most notably, the introduced imputation increased average[5] indicator coverage from 47% to 85% of outstanding debt in the case of certain indicators for the loan portfolio. However, it is important to acknowledge that the applied imputation approaches are relatively simple and are still a work in progress. They therefore carry the risk of measurement error and are subject to substantial uncertainty. Second, to enhance the level of accuracy in comparing relative carbon indicators between countries and over time, the indicators have been adjusted to account for price and exchange rate effects by constructing exchange rates and sector and country-specific deflators that isolate changes in quantity from price fluctuations. This is a common approach in many macroeconomic statistics, but is an important novelty when analysing carbon footprint indicators. Third, a balancing approach is incorporated to accommodate compositional changes over time. The balancing aims to smooth the composition with respect to missing data while allowing investment and divestment decisions to influence the results. Moreover, to allow for more meaningful interpretations of changes in the indicators over time, a decomposition is introduced to distinguish between, among other aspects, decarbonisation of the underlying assets and alterations in carbon footprints resulting from investment decisions. The decomposition, along with the adjustment for sample composition, facilitates ceteris paribus analyses of the indicator in relation to emission changes.

To keep the dependence on proprietary data low, single entity carbon emission indicators are compiled using financial data inferred from the internal ESCB Register of Institutions and Affiliates Data (RIAD).

Future work is expected to result in updates to the carbon emissions indicators, driven by further methodological improvements and the inclusion of additional data.

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[5] Average indicator coverage is calculated in the euro area over the studied time frame.

These future methodological enhancements will focus on refining current imputation strategies and aim to introduce new ones to improve coverage and facilitate even more meaningful comparisons across countries and over time. Special emphasis will be placed on attempting to impute Scope 2 emissions associated with bank loans by utilising Input-Output (I/O) tables. Meanwhile, further efforts will be made to refine the time series decomposition. Contingent on data availability and quality, forward-looking emissions indicators and Scope 3 emissions will be explored. Additionally, consideration will be given to broaden the scope of reported exposures to central banks, along with the potential inclusion of sovereign and supranational bonds, as well as mortgages as instruments.

When analysing the carbon emission indicators on the euro area aggregate level, the following key findings emerge: we find that the methodological and data enhancements described above lead to an overall smoothing of the time series. The carbon emission indicators on Scope 1 emissions of bank loan portfolios (studied at single entity-level) show a downward trend over the studied time frame from 2018 to 2021. As for the securities portfolio (when studied at group-level), the relative indicators on Scope 1 and 2 emissions largely exhibit a downward trend as well, albeit less pronounced compared with the loan portfolio. In contrast, the financed emission indicator on the securities portfolio shows an upwards trend over the studied time frame for Scope 1 emissions and a stable dynamic for Scope 2 emissions. These findings align with the notion that banks' initiatives to address transition risks have in part led to reduced exposures to high-emitting economic activities, though substantial heterogeneity exists across holder/creditor country and issuer/debtor sector figures. A decomposition of the financed emission indicators for the loan portfolio reveals that the downward trend is primarily driven by emission reductions, while in the case of the securities portfolio, investment decisions play a more important role. In general, the decomposition proves valuable for uncovering dynamics within indicator components, shedding light on anomalies in the microdata and highlighting the sensitivity of these indicators to changes in financial components.

Physical risk indicators

The third set of indicators measures exposures of financial institutions to physical risks stemming from catastrophes, such as floods, windstorms and wildfires, and chronic phenomena, like heat and water stress.

The process of compiling the indicators involves several steps. First, different types of risk are identified at specific locations, based on geospatial data. The potential impact is calculated for individual entities as scores ranging from low- to high-risk and, if additional financial and vulnerability data are available, also in terms of potential monetary damage. Second, those risk scores and expected losses are calculated for companies that are counterparties of financial institutions, and aggregated to the sector and country level. Lastly, risk mitigation strategies, such as collateral and insurance, are incorporated to reflect possible reductions in the financial consequences of exposures to physical risks.

Like the carbon indicators, the main focus is on risks incorporated in the portfolios of euro area financial institutions via their lending to non-financial corporations. However, the developed framework can also be applied more broadly, such as to the entire corporate sector of the economy or to physical risk exposures of individual banks. At the same time, it should be noted that the methodology is at an early stage and is applied without accounting for potential risk amplification within the financial system. In addition, the underlying climate data and scenarios are similarly characterised by uncertainties.

The current methodology incorporates solutions for a number of key challenges, affecting both the climate-related and financial dimensions of the indicators. With respect to hazard information, we mostly rely on established public datasets and modelling conducted by climate experts, as well as methods developed for the purposes of disaster risk management. However, for windstorms and wildfires, the models were enhanced by ESCB statisticians to fit the purpose of the statistical indicators. For several hazards (flooding, water stress, wildfire, drought), the baseline indicators computed on historical data are accompanied by the future projections under different climate scenarios and time horizons.

In the case of risks associated with floods and windstorms, the indicators are presented to show both expected annual losses and losses over the entire maturity of a loan instrument. The collateral pledged against the loans is also factored in to the evaluation to account for mitigation against potential losses, while recognising that the collateral itself is subject to physical risk and could decrease in value. Finally, insurance coverage was incorporated for certain risks.

Exposure to physical risk among financial institutions, as examined in this paper, largely mirrors the geographical distribution of hazards. For temperature- and precipitation-related hazards, the outcomes derived for an adverse climate scenario indicate an escalated risk compared to the baseline. While climate adaptation strategies will certainly play a crucial role in the future, current data on these measures are largely limited to flood protection. While the existing defences demonstrate high effectiveness in reducing flood risk, without continuous investment they may become inadequate to cope with the anticipated intensification of floods. In terms of minimising financial losses, collateral pledged against loans and insurance coverage serve as robust mitigating factors. However, national practices do vary, which significantly influences country risk profiles.

Many challenges remain and should be the subject of further work. Notably, the current indicators do not take into account the compounded effects of co-occurring or cascading hazards, like flooding and landslides[6], which often result in greater overall damage than each event individually. Accurately predicting such compound events is difficult, due to their dynamic and interacting nature. Additionally, expected loss-based indicators fail to capture secondary effects, such as business disruptions and spillovers in the supply chain, as well as broader economic risks, such as an overall reduction in labour productivity due to heat stress. Lastly, the risk

[6] For example, heavy rainfall – often associated with flooding – can also trigger landslides when saturated soil loses its stability in elevated areas with steep slopes.

assessment relies on a company's registered address, while precise information on the exact location of production plants and other key facilities would also be necessary in order to reliably identify the physical risk. European statisticians are currently working to close this data gap by exploring national sources of location information on businesses. More broadly, continued enhancements of climate models, and improvements in the quality and coverage of relevant data sources will be incorporated in future releases.

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The climate-related statistical indicators vary in their level of maturity. The sustainable finance indicators are currently classified as experimental statistics since they align with many (if not all) official ECB statistics quality requirements.[7] In contrast, the carbon emission and physical risk indicators are accompanied by more substantial caveats and limitations, as discussed in this paper. Consequently, they are released as analytical indicators, explicitly signalling the disparity in quality.

In the following sections we provide an overview on the common methodology and underlying data, explain each set of climate-related statistical indicators in detail and present key aggregate results, emphasising prevailing limitations and areas for future development.

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7 For a detailed description of this classification, please refer to the ECB's website.

2 Common methodological framework for indicators and data sources for financial information

Sustainable finance indicators

The indicators on issuances and holdings of sustainable debt securities are compiled exclusively using granular data obtained from official ESCB data sources, namely the Centralised Securities Database[8] (CSDB) and Securities Holdings Statistics (SHS). Meanwhile, the indicators on issuances of sustainable debt securities are integrated in the existing CSDB Securities Issues Statistics[9] (CSEC) dataset, whereas the indicators on the holdings of sustainable debt securities are part of the Securities Holdings Statistics by Sector[10] (SHSS) dataset.

Carbon emission and physical risk indicators

The carbon emission and physical risk indicators allow for the study of climate-related risk in the euro area financial system by monitoring bank loans as well as the securities portfolios of different types of financial institutions (banks, investment funds, insurance corporations and pension funds). Due to data availability issues, currently the statistics cover only exposures towards non-financial companies.[11]

For an overview of which micro-level datasets are used in a bottom-up approach to compile the physical and transition risk indicators, please refer to **Figure 1**. The loan

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8 The Centralised Securities Database (CSDB) is a fully automated, multi-sourced (commercial data providers, national central banks, and internal ECB sources) system that holds complete, accurate, consistent and up-to-date information on reference, price and ratings data on individual securities and their issuers. The data quality framework is based on Guideline ECB/2022/25 on the CSDB and the production of securities issues statistics, which is complemented by Recommendation ECB/2022/26 on the CSDB and the production of securities issues statistics.

9 The CSDB Securities Issues Statistics (CSEC) is a statistical dataset that covers the monthly issuance of debt securities and listed shares with an ISIN code by euro area and non-euro area EU residents, following the European System of National and Regional Accounts (ESA 2010) classification system. The data are compiled on the basis of Guideline ECB/2022/25 on the CSDB and the production of securities issues statistics, which is complemented by Recommendation ECB/2022/26 on the CSDB and the production of securities issues statistics.

10 The Securities Holdings Statistics by Sector (SHSS) data, collected on a security-by-security basis, provide aggregate information on securities held by selected categories of euro area investors, broken down by instrument type, holder country and further classifications, following the European System of National and Regional Accounts (ESA 2010) classification system. Holdings data are collected on a security-by-security level based on Regulation ECB/2012/24 concerning statistics on holdings of securities and compiled on the basis of Guideline ECB/2013/7 concerning statistics on holdings of securities.

11 The loan portfolio of financial institutions is analysed by using individual loan-level data retrieved from AnaCredit on loans from deposit-taking corporations except central banks (S122) to euro area non-financial corporations (S11). The securities portfolio covers euro area holdings of debt securities and listed shares from the SHSS database. The classification coding system used here relies on the European System of Accounts (ESA) standard. See "European system of accounts – ESA 2010", Eurostat, 2013.

and securities portfolios of financial institutions are inferred from AnaCredit[12] and SHSS, respectively. Company identifiers and address information[13] used to establish physical risk exposure are obtained from the Register of Institutions and Affiliates Data (RIAD)[14], thus making RIAD essential for linking climate information tailored to each set of indicators with financial datasets. It is also used to obtain financial information on single-entity debtors and – in case of physical risk – issuers as well. Any missing financial data is imputed as described in Section 3.2.2. RIAD also contains information describing relationships between units, thus allowing us to model corporate group structures. For group-based indicators, RIAD is used to specify whether a debtor or issuer is a group head, group member, or single entity. To retrieve RIAD information on the security issuer, SHSS is linked with RIAD using the CSDB.[15] For group-level carbon indicators, financial information is taken from ISS (a commercial data provider) and missing data is imputed as described in Section 3.2.2.

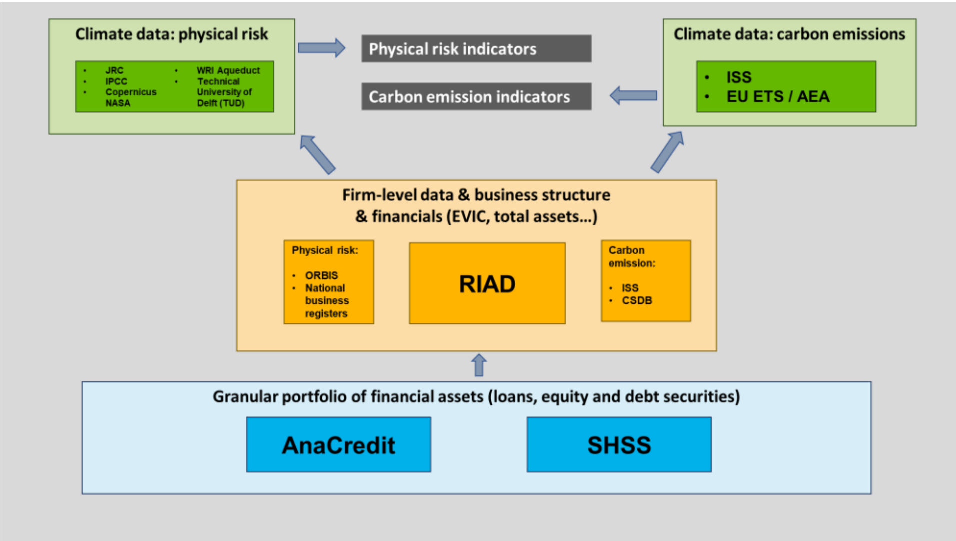
[12] Analytical credit datasets (AnaCredit) provide information on individual bank loans in the euro area, collected under Regulation (EU) 2016/867 on the collection of granular credit and credit risk data (ECB/2016/13), and complemented by ECB/2017/38 on the procedures for the collection of AnaCredit data from NCBs.

[13] Coverage of counterparty addresses in RIAD is almost complete. However, specific address attributes, such as the country, city, postal code, street and house number, are reported with varying levels of quality. Georeferencing tools, such as OpenStreetMap, used to translate address information to latitude and longitude, can also suffer from low coverage and inconsistencies. These elements collectively influence the precision of the geocoding employed in this paper. For details on the implementation of the geocoding, please see Franke, J., Aurouet, D. and Osiewicz, M., "Geocoding millions of addresses in a reproducible manner for Big Data Climate Risk analysis", Conference on New Techniques and Technologies for Statistics, 2023.

[14] The Register of Institutions and Affiliates Data (RIAD) serves as the central master data system within the ESCB. It provides reference information (e.g. name, address, legal form, institutional sector) on various types of organisational units, such as legal entities and branches, and on group-level relationships between parent companies and subsidiaries. Further information can be found here.

[15] SHSS data are linked with the CSDB using the International Securities Identification Number (ISIN), while the RIAD identifier is used to link the CSDB with RIAD.

Figure 1
Overview of data sources used to compile carbon emission and physical risk indicators



Notes: ISS is a commercial data provider offering carbon emission information at company level. EU ETS denotes the European Emission Trading System and AEA the Eurostat Air Emissions Accounts. JRC: Joint Research Centre. IPCC: Intergovernmental Panel on Climate Change. WRI: World Research Institute. RIAD: Register of Institutions and Affiliates Data.

The carbon emission indicators were calculated using two complementary approaches regarding the level of counterparty consolidation: (i) the residency principle, using financial information and emissions data at single entity level restricted to euro area non-financial corporations; and (ii) consolidation at group level, encompassing the whole group and with a global perimeter for financial data and emissions information. For loan portfolios, both entity-level (local) emissions of euro area non-financial corporations, and consolidated group-level (global)[16] emissions of global non-financial corporations are compiled, while for securities portfolios, only consolidated group-level (global) emissions are included.

The physical risk indicators are presented exclusively at the single entity-level. Consolidation at group level requires assumptions on risk sharing within a group, and good coverage of the debtor's accounting data, such as revenues or total assets, to distribute potential losses across the group structure. There are still outstanding quality issues with firm level data, as well as with the group structure itself. Unlike emissions data, which for some firms might be available at consolidated level only, hazard data can be identified directly, based on the company's registered address, and indicators based on the single entity were deemed more robust at this stage.

16 Notably, the distinguishing factor between entity-level and group-level indicators is not the entities or financial instrument being covered, but the consolidation level at which financial and emissions information is considered.

3 Statistical climate-change related indicators – underlying data, methodology and results

3.1 Sustainable finance indicators

3.1.1 Climate data on sustainable bond flag and assurance

For the compilation of the sustainable finance indicators, we rely on granular information on the sustainability classification of the sustainable debt securities retrieved from the CSDB: Green – debt securities where the proceeds are used to finance green projects; Social – debt securities where the proceeds are used to finance social projects; Sustainability – debt securities where the proceeds are used to finance a combination of both green and social projects; and Sustainability-linked – debt securities where the issuers are committed to future improvements in sustainability outcome(s) within a predefined timeline, but with no restrictions on how the proceeds may be used. For this type of bonds where there are no restrictions on the use of proceeds, the financial and/or structural characteristics may vary, depending on whether the issuers achieve the predefined sustainability objectives.[17]

In the initial indicators published for the first time at the beginning of 2023, all sustainable debt securities classified as such in the CSDB are considered when calculating the aggregate figures, irrespective of the level of assurance (including also only self-labelled). In addition, the underlying standard/framework against which the sustainability classification of the sustainable debt security is aligned (e.g. International Capital Market Association (ICMA) or Climate Bonds Initiative (CBI)), as available in the CSDB, is not used to restrict the universe. In other words, all underlying standards are considered. The new indicators provide further information on the level of assurance, separately showing the universe of the sustainable debt securities' market to those securities that have obtained a second party opinion (SPO). These additional breakdowns have been presented as "of which" [sustainable debt securities] that have a second party opinion. However, for these new aggregates once again no restriction on the underlying standards has been applied. Additional breakdowns based on alignment with the EUGBS are expected to be made available in the future.

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[17] An example of a sustainability-linked bond is a bond whose coupons are linked to sustainability performance targets. In this case, if the issuer of such a sustainability-linked bond fails to achieve its sustainability targets, the cost of funding would increase and the issuer would have to pay a higher coupon to the holders of its bond.

3.1.2 Methodology applied

The indicators on both issuances and holdings of sustainable debt securities are calculated directly from CSDB security-by-security information, the former (issuances) as part of the CSEC and the latter (holdings) as part of the SHS compilation. All calculations are based on attributes associated with individual securities, which are then used to calculate aggregate series. More precisely, the sum of all debt securities issued or held which are (at least self-labelled) green, social, sustainability or sustainability-linked in the CSDB is used to calculate the issuances and holdings indicators. For the new/additional indicators, only green, social, sustainability or sustainability-linked debt securities issued or held that have obtained a second party opinion are considered.

The following groups of experimental indicators on issuances of sustainable debt securities are published:

- amount outstanding of euro area (EA) and/or European Union (EU) issuances of all (at least self-labelled) sustainable debt securities broken down by sustainability classification
    - of which with an SPO
- amount outstanding of EA issuances of all (at least self-labelled) green debt securities by institutional sector
    - of which with an SPO
- amount outstanding of issuances of all (at least self-labelled) green debt securities by individual EA country
    - of which with an SPO
- net EA issuances (financial transactions) of all (at least self-labelled) green debt securities
    - of which with an SPO.

Data on amounts outstanding are made available at face, nominal and market value, whereas data on transactions are at face and market value. As part of the CSEC compilation process, the indicators on issuance of sustainable debt securities are published on a monthly frequency and disseminated at around t+10 working days after the end of the reference month. Data are available for reference periods from December 2020 onwards.

As for the experimental indicators on holdings of sustainable debt securities, the following aggregates are published:

- EA holdings of all (at least self-labelled) sustainable debt securities broken down by sustainability classification and counterparty issuing area (EA, EU, Rest of-the World, and Total)

    - of which with an SPO
- EA holdings of all (at least self-labelled) green debt securities by institutional sector
    - of which with an SPO
- holdings of all (at least self-labelled) green debt securities by individual EA country
    - of which with an SPO
- net EA acquisitions (financial transactions) of all (at least self-labelled) green debt securities: total net acquisitions (at market value) of green debt securities issued by residents in the EA
    - of which with an SPO

Data on positions are made available at face and market value, whereas data on transactions are at market value. As part of the SHS compilation process, indicators on holdings of sustainable debt securities are published on a quarterly basis and disseminated at around t+2 months after the end of the reference quarter. Data are available for reference periods from Q1 2021 onwards.

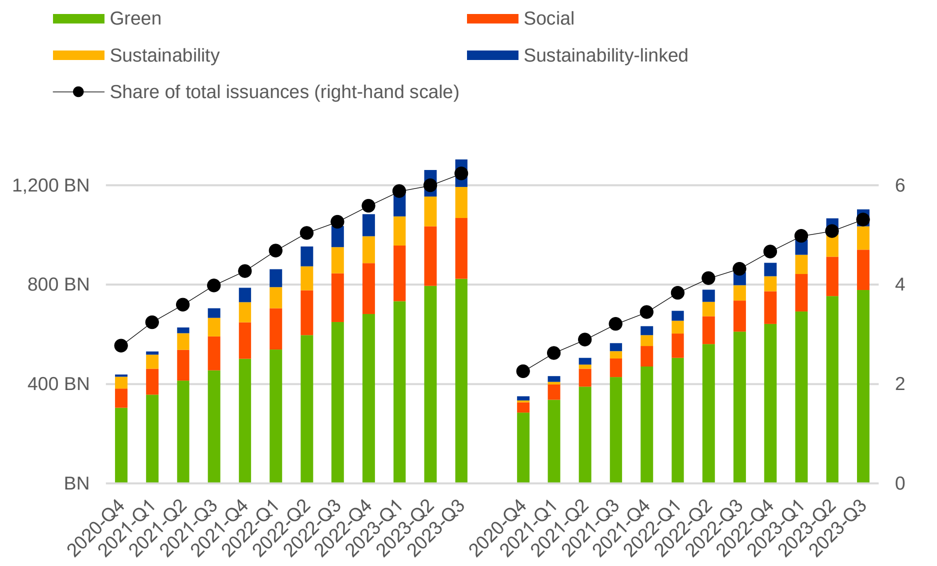
3.1.3 Results

Issuances of sustainable debt securities in the euro area

The outstanding amount of sustainable debt securities issued in the euro area has more than doubled in the last three years. Securities designed to finance green projects, which account for the majority of the market (**Figure 2**), have recorded a particularly strong increase. Over the same period, sustainability-linked bonds recorded the highest growth rate. However, even when using a relatively broad definition (all levels of assurance are considered, and no restrictions are imposed on the underlying sustainability standard or taxonomy), these instruments still account for a relatively small part of the wider debt securities market, representing 6% of total issuances in Q3 2023 (**Figure 2**). Overall, euro area issuers of sustainable debt deem to obtain an external review of their sustainable bond issuances, with around 85% of all sustainable debt in the EA having obtained an SPO (**Figure 3**), thus providing investors with assurance that their issuances are aligned with accepted market principles and meet certain international standards. A very large proportion of green debt securities issued in the euro area have obtained a second party opinion. Similarly, more than 80% of the sustainability-linked debt securities have been reviewed by an external provider (SPO). Social and sustainability instruments have slightly lower SPO assurance levels, albeit typically above 55%.

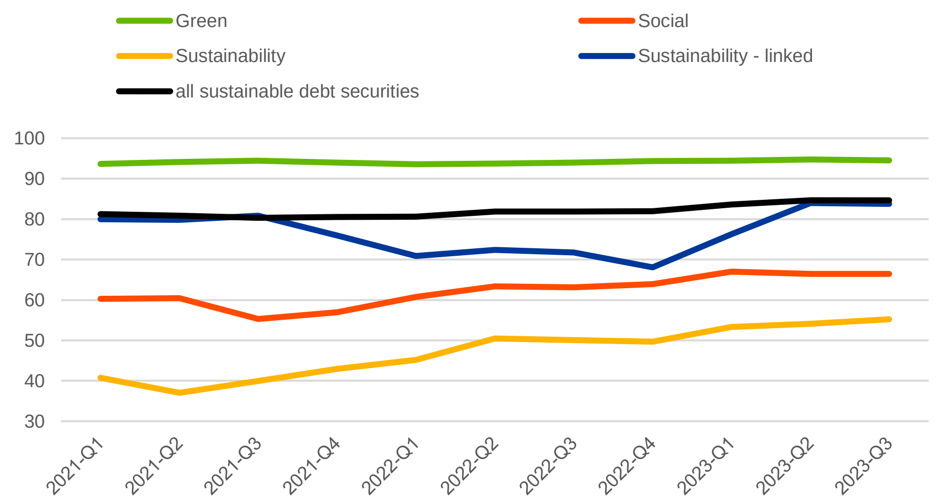
Figure 2
Euro area issuances of sustainable debt securities

All sustainable debt securities (including also only self-labelled)	Sustainable debt securities with an SPO



Left-hand scale: EUR billions, outstanding amounts at face value; right-hand scale: percentages.
Sources: CSDB.
Notes: The share of total issuances refers to the amount of all sustainable debt securities as a share of all debt securities issued in the euro area (left graph) and to the amount of the sustainable debt securities with a second party opinion as a share of all debt securities issued in the euro area (right graph).

Figure 3
Share of euro area issuances of sustainable debt securities with a second party opinion



Left-hand scale: percentages.
Source: CSDB.
Notes: The share of issuances with a second party opinion refers to the sustainable debt securities with a second party opinion as a share of all sustainable debt securities issued in the euro area.

Holdings of sustainable debt securities in the euro area

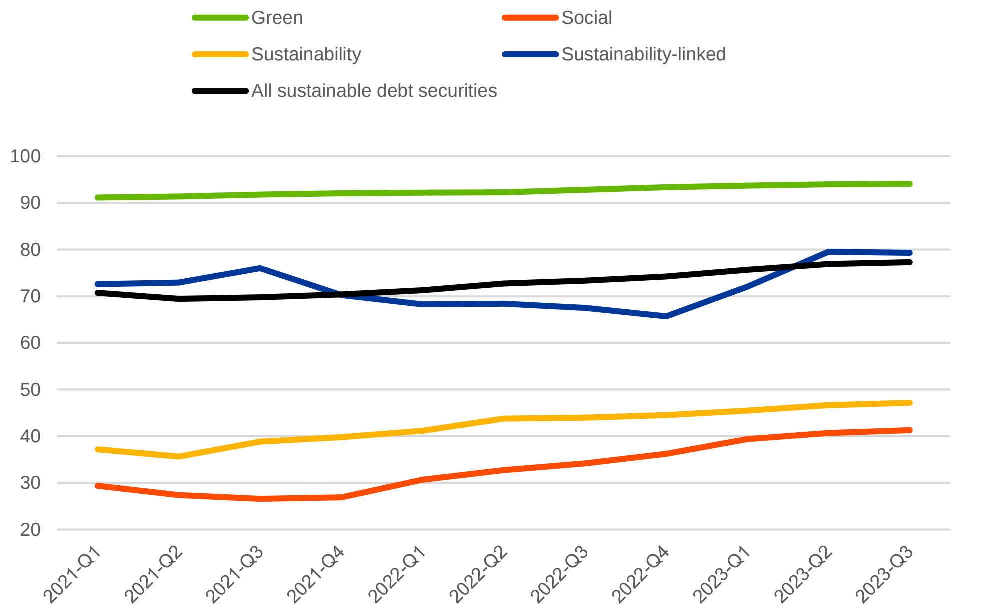
Since the beginning of 2021 euro area holdings of sustainable debt securities have grown continuously, similar to the trend observed for euro area issuances. While these instruments are becoming increasingly relevant investment alternatives, they are still a relatively minor portfolio item, accounting for 6.5% of total holdings in Q3 2023 (**Figure 4**). While euro area investors seem to prefer sustainable debt securities issued in the euro area, the euro area as a whole is a net buyer of these instruments – that is, its holdings exceed euro area issuances. Most (77%) euro area holdings of all sustainable debt securities have obtained a second party opinion (**Figure 5**). However, when zooming in on the different sustainable categories, we can observe that holdings of social and sustainability bonds with a second party opinion are significantly lower (below 50%) than holdings of green and sustainability-linked bonds with a second-party opinion. This is because euro area investors buy a large proportion of social and sustainability bonds issued by non-EU residents, which have not obtained a second party opinion. Conversely, euro area investors invest mainly in domestically issued green and sustainability-linked bonds that have been externally reviewed.

Figure 4
Euro area holdings of sustainable debt securities

All sustainable debt securities (including also only self-labelled)	Sustainable debt securities with an SPO

Left-hand scale: EUR billions, outstanding amounts at face value; right-hand scale: percentages.
Sources: CSDB and SHSS.
Notes: The share of total holdings refers to the amount of all sustainable debt securities as a share of all debt securities held in the euro area (left graph) and to the amount of the sustainable debt securities with a second party opinion as a share of all debt securities held in the euro area (right graph).

Figure 5
Share of euro area holdings of sustainable debt securities with a second party opinion



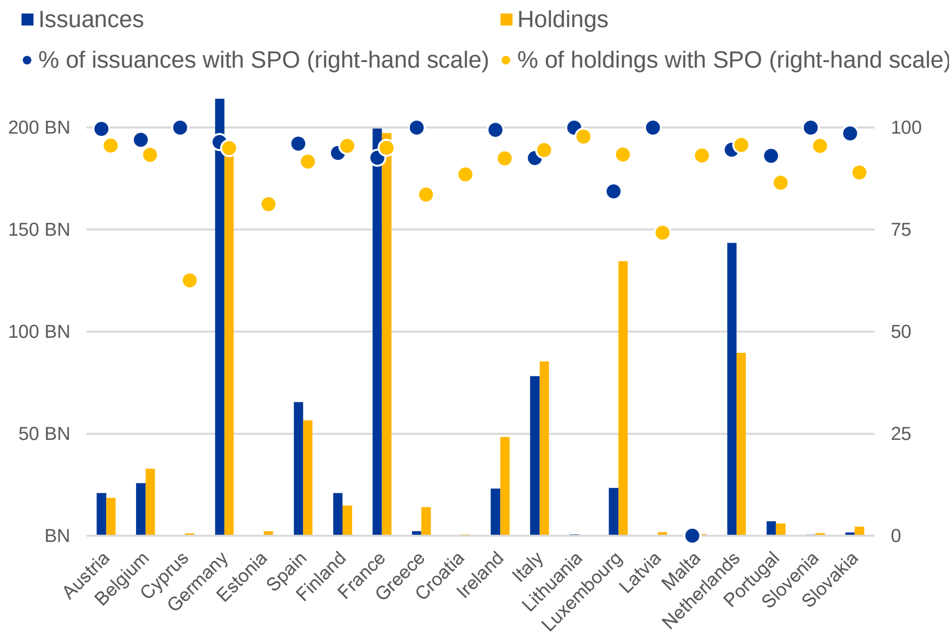
Left-hand scale: percentages.
Sources: CSDB and SHSS.
Notes: The share of holdings with a second party opinion refers to the sustainable debt securities with a second party opinion as a share of all sustainable debt securities held in the euro area.

Issuances and holdings of green debt securities by country and sector

France and Germany are the biggest issuers and holders of green debt securities in the euro area, together accounting for more than half of the market (**Figure 6**). The Netherlands is the third-largest issuer and Luxembourg is the third-largest holder[18]. The remaining euro area countries represent a comparatively small share of the green bond market (both issuances and holdings). Some countries have only residually entered the market or have yet to enter it. This analysis remains equally valid for green debt securities with a second party opinion.

[18] Investment funds are the main investors in green bonds in Luxembourg, making Luxembourg the third-largest holder of green debt in the euro area.

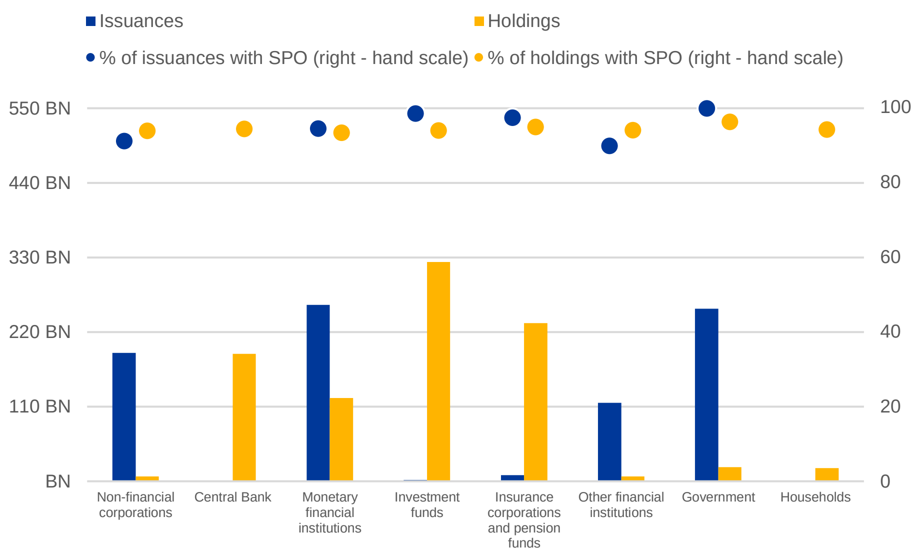
Figure 6
Issuances and holdings of green debt securities by country



Left-hand scale: EUR billions; Q3 2023, outstanding amounts at face value; right-hand scale: percentages.
Sources: CSDB and SHSS.

Governments and monetary financial institutions are the leading issuers of green debt securities in the euro area, representing comparable shares of the market (**Figure 7**). Virtually all green bonds issued by euro area governments have obtained a second party opinion, highlighting the importance of meeting the growing market demand for independent, external reviews on the alignment of labelled green bonds with international standards and the expected contribution of the financed projects to climate outcomes. Similarly, most of the green bonds issued by all other sectors have obtained a second party opinion. With regard to holdings of green debt securities by euro area residents, investment funds together with insurance corporations and pension funds are the main market players, followed by central banks and monetary financial institutions. The remaining sectors play a very residual role, with households entering the green debt market only indirectly, via investment funds. As with issuances, most of the green bonds held by all sectors have been externally reviewed.

Figure 7
Issuances and holdings of green debt securities by sector



Left-hand scale: EUR billions; Q3 2023, outstanding amounts at face value; right-hand scale: percentages.
Sources: CSDB and SHSS.

Comparison with other sources of climate risk metrics and publications

To assess the quality of the sustainable finance indicators, comprehensive comparisons with other publicly available datasets have been performed. For issuances of sustainable debt securities in the euro area, comparisons against the International Monetary Fund (IMF) Green Bonds dataset and the Climate Bonds Initiative (CBI) Interactive Data Platform were conducted. The IMF Green Bonds dataset contains information on issuances of green bonds by country since (reference period) 1985, whereas the CBI provides information on the issuance of green, social and sustainability bonds since (reference period) 2014, with geographical, issuer type, use of proceeds and currency breakdowns. In broad terms, both the IMF and the CBI follow the same “use of proceeds” concept to define sustainable instruments (at least self-labelled), namely all fixed income instruments where the proceeds are directed to finance, or re-finance, new and/or existing green, social, or a combination of both, projects. For green bonds, the CBI definition is stricter, as it considers bonds which are expected to fully allocate (100%) their net proceeds to aligned green assets, projects or activities. In order to align with the definition of green bonds provided by the IMF and CBI datasets, for this comparison we used the existing indicators that consider all (at least self-labelled) sustainable debt securities classified as such in the CSDB, i.e. irrespective of the level of assurance. The results of the analyses on issuances of green bonds within the euro area in 2021 and 2022 show alignment between the three datasets, especially between CSEC and the IMF, where the amount issued differs by 3% and 4% respectively. The higher difference with the CBI (euro area issuance of green bonds in 2021 and 2022, as calculated in CSEC, is 12% and 15% higher, respectively) can be broadly explained by the stricter universe considered by the CBI, i.e. due to the restriction of green bonds with 100% of their proceeds allocated to financing green projects.[19] Furthermore, in a European Securities and Market Authority (ESMA) paper,[20] outstanding sustainable bonds issued in the European Economic Area (EEA30, i.e. EU plus United Kingdom, Norway and Iceland) totalled €1.7 trillion in the second half of 2023, revealing an increase of 28% in one year (from June 2022 to June 2023), with green bonds dominating the market (63%). Meanwhile, outstanding sustainable debt securities issued in the EU as calculated in CSEC came to almost €1.65 trillion in June 2023, showing an annual increase of 31% from June 2022, with green debt accounting for the majority of the market (64%). For the holdings of sustainable debt securities, there is not enough publicly available information to make reliable comparisons. However, as information on issuances and holdings tends to be closely aligned, there is no good reason to doubt the quality of the holdings information.

3.2 Carbon emissions indicators

The analytical indicators on carbon emissions financed by the financial sector and the associated risks related to transitioning to a carbon-free economy cover two key aspects. First, they cover the direct (and in part also indirect) emissions financed by the financial sector. Second, they address the exposure of the financial sector to counterparties with emission-intensive activities.

Carbon emission indicators allow users to evaluate how the financial sector contributes to the funding of carbon-related activities and, by extension, assess the associated risk of carbon-intensive sectors transitioning to a low-carbon economy. The indicators offer insights into developments over time and disparities between countries in the financing of emission-intensive economic activities. Similar to all other carbon emission indicators, the indicators explained in this paper currently have limitations, such as variations in data coverage across time frames and jurisdictions, and therefore a significant portion of emissions and financial data have been imputed. In addition, the preference of relying on a homogenous set of data sources across jurisdictions means that the data (especially financial data) can vary in quality. Therefore, performing certain types of analysis of these indicators, such as cross-country comparisons, requires careful consideration of the underlying caveats.

All the indicators included in this dataset are classified as analytical due to the inherent limitations associated with the microdata that underlie them and the assumptions made to integrate disparate data sources with distinct characteristics.

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[19] In addition, the exchange rate effect shall also be considered as amounts in the IMF and CBI databases are expressed in USD.

[20] "The European sustainable debt market – do issuers benefit from an ESG pricing effect? (ESMA50-524821-2938)"

3.2.1 Climate data on emissions

Two different approaches are used to estimate carbon emissions linked to loan exposures at a local and global level. The single entity view looks solely at financing via loan exposures among deposit-taking corporations. Group-level indicators provide a global view on financing via corporate loan exposures among deposit-taking corporations. Meanwhile, loan-based group-level indicators complement the group-level indicators that study global financing via debt and equity securities issued by non-financial corporations.

To compile local emissions, we rely on publicly available verified emissions data from the EU ETS.[21] Any missing data from this source were imputed using aggregate data from Eurostat Air Emissions Accounts (AEA)[22] according to a waterfall model.[23] The proportional approach of the waterfall model ensures that the allocated emissions do not exceed the total emissions of a specific country. In addition, even though the approach does not reduce the level of uncertainty of imputation at the micro level, once the results are aggregated, potential errors at the micro level partially offset each other and increase the reliability of the aggregated indicators compared to alternative imputations (see Annex 6.3.6.2). RIAD data were used to cover the balance sheet information for single entity debtors and when this information was not available, the data were imputed using a median approach following the procedure described in Section 3.2.2.

Global carbon emissions data on loans and securities are obtained from ISS, a commercial data source, as there is currently no publicly available data source offering a comparable level of granularity and data quality. The data sources used for group-level indicators differ from those at local single entity-level as the estimations made to approximate local emissions do not fully capture exposures to global transition risks. Financial data for group-level computations are also obtained from ISS. Any missing carbon and financial data are imputed through a split approach, employing a fixed effects model and region-sector-year-specific medians, as described in Section 3.2.2.

3.2.2 Methodology for the construction of indicators

Four types of carbon emissions indicators are compiled, for both the portfolios of loans (single entity and group-level) and securities holdings (group-level), resulting in a total of 12 sets of indicators. In both cases, the financial institutions issuing the loans or holding the securities are restricted to those located in the euro area. The Financed emissions and Carbon intensity indicators show the amount (share) of carbon emissions that can be attributed to financial institutions via their securities

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21 Further information on the EU ETS can be found available on the European Commission's website.

22 More information on AEA is available on the Eurostat's website.

23 A waterfall model is used to make emission estimations for single entities, relying on ETS data when available or otherwise average sector-country-year intensities times the size of a firm (measured by the number of employees). The method applies an adjustment for sectoral biases in employment figures per sector within country. The imputation process relies on the availability of both employment data and sector classification, and is only carried out when both are accessible. Specific information about the imputation methods used in the indicator compilation is provided in Annex 6.3.1.

and loan portfolios. Consequently, these indicators provide insights into the financial sector's monetary contribution to high-emitting economic activities. The indicators on the financing of carbon-intensive activities allow us to assess how the emissions of the debtors/issuers evolve over time ahead of (and in preparation for) the transition to a net-zero economy (henceforth referred to as "indicators on financing the transition"). The Weighted average carbon intensity and Carbon footprint indicator asses the transition risks for the financial sector, due to the exposure of the portfolios in this sector to economic activities with elevated risks (henceforth referred to as "indicators on transition risk").

The indicators are constructed using two complementary approaches that vary in the level of consolidation of the financial and emissions data. Consolidation is either performed at single entity or corporate group level. The single entity approach focuses on local emissions and can be used to monitor the contribution of the local financial sector in aligning the non-financial corporate sector with domestic climate objectives, most notably the European Green Deal, which aims to achieve net zero emissions by 2050. Group-level consolidation goes beyond the boundaries of the domestic economy to incorporate global emissions of the corporate group. It is therefore particularly useful for analysing global transition risks. As an extension to the previous year's release, group-level emissions financed through loans are included.

Importantly, single entity and group-level indicators based on AnaCredit encompass only Scope 1[24] emissions, while SHSS-based indicators can also be computed using Scope 2 emissions, thus considering indirect emissions from energy purchases. This main reason for this distinction is the current lack of emissions data for various, relatively small, enterprises on the debtor side in the AnaCredit dataset. Attempting to correct this issue at the current juncture would require a substantial enlargement of the imputation scheme developed for Scope 1 emissions to cover Scope 2 emissions.[25] Similarly, in order to maintain comparability when reporting AnaCredit-based indicators, group-level consolidation is limited to Scope 1, even if Scope 2 emissions data is available for a subset of firms.

Carbon emission indicators can be computed at various levels of aggregation. For the purposes of this paper, the indicators are compiled primarily by country of the creditor/holder and encompass the period from 2018 to 2021, with data reported on an annual basis. To illustrate the compilation process, we first introduce some notation. Let b denote a given financial institution out of set B within country c and let i denote the respective debtor/issuer (a non-financial corporation). Moreover, assume the following notation for the key compilation variables: e_i: emissions of firm i; r_i: measure of company production value, i.e. revenues of firm i; v_i: value of firm i

24 Scope 1 encompasses an entity's direct emissions. Scope 2 quantifies indirect emissions resulting from electricity, heat and steam consumption. Scope 3 encompasses all indirect emissions associated with an entity and its products, excluding those covered by Scope 2. This includes emissions across the entity's value chain, including suppliers, customers and other sources beyond its immediate operations.

25 Specifically, single entity level AnaCredit-based indicators hinge decisively on the imputation of emissions to increase coverage. However, Scope 1 and Scope 2 emissions require different imputation procedures due to their different natures, meaning that the imputation mechanism applied to Scope 1 emissions cannot be used for Scope 2 emissions. An implementation using Input-Output tables was developed and tested for Finland and could be further explored in future releases.

(total assets or enterprise value including cash (EVIC)); and $l_{b,c,i}$: loan of a bank or security holding of a given financial institution b in ctry c to firm i.

(1) Financed emissions (FE) of country c is computed by taking the GHG emissions of debtor/issuer i over i's enterprise value, weighted by b's investment in these activities, summed over all debtors/issuers i and all financial institutions b.

$$FE_c = \sum_{b \in B} \sum_{i \in N} \frac{l_{b,c,i}}{v_i} e_i \ \forall \ c$$

(2) Carbon intensity (CI) of country c: Financed emissions divided by the country's "invested share in the revenue", where the latter is calculated by taking the revenue of each debtor/issuer i, over its enterprise value, weighted by b's investment in these activities, summed over all debtors/issuers i and all financial institutions b. Essentially, CI is Financed emissions over Financed revenue, at country level.

$$CI_c = \sum_{b \in B} \sum_{i \in N} \frac{l_{b,c,i}}{v_i} e_i / \sum_{b \in B} \sum_{i \in N} \frac{l_{b,c,i}}{v_i} r_i \ \forall c$$

Indicators on financing the transition measure the financed emissions of a counterparty (either individually or at sector or country level) and can be used to understand how the emissions of the most emitting debtors/issuers evolve over time in anticipation of the need to transition to a net-zero economy. Notably, the indicators do not provide information on whether the financing is targeted to make businesses greener: a gap that is complemented by sustainable finance indicators, as discussed in Section 3.1. However, the indicators can help to monitor the overall reduction targets of economic activities and the correlation of financing (both over time and cross-sectionally) in these developments.

Indicators on transition risks measure the exposure to transition risks by capturing the relative amount of financing into economic activities that may be affected by the transition to net zero. Notably, as opposed to the indicators related to financing the transition, these indicators use the portfolio value of the creditors/security holders as a standardisation variable and thus take an investor perspective. Therefore, while the metrics should not be viewed as risk measures by themselves, they do serve as exposure metrics that can inform practitioners in their risk assessment. Notably, at this stage all indicators focus exclusively on the emission-intensive activities of the debtors/issuers and do not account for risks associated with business models reliant on emission-intensive intermediary products, such as emissions generated throughout the value chain.

(3) Weighted average carbon intensity (WACI) of a country c: the GHG emissions of a debtor/issuer standardised by the debtor's/issuer's revenue, weighted by the financial institution's investment in these activities over the total investment portfolio value in a country, summed over all debtors/issuers i and all financial institutions b.

$$WACI_c = \sum_{b \in B} \sum_{i \in N} \frac{e_i}{r_i} (l_{b,c,i} / l_c) \ \forall c$$

(4) Carbon footprint (CFP) of country c: Financed emissions standardised by the total investment portfolio value among financial institutions in a country, l_c.

$$CFP_c = \frac{1}{l_c} \sum_{b \in B} \sum_{i \in N} \frac{l_{b,c,i}}{v_i} \, e_i \; \forall c$$

The four indicators align closely with those suggested by the Task Force on Climate-related Financial Disclosures (TCFD)[26], the Partnership for Carbon Accounting Financials (PCAF)[27], and the ECB/ESRB Project Team on climate risk monitoring (ECB/ESRB Project Team on climate risk, 2023). However, the methods and specific implementation assumptions may vary significantly among compilers, resulting in divergent outcomes, revealing a clear need to establish standardised methodologies and compilation criteria.

Based on the literature, the most widely recommended financial metric for calculating carbon intensities is value added (or GDP on a macroeconomic scale) (Bokor, 2021), as it excludes external purchases and narrows the denominator variable to the entity concerned. However, this kind of detailed information is often lacking, leading to the use of revenue, which is an output concept. The problem with relying on revenue is that it poses a potential bias risk in production-related (Scope 1 and 2) emission intensities, especially if significant portions of the production process are outsourced to suppliers.

The indicators incorporate various methodological improvements to address caveats, including inadequate coverage of financial and emissions data, the absence of price adjustments, and the effects of changing compositions over time.

First, to improve indicator coverage, novel imputation methodologies for GHG emissions as well as financial data were applied. The choice of strategy depends on whether single entity or group-level data are imputed, since the characteristics of the underlying sample population varies, e.g. company size or whether the emissions occur locally or globally.

Single entity-level imputations

Where data on debtors studied at single entity-level, such as balance sheet total, revenue or number of employees, are not available via RIAD, the missing information is imputed instead using a median approach. The number of employees is directly implemented by calculating medians on groups formed at year, country and sector level. Meanwhile, balance sheet total and revenue are calculated indirectly, based on imputations of the asset ratio (outstanding nominal amount (ONA) to balance sheet total) and the revenue ratio (ONA to annual revenue), respectively. Medians regarding both ratios are imputed at year, country, sector and employee category level.[28] Imputations are calculated on a restricted sample that

26 For further information, please visit the TCFD website.

27 For further information, please visit the PCAF website.

28 In case where the group on which a median is calculated include less than 50 observations, one level of granularity is dropped.

exhibits higher data quality and a distinct distribution of key variables when compared to the complete RIAD sample.[29] For further information, please see Annex 6.1.

Group-level imputations

At the group level, Scope 1 and 2 emissions and financial data, i.e. revenue and EVIC, are imputed using a split-level approach. The approach distinguishes between (i) entities for which some within-firm data across time are available and (ii) entities with no observed data. In both cases, imputations are calculated on a subset of the RIAD data that does not include debtors that are single entities or group members (for a detailed description, see Annex 6.3.2). For entities with some observed data, imputations are calculated via a fixed effects model with an entity-specific mean and a sector-specific time trend. For entities with no observed data, imputation is based on region-sector-year-specific[30] medians. Outliers are defined using Cook's distance (Cook R. D., 1977) as influential observations that have a disproportional impact on the estimated parameters and are removed when constructing the imputations. For more information, please refer to Annex 6.3.2.

For both single-entity and group-level indicators, the vast majority of the underlying financial and emissions data are estimated through imputation methods.[31] Continued efforts to explore and utilise national data sources will be essential for improving the quality of firm-level information.

Inflation and exchange rate adjustments

Second, to allow for a more accurate comparison of relative carbon indicators over time and between countries, the WACI indicator is corrected to account for price and exchange rate effects.[32] Economic sector-country-specific deflators and country-dependent exchange rates are constructed to monitor changes in relative carbon indicators due to fluctuations in quantity while factoring out price changes. Revenues are adjusted for inflation effects and exchange rates, whereas the ONA of loans and the market values of bonds and equities are adjusted for exchange rate effects only. We do not (yet) focus on market price corrections because ONA is not subject to inflation or market price fluctuations. In addition, filtering out price effects from market values requires the inclusion of more detailed data on market prices – available, e.g., in CSRD – than currently used in the analysis. Given the challenges posed by correcting other indicator components, such as enterprise value, these

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29 The imputation is performed on a restricted RIAD sample including only non-financial corporations (S11) also prevalent in AnaCredit, SHSS, or both.

30 Region encompasses the following categories: Africa, Americas, Asia, Europe, Oceania and Unknown.

31 Imputations are necessary since there is a high share of missing emissions information and, to a smaller degree, financial information. A large share of carbon emissions information at company level is missing since the EU ETS includes only large companies operating in energy-intensive sectors. Moreover, reporting remains largely voluntary and due to a lack of disclosing standards, only a fraction of companies deliver reliable carbon emissions reports. In a broader context, financial data at the firm level are missing due to restricted coverage in available sources (especially the exclusion of smaller companies), reporting delays, and instances of missing or inaccurate information.

32 Previous research has shown that relative carbon indicators are especially sensitive to inflation and exchange rate effects (Janssen et al., 2021).

corrections have been applied only to WACI and not to the other indicators.[33] Revenues are expressed in constant 2018 prices using chain-linked indices and a uniform yearly average exchange rate, basing the currency on the issuer/debtor country. Market values and ONA are adjusted for exchange rate effects using end-of-year rates. Sector-country-specific deflators are constructed using Gross Value Added data[34] from national accounts statistics provided by Eurostat, while for the exchange rate correction, euro foreign exchange reference rates have been applied.[35] For further information, please refer to Annex 6.3.3.

Flex balancing

Third, to account for compositional changes in the sample over time, the indicators are reported for both a balanced and an unbalanced sample. The unbalanced nature of the sample stems from two sources, namely: (i) missing emissions or financial data of a debtor or issuer in a given year; and (ii) investments and divestments of holders and creditors, respectively. As opposed to a standard (strict) balancing exercise, which would enforce the existence of a debtor/issuer in every period of interest, our indicators are balanced with the aim of smoothing the composition over time for missing data, while, at the same time, allowing for investment and divestment decisions to prevail. For example, if a non-financial corporation is present in the data as a borrower or security issuer in one period but has missing financial or emissions data, it is removed from the sample in all periods so as to prevent bias. In contrast, if a non-financial corporation does not appear in the data as a borrower or a security issuer in one or more periods but has complete financial and emissions information in the other periods, we allow for the impact of disinvestment from the firm in the period under consideration and keep the company in the dataset for the other periods in which we observe full information regarding emissions and financial information. As a result, firms with complete information remain in the data even if their actual in-sample presence is below the total number of years covered in the dataset. For a graphical illustration and a more detailed description, see Annex 6.3.4. This concept is hereinafter referred to as “flex balancing”.

Time series decomposition

Furthermore, to disentangle the drivers of the indicators, the time series are decomposed into their various components using the Marshall-Edgeworth-type

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33 The remaining indicators – FE, CI, and CFP – all incorporate enterprise value as a component, and adjustments for inflation and exchange rate effects will be applied once a suitable methodology is established. However, incorporating these adjustments for enterprise value is particularly challenging due to the intricate task of isolating and accurately quantifying the impact of inflation and exchange rate fluctuations on the comprehensive economic value measure. The dynamic nature of financial markets and the availability of reliable, comprehensive data further complicate the precise integration of inflation and exchange rate effects in calculating enterprise value.

34 While output-based deflators were the preferred choice, their implementation was not feasible due to limited country coverage.

35 If revenue is corrected for the exchange as well as inflation rate, a three-step process is applied. Revenue is first converted to the official exchange rate (local currency unit (LCU) per US dollars). Second, the inflation correction is applied in LCU and as a third step, exchange rates from 2018 are used to convert the revenue to euro.

decomposition (Marshall, 1887; Edgeworth, 1925).[36] This decomposition elicits the drivers of intertemporal variation and, in conjunction with the adjustment for sample composition, allows us to run ceteris paribus analyses of the indicator with regard to emission changes. The decomposition is performed on the FE, WACI and CFP indicators and distinguishes between greening of the underlying assets, changes in firms' financial characteristics and changes due to investment decisions. The time series is decomposed into year-on-year changes and can be aggregated to study changes over multiple years. Changes in FE are decomposed into the impact of changes in investment share (loan or holding size relative to total assets or enterprise value) and changes in firms' carbon emissions. WACI is disaggregated into changes due to an issuer's/debtor's emissions, revenue, and portfolio reallocation performed by the creditors/holders. Meanwhile, CFP is split into changes due to an issuer's/debtor's emissions, value of the non-financial corporation, and capital reallocation. Additional information is provided in Annex 6.3.5.

Outlier detection

Three types of outlier removals are performed to ensure the consistency of the constructed indicators (e.g. the financed emission indicator should exceed reported emissions) and to reduce excessive over-year variation. Two outlier detections are performed on the constructed microdata aggregated on the creditor/holder-debtor/issuer level after imputation. To ensure consistency, observations are dropped from the sample if the total value of investments is larger than the firm's value[37], and also for the loan-based indicators, if the ONA is more than 100 times larger than the yearly revenue.[38] To reduce excessive over-year variation, two ratios – carbon emission (Scope 1) over enterprise value (total assets or EVIC) and carbon emissions over revenue – are computed for each set of indicators (single entity-level loans, group-level loans, and group-level securities), based on country-year breakdowns. Observations that exceed the 99.5th percentile in at least one of these ratios are excluded.[39] In addition, on the compiled indicator level, outliers are identified using Cook's distance as observations that have a large impact on the yearly mean with a regression model estimating the logarithmic growth rates with year-specific fixed effects.[40] Entities with outliers were subjected to a cubic

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36 Besides the Marshall-Edgeworth decomposition, two other methods were considered: growth accounting (Berkhout et al., 2023) and Paasche-type decomposition (De Boer & Rodrigues, 2020). The Marshall-Edgeworth decomposition method was selected, as it fulfils properties considered important, i.e. exhaustiveness, time reversal, translation and symmetry in terms of the reference period (Huerga & Steklacova, 2008).

37 For AnaCredit-based indicators, the outlier detection ensures that the value of the total assets does not exceed the ONA; for SHSS, that the total market value of the securities issued by a group head and held by a euro area financial institution in a given year is not larger than EVIC in the same year.

38 For the group-based loan indicators, we further control for over-time changes in EVIC, revenue, Scope 1 and Scope 2 emissions so as to account, for example, for changes in firm value due to major restructuring by smoothing the EVIC.

39 This outlier approach leads only to a decrease in coverage of less than 0.4 percentage points.

40 Region, sector and year-specific fixed effects models have also been tested but are less intuitive and parsimonious since they also catch region- and sector-specific outliers.

smoothing spline (Green & Silverman, 1993, pp. 11-28).[41] Future work is expected to refine the applied outlier detection strategies.

Besides the implemented methodological changes outlined above, several alternative specifications with respect to data sources, imputations of financial and carbon information, and consolidation were tested and will be discussed further in Annex 6.3.6.

3.2.3 Results

In this section, we introduce the main descriptive findings of the paper. We highlight and interpret trends in the carbon emission indicators over time and disentangle year-on-year variations to reveal the components driving intertemporal variation. We also highlight key methodological choices and their quantitative impact, namely new imputation strategies for emissions and financial data, flex balancing, and adjustments for inflation and exchange rates.

Figure 8 further below shows the euro area aggregate of all four carbon indicators, including and excluding methodological and data enhancements, focusing on exposures through loans to single entities. The figure allows for an interpretation of the temporal variation in the indicators and illustrates how the methodological changes and data imputations that have been introduced affect their magnitude. More detailed analyses can be made when interpreting the decomposition results.

Across all four types of indicators, a downward trend is observed over the studied period from 2018 to 2021, exhibiting varying degrees of decrease among the different indicators. More precisely, there is an overall decline in the absolute indicator measuring Scope 1 emissions financed by the euro area banking sector through loans (see panel a in **Figure 8** below). Additionally, both carbon intensity indicators, which standardise companies' emissions by revenue, show declines (see panels b and c). The carbon footprint indicator (depicted in panel d), standardising financed emissions by investment value, exhibits a slightly downward pattern. The observed 2020 downturn in carbon indicators could be attributed to the diverse impacts of the COVID-19 pandemic on the global economy, including disruptions to supply chains, widespread business closures, and a decline in global trade. These developments altered the economic dynamics and continue to influence emissions and financial variables such as revenues or the value of a company's investment portfolio, with varying impacts across countries and industrial sectors. Moreover, the overall decrease in the indicators may also be influenced by other economic factors or a broader time trend. A clearer assessment is anticipated with the inclusion of additional years in the series. The decomposition analyses described later in this section can also shed light on the degree to which each underlying component affects the temporal trends seen in the indicators.

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[41] In addition, smoothing using moving averages was tested. However, it is less flexible in particular for the currently short time series as it requires observed values at the beginning or end of the time series. Smoothing was also tested with a fixed effects model but was considered too restrictive for our purposes.

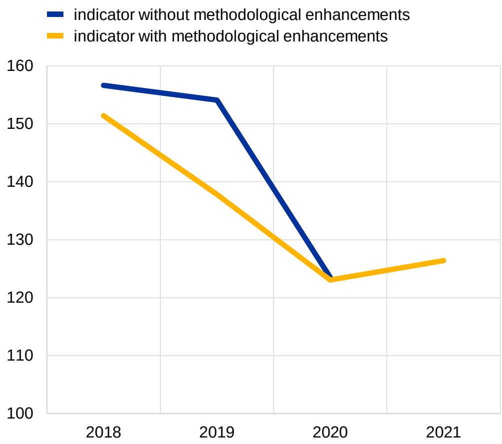
When taking a closer look at the effect of all the methodological and data enhancements on the indicators, it becomes evident that the changes introduced led to an overall smoothing of the time series, especially for the CI and WACI indicator (see panels b and c). The financed emissions indicator is of similar magnitude with and without the methodological and data changes, as the imputation and the outlier detection cancel each other out. Increased coverage of the loan portfolio through imputations of missing information translates into increased levels of the financed emissions indicator, whereas the outlier removal approach that drops observations with extreme emissions to financials ratios leads to a decrease in the indicator. The effects of increased coverage on the relative indicators, which normalises firms' financed GHG emissions by the respective production or investment portfolio values, are more nuanced and depend also on the interaction of various partial effects in the numerator and denominator. In general, relative metrics such as WACI are less sensitive to compositional changes over time (which occur more often without imputation of missing data), as opposed to absolute indicators. Meanwhile, some relative indicators may be particularly sensitive to outliers in the components, such as firm revenues.

The overall smoothing of the time series is achieved through time series adjustments, encompassing corrections for compositional effects, removal of extreme outliers, and exchange rate and inflation adjustments for WACI. These adjustments contribute to a statistically more robust time series analysis. **Figure 8** shows the total change due to the methodological and data enhancements introduced, while the individual effect of each adjustment will be explored in greater detail below. Aside from the time series adjustments, imputations also have a large impact on the indicators. The large impact of the imputations introduced on the indicators reflects the sensitivity of the indicators to varying input data. Given the analytical nature of the indicators, it is imperative to interpret all analyses conducted, taking into account the various limitations associated with these indicators. Despite a substantial increase in coverage compared to before the imputations, it is important to acknowledge that the imputations of emissions and financial variables applied could be subject to measurement error and high uncertainty. Thus, while they do increase coverage, they may also introduce a degree of bias. We discuss such biases in more depth in Annex 6.1 and 6.3.2.

Figure 8
Comparison of carbon indicators with and without methodological and data enhancements: loans from banks, compiled at the single entity-level

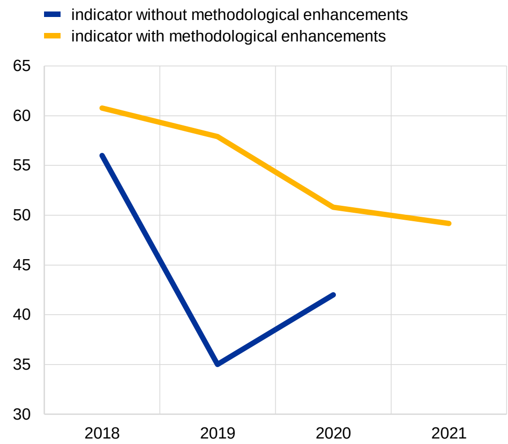
a) Financed emissions (FE), Scope 1, euro area aggregate

million tonnes of CO2



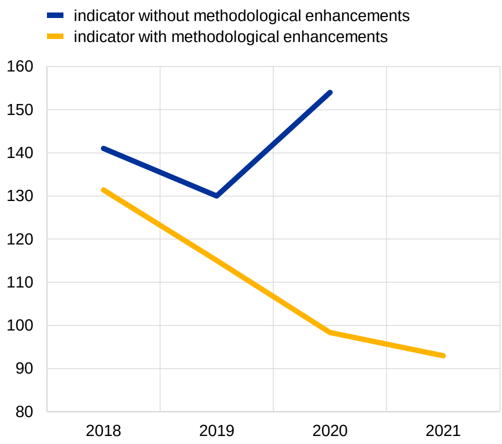
b) Carbon intensity (CI), Scope 1, euro area aggregate

tonnes of CO2 per million euro



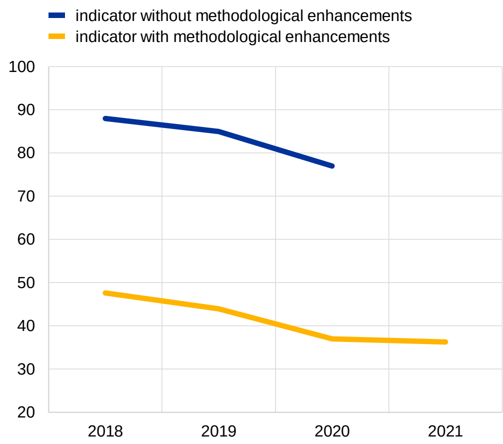
c) Weighted average carbon intensity (WACI), Scope 1, euro area aggregate

tonnes of CO2 per million euro



d) Carbon footprint (CFP), Scope 1, euro area aggregate

tonnes of CO2 per million euro



Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: The charts comprise only loans computed at single entity-level for Scope 1 emissions. WACI is adjusted for inflation and exchange rate effects.

Figure 9 below illustrates the euro area aggregate for all four carbon indicators, incorporating and excluding methodological and data enhancements. Securities data are consolidated at the corporate group level and listed shares and debt securities are analysed jointly. The analyses presented in this section focus on securities held by deposit taking corporations to increase comparability with the loan-based indicators. For an overview of securities held by non-money market fund investment funds (S124), please refer to **Figure 48**, and for insights into holdings by insurance corporations and pension funds (S128 and S129), consult **Figure 49**. In general, the indicators on indirect (Scope 2) emissions are substantially smaller in magnitude than those relating to direct (Scope 1) emissions, as they cover only emissions associated with purchased or acquired energy.

For the Financed emissions indicator relating to Scope 1 emissions, we can observe an increasing trend, with a dip in 2020 but a stable pattern for Scope 2 emissions (panel a). Economic sentiment links the trends in Financed emissions to pandemic restrictions in the aftermath of the COVID-19 outbreak, which affected the level of emissions via a dampening of global output. However, given the lack of a setup in which this hypothesis could be tested using a counterfactual scenario, any causal interpretation needs to be assessed with caution.

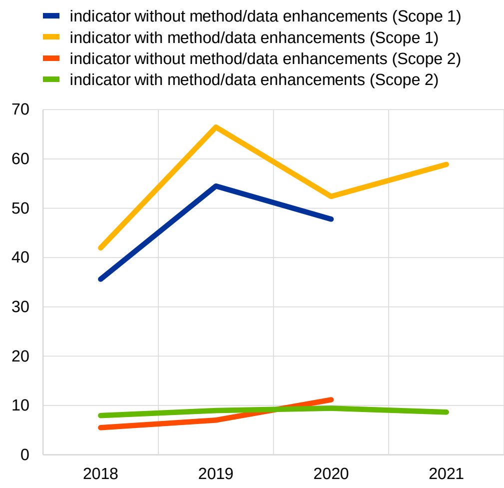
The relative indicators on Scope 2 emission all show a downward trend (see panels b, c, and d). Scope 1 emissions show a decreasing trend in the CI and, to a lesser extent, the WACI indicator (panels b and c). The CFP indicator increases in 2019 and decreases thereafter (panel d). Overall, the relative indicators for Scopes 1 and 2 largely exhibit a declining trend. However, this pattern is more pronounced in the loan portfolio, which could be for multiple reasons. For example, as loans tend to come with longer-term commitments compared with securities, they may exhibit a more pronounced reduction in carbon intensity if changes in lending practices or policies favouring lower carbon intensity are implemented over time. The time series decomposition presented later in this section helps us to understand which components are driving the developments we can observe here.

In the case of the securities portfolio, the impact of the implemented methodological and data enhancements is less pronounced. This can be attributed to one of the methods introduced, namely the imputation method, which has a smaller effect when compared with the loan portfolio. The reason for this is that the effect of the imputation method on the indicators is mitigated by a lower rate of imputed observations. This is due to the securities portfolio having a larger coverage before imputation compared with the loan portfolio.

Figure 9
Comparison of carbon indicators with and without methodological and data enhancements: securities held by deposit-taking corporations, compiled at the group-level

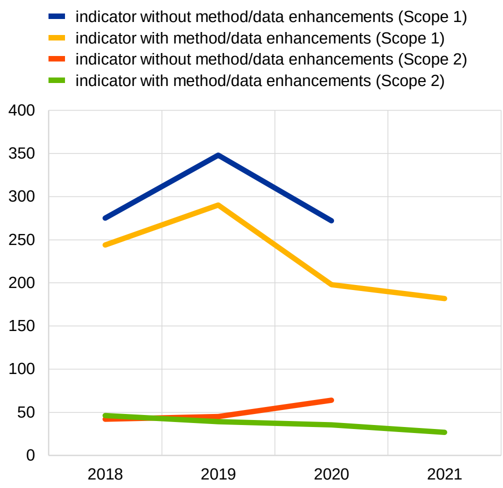
a) Financed emissions (FE), euro area aggregate

million tonnes of CO2



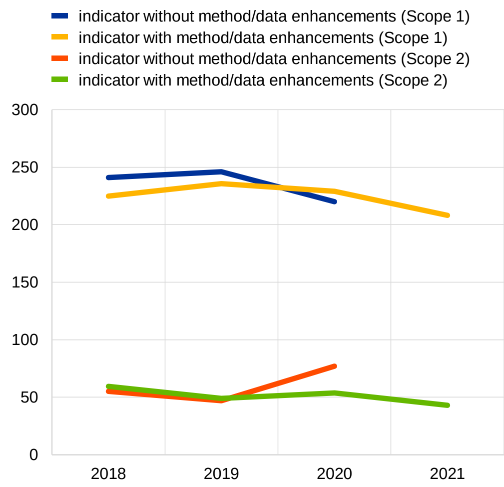
b) Carbon intensity (CI), euro area aggregate

tonnes of CO2 per million euro



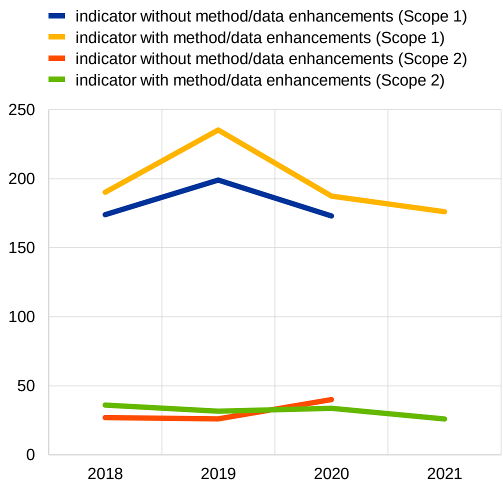
c) Weighted average carbon intensity (WACI), euro area aggregate

tonnes of CO2 per million euro



d) Carbon footprint (CFP), euro area aggregate

tonnes of CO2 per million euro



Sources: ESCB calculations based on data from Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), and Institutional Shareholder Services (ISS).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. The charts comprise Scope 1 and Scope 2 emissions. WACI is adjusted for inflation and exchange rate effects.

The findings are consistent with the view that initiatives among banks to address transition risks have been partly responsible for a reduction in their loan and to a lesser degree in their securities exposures to high-emitting economic activities over the study period. Notably, this pattern masks substantial heterogeneity across holder/creditor country and issuer/debtor sector figures. **Figure 10** illustrates the range between the 10th and 90th percentiles for WACI across euro area countries and the range between the lowest and the highest value across industry sectors (see

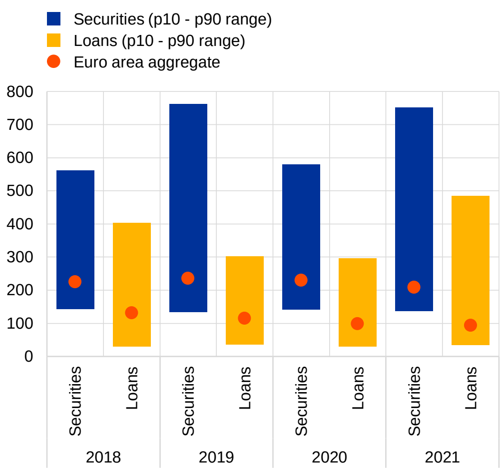
Annex 6.2. for details of the sectoral classification applied). The charts show substantial variation among some countries and sectors, underscoring the need for careful consideration when interpreting indicators aggregated at the euro area level or across sectors. Dynamics at the individual country and sector levels may differ significantly from aggregate values. Importantly, cross-country as well as cross-sector comparisons hinge on varying composition and coverage levels, making them particularly sensitive to data limitations as well as outliers. We therefore abstain from delving into country-specific disparities as well as temporal variations in specific countries, reserving such detailed analyses for future work.

Notably, the variation in the WACI among countries is only partially attributable to the differing shares of carbon-intensive sectors within each country. For additional insights on this aspect, please consult **Figure 50**.

Figure 10
Range between the 10th and 90th percentiles across euro area countries and the full range for industrial sectors

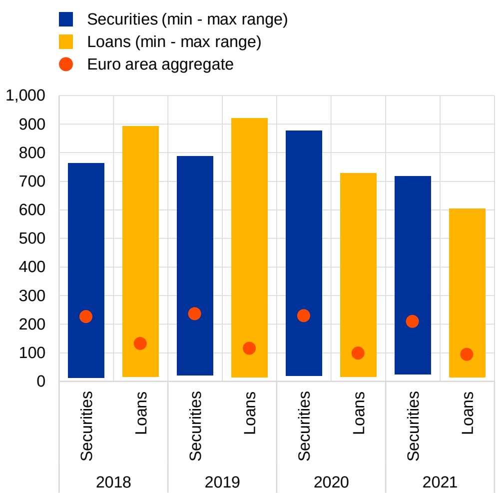
a) Weighted average carbon intensity (WACI), across euro area countries

tonnes of CO2 per million euro



b) Weighted average carbon intensity (WACI), euro area aggregate, across industrial sectors

tonnes of CO2 per million euro



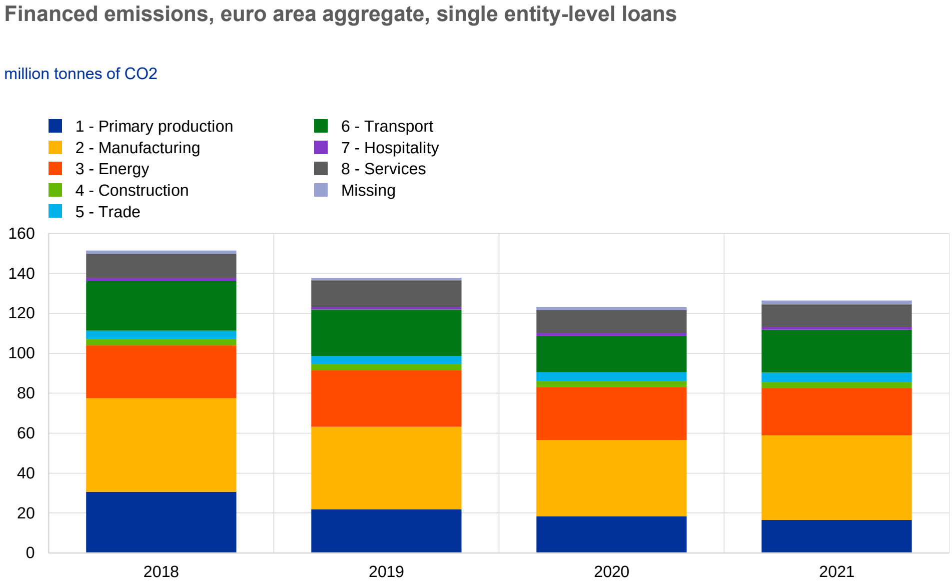
Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), Institutional Shareholder Services (ISS), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. Loans are computed at single entity level. The charts comprise only Scope 1 emissions. WACI is adjusted for inflation and exchange rate effects. Euro area aggregates are not computed as a simple mean across all countries. Instead, WACI at the euro area aggregate level is calculated by first determining the total portfolio value in the euro area in a given year by summing up the outstanding nominal amount/investment value in that year. Second, a WACI is calculated for each creditor-debtor/issuer-holder relationship using the equation described in Section 3.2.2, incorporating the portfolio value in the euro area. Third, by summing up all these microdata-level WACI indicators, we obtain the euro area aggregate WACI. This approach ensures that the euro area average considers the diverse sizes of portfolio values.

Figure 11 below depicts the sectoral breakdowns of financed emissions relating to single-entity loans over time. Two noteworthy findings emerge: first, the share of most sectors stays broadly stable, although the primary production sector shows a downward trend over the studied time frame. Second, the sectors accountable for the most substantial share of financed emissions are manufacturing, energy, primary production, and transport, while the contribution from other sectors is comparatively minor.

For the group-level indicators relating to the loans and securities portfolios, the sector classifications are less reliable, since multinational global corporations are more prone to sectoral misclassifications.[42] We therefore abstain from delving into sectoral disparities as well as temporal variations in specific sectors for the group indicators, reserving such detailed analyses for future work.

Figure 11

Industry sector breakdown of financed emissions



Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: Loans are computed at single entity level. The charts comprise only Scope 1 emissions.

To disentangle the drivers of variation over time, **Figure 12** shows a decomposition of the yearly changes in FE, WACI and CFP into their respective components. The decomposition allows us to distinguish between greening of the loan or securities portfolio (either in terms of greening of the underlying assets for an unchanged portfolio composition or from portfolio rebalancing towards greener investments or away from emission-intensive firms) and changes due to investment decisions. However, it is important to interpret the relative changes in the indicator components while considering the prevailing constraints, such as sensitivity to outliers and the imputation approaches applied due to a high share of missing data. The current imputation methods are relatively simple and remain a work in progress and hence can lead to measurement errors and substantial uncertainty. Regarding the FE indicator on the loan portfolio, which is decomposed into over-time changes attributable to changes in investment share and carbon emissions, we see that the development of the indicator is primarily driven by decreases in the emissions. Meanwhile, over-time changes in the FE indicator constructed on the securities

[42] Multinational global corporations are likely more prone to sectoral misclassifications due to the diverse nature of their business operations across multiple countries and industries. The complexity of their organisational structure, diverse revenue streams, and engagement in various sectors can pose challenges in accurately categorising their activities. Additionally, differences in reporting standards and regulatory frameworks across jurisdictions may contribute to variations in sectoral classifications, leading to potential misclassifications in analyses and reporting.

portfolio appear to be driven mainly by investment decisions and only to a smaller extent by emission changes. This disparity underscores the importance of the decomposition method in revealing dynamics within the indicator components that remain concealed when focusing on year-on-year changes in the indicators.

Regarding WACI, dissected into changes attributed to an issuer's/debtor's emissions, revenue and capital reallocation, and the CFP indicator, divided into changes from emissions, the value of the non-financial corporation, and capital reallocation, a substantial rise in emissions from 2020 to 2021 can be seen. However, this increase is counterbalanced by a rise in revenue, which produces a decrease in the indicator, given its placement in the denominator of the equation. This pattern of increasing emissions and increasing revenues is also visually prevalent in the securities portfolio, albeit to a lesser degree. A possible explanation for this observed dynamic could be attributed to an economic recovery following pandemic-related restrictions. Furthermore, in the securities portfolio, a contrasting trend is evident – emissions and revenues both decrease from 2019 to 2020. This decline could be attributed to disruptions in the economy resulting from pandemic-related restrictions. Changes in the portfolio share component have only a minor impact in comparison with the other components on the WACI and CFP indicators in the loan portfolio.

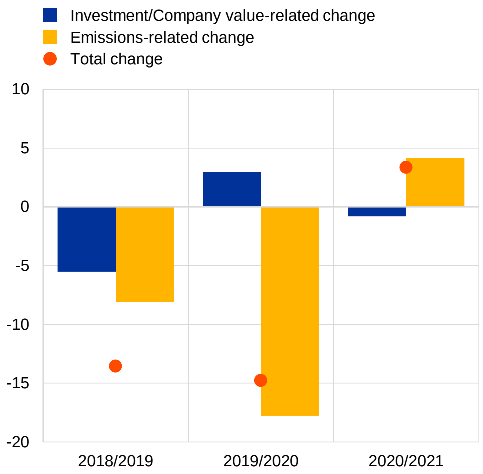
In the case of the securities portfolio, changes in the CFP are mainly driven by changes in the portfolio share and, to a slightly smaller extent, by changes in enterprise value. Notably, changes in emissions have only a minor impact on the CFP indicator during the studied time frame.

Despite a downward trend in the indicator totals, for both the loans and the securities portfolios, neither of the indicator components exhibits a consistent upward or downward trend over the studied time frame. The decomposition reveals the indicators' sensitivity to changes in financial components, such as the company's value measured, for example, using EVIC, which is inherently volatile. As such, the decomposition proves useful in corroborating time series dynamics and in spotting potential anomalies in the underlying microdata.

Figure 12
Time series decomposition for the loan and securities portfolios

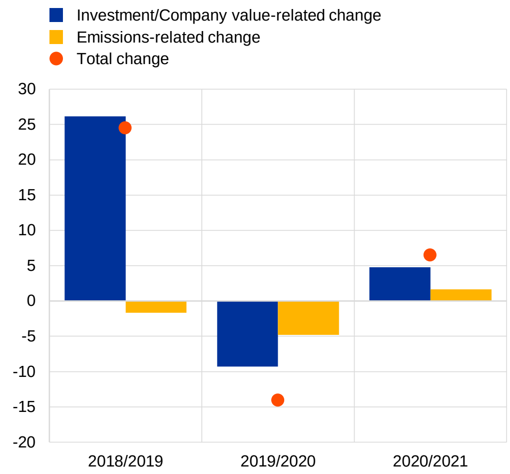
a) Decomposition of Financed emissions (FE), single entity-level loan portfolio, euro area aggregate

million tonnes of CO2



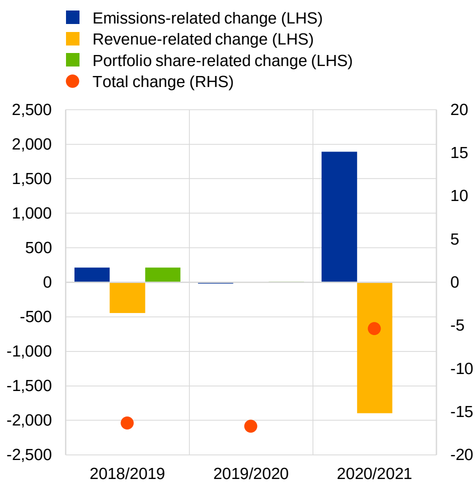
b) Decomposition of Financed emissions (FE), corporate group-level securities portfolio, euro area aggregate

million tonnes of CO2



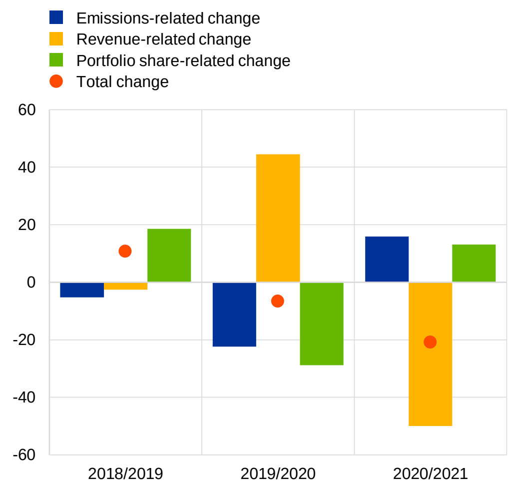
c) Decomposition of Weighted average carbon intensity (WACI), single entity-level loan portfolio, euro area aggregate

left-hand scale (LHS) and right-hand scale (RHS): tonnes of CO2 per million euro



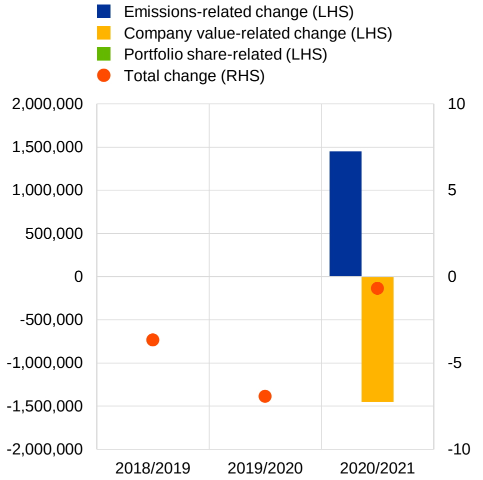
d) Decomposition of Weighted average carbon intensity (WACI), corporate group-level securities portfolio, euro area aggregate

tonnes of CO2 per million euro



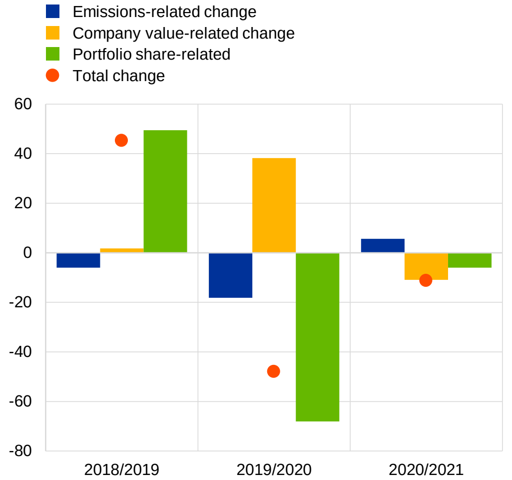
e) Decomposition of Carbon footprint (CFP), single entity-level loan portfolio, euro area aggregate

left-hand scale (LHS) and right-hand scale (RHS): tonnes of CO2 per million euro



f) Decomposition of Carbon footprint (CFP), corporate group-level securities portfolio, euro area aggregate

tonnes of CO2 per million euro



Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), Institutional Shareholder Services (ISS), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. Loans are computed at single entity level. The charts comprise only Scope 1 emissions.

Figure 13 illustrates the changes in coverage for the reference year 2020 due to the impacts of the imputation methods introduced and the application of the flex balancing method (for more information, please refer to Section 3.2.2). Coverage increased substantially due to the imputations, especially regarding the loan portfolio, thus mitigating variations in data availability across countries. This expanded and more harmonised coverage across countries amplifies the informative value of the analyses, enabling more comparable insights over time and across countries. However, as we explained earlier in this paper, increased coverage exacerbates data limitations and may introduce biases that limit the quality of the indicator. The figure confirms that implementation of the flex balancing algorithm results in only a minor loss in coverage.[43]

[43] To assess the impact of flex balancing on the group-level loan coverage, please see **Figure 51** in the Annex.

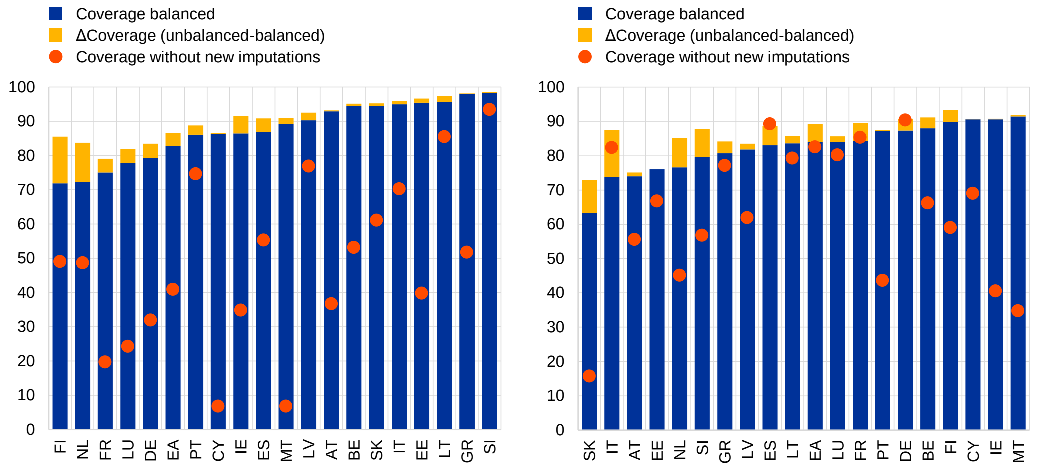
Figure 13
Coverage by country, in 2020

a) Coverage by country for loans compiled at the single-entity level

percentage of total financing volume covered

b) Coverage by country for securities compiled at the group-level

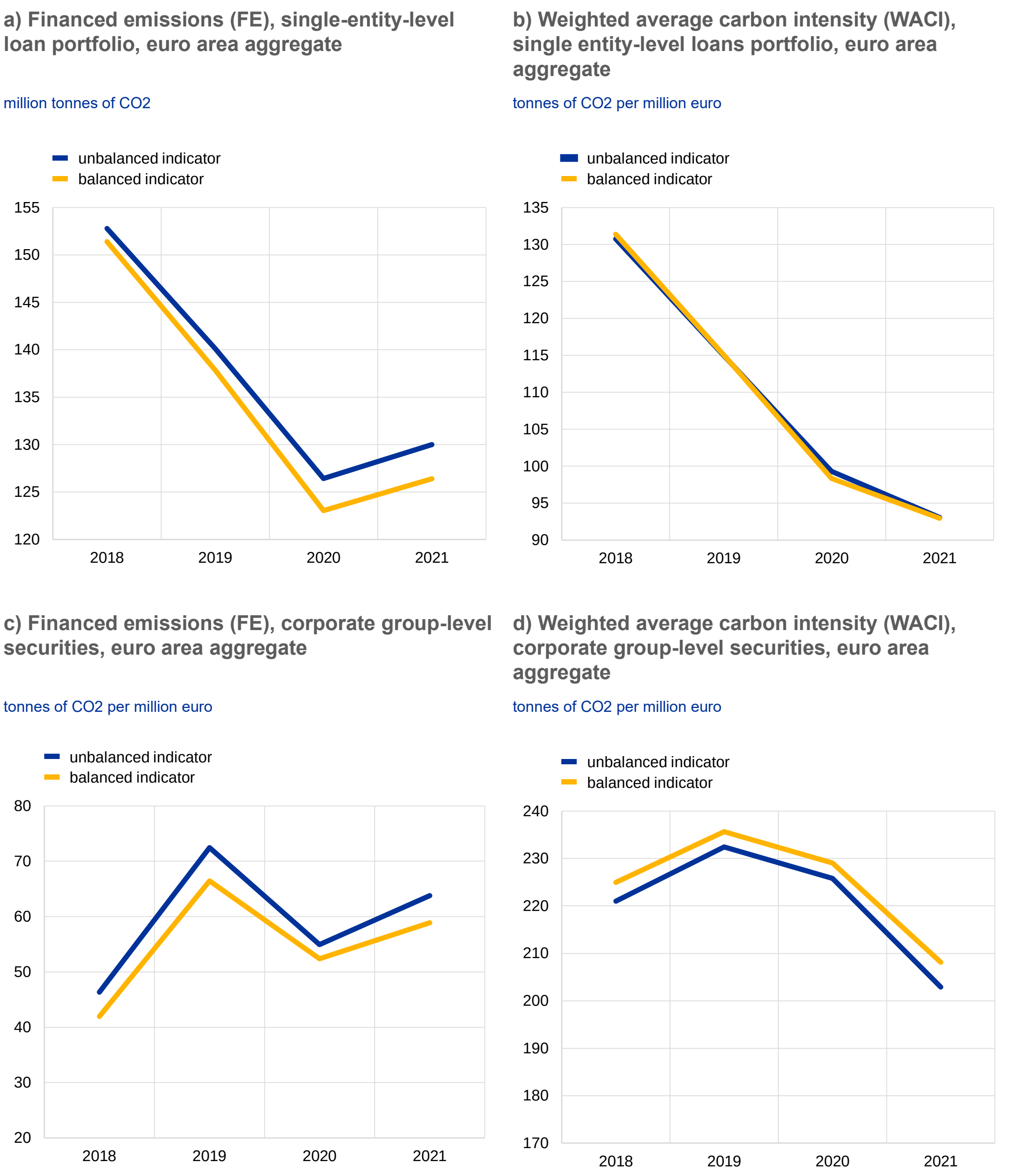
percentage of total financing volume covered



Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), Institutional Shareholder Services (ISS), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. Loans are computed at single entity level. The charts comprise only Scope 1 emissions.

Figure 14 below depicts the impact of applying the flex balancing, as described in Annex 6.3.4, on the FE and WACI indicators. The chart differentiates between balanced and unbalanced FE and WACI indicators for the euro area via loan and security exposure of deposit-taking corporations. As expected, as an absolute indicator, the FE indicator is sensitive to changes in coverage and since observations are dropped due to the balancing, the balanced indicator lies below the unbalanced one. In general, the flex balancing algorithm leads to a smoothing of over-time variation due to noise reduction by alleviating compositional effects. The smoothing effect is less apparent in the euro area aggregate but more evident at country level. Moreover, when comparing the interquartile range of the growth rate between the balanced and unbalanced time series at the most granular breakdown the balanced sample exhibits a smaller interquartile range of the growth rate than the unbalanced sample. Specifically, for the securities (loan) portfolio, the interquartile range in the unbalanced sample is 59.93 (28.31), while in the balanced sample, it falls to 58.05 (28.02).

Figure 14
Comparison of balanced and unbalanced carbon indicators on the loan and securities portfolios



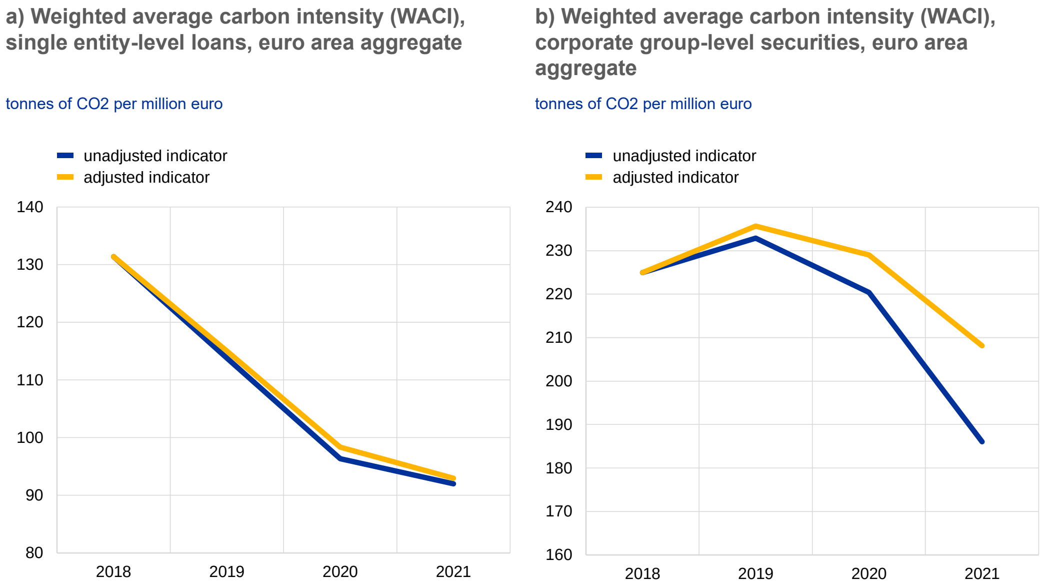
Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), Institutional Shareholder Services (ISS), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. Loans are computed at single entity level. The charts comprise only Scope 1 emissions. WACI is adjusted for inflation and exchange rate effects.

An adjustment for price and exchange rate effects is key to separating valuation effects from actual movements in real economic quantities. **Figure 15** illustrates the effect of adjusting WACI for inflation and exchange rate effects.[44] Notably, the figures illustrate that correcting for price changes induces additional smoothing of the time

[44] For an explanation as to why only WACI is currently adjusted for inflation and exchange rate effects, please refer to Footnote 33.

series, which is particularly pronounced for the securities-based indicators.[45] The importance of these adjustments will grow as we analyse longer time series.

Figure 15
Effect of exchange rate and inflation adjustment on carbon indicators on the loan and securities portfolios



Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), Institutional Shareholder Services (ISS), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. Loans are computed at single entity level. The charts comprise only Scope 1 emissions.

A key feature of this publication is the introduction of a loan-based group-level indicator that measures the exposures of euro area deposit-taking corporations to consolidated emissions of debtors irrespective of their location. Notably, the indicator thus allows us to assess the global transition risk of the banking sector through the lending channel. **Figure 16** provides a comparison between the single entity and the newly developed group-level indicators for the loan portfolio. Two findings emerge: first, the group-level indicators exhibit a slightly more volatile dynamic than the single entity-level ones throughout the studied time frame. Second, as expected, the FE group-level indicators exhibit higher levels, as single entity-level financed emissions include only local (euro area) emissions, while the group indicators encompass

[45] The impact of the price adjustment is likely more pronounced for the securities portfolio, driven by two factors related to exchange rate effect adjustments. Firstly, revenues associated with the securities portfolio undergo adjustments to account for exchange rate effects, unlike the single entity-level loan portfolio, where no exchange rate adjustments are necessary, as the revenues were originally expressed in euro, given that the exercise was limited to creditors in the euro area. Secondly, while both market values of securities and the ONA of loans undergo adjustments to account for exchange rate effects, the securities portfolio is expected to experience a more significant impact. This larger effect is likely due to a higher proportion of securities held by euro area banks that are issued in a currency other than the euro, in contrast to bank loans issued by euro area banks. Over the studied time frame, approximately 60% of the total investment value of all securities was denominated in a currency other than the euro, compared to only about 10% for the single entity-level loan portfolio.

global emissions. Similar to the single entity-level indicator, the group-level indicator also exhibits a downward trend in the relative indicators (see panels b, c and d).[46]

Despite substantial similarities in design, it is important to recognise certain constraints when comparing group-level and single entity-level indicators. These limitations arise from variations in carbon emissions data sources and, more notably, diverse imputation approaches for both carbon and financial data (for more information on the underlying emissions data sources and construction of the indicators, please refer to Section 3.2.1 and Section 3.2.2).

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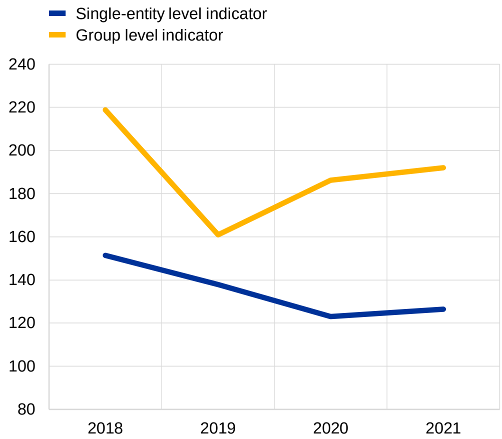
46 See **Figure 52** for a comparison of WACI, unadjusted for inflation and exchange rate effects, for the single entity-level and group-level carbon indicators on the loan portfolio. The observed gap between single entity and group-level unadjusted WACI mirrors the gap seen in the adjusted WACI. This suggests that variations between single entity and group-level WACI are not primarily influenced by inflation and exchange rate effects.

Figure 16
Comparison of single entity and group-level carbon indicators on the loan portfolio

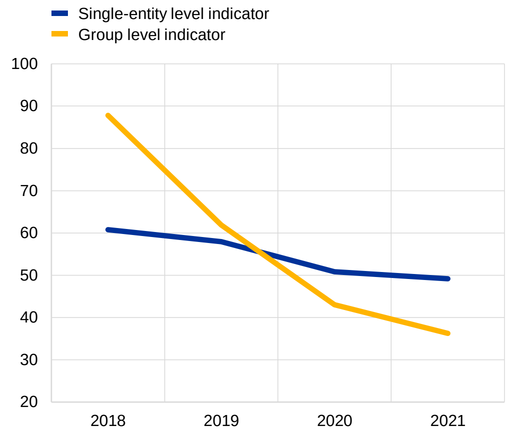
a) Financed emissions (FE), Scope 1, euro area aggregate

million tonnes of CO_2



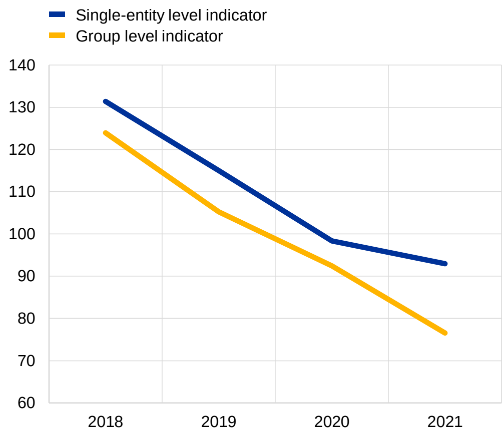
b) Carbon intensity (CI), Scope 1, euro area aggregate

tonnes of CO_2 per million euro



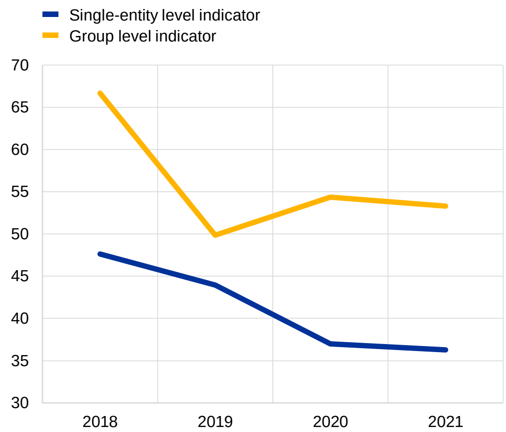
c) Weighted average carbon intensity (WACI), Scope 1, euro area aggregate

tonnes of CO_2 per million euro



d) Carbon footprint (CFP), Scope 1, euro area aggregate

tonnes of CO_2 per million euro



Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), Institutional Shareholder Services (ISS), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. Loans are computed at single entity level. The charts comprise only Scope 1 emissions. WACI is adjusted for inflation and exchange rate effects.

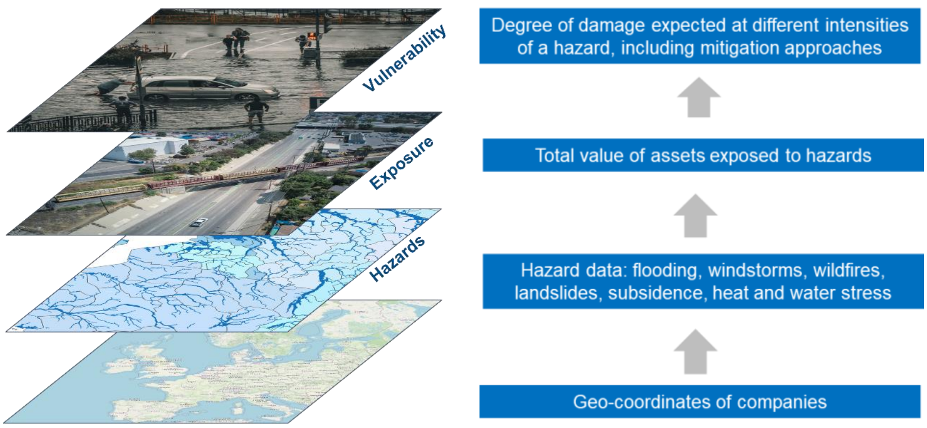
3.3 Physical risk indicators

The analytical indicators on physical risk aim to capture financial system exposures to companies located in areas susceptible to natural disasters (such as flooding, windstorms, wildfires or droughts) and chronic physical risks (heat and water stress) stemming from climate change. While the location of a financial institution itself can be also affected by a natural catastrophe, operational risk is limited, in the sense that financial services can be relocated or conducted remotely. Financial investment can be the source of much higher risk and notably our indicators focus on physical risk affecting loan, debt securities and equity portfolios.

All the indicators are compiled using a bottom-up approach. Our starting point is the registered address of the company concerned – a debtor in case of loan obligations or an issuer in the case of securities. For each location, a hazard intensity and probability under different climate scenarios is extracted from geospatial data available in the form of maps. Each type of hazard has its own specificities. For example, flood intensity is expressed as water depth (in metres) and available at 100 m resolution, while windstorms are based on maximum gust speed estimated at regional (NUTS3)[47] level. The climate data are then linked to the exposures: (i) the company's buildings and other physical assets such as machinery; and (ii) the company's financial obligations, such as loans, equity and debt securities held by euro area financial institutions. Lastly, the vulnerability of those assets is assessed by applying what are known as damage functions, which translate hazard intensities into potential monetary damages. Estimating damage functions requires information on past losses of natural disasters in the same geographical area. As such data are rarely available, damage functions are provided for a few acute hazards, such as floods and windstorms.

Figure 17

Stylised composition of physical risk indicators



Source: ECB, Climate change-related indicators, Methodological report, January 2023, based on the United Nations Office for Disaster Risk Reduction (UNDRR) terminology.

47 The nomenclature of territorial units for statistics (NUTS) is the statistical classification in Europe, dividing the EU into over 1,000 regions at three levels of detail, which are also presented by breakdowns indicating dominant terrain characteristics, such as urban-rural, metropolitan areas, islands, coastal, mountainous, and border regions. Geospatial files that include boundaries of NUTS regions can be found on the Eurostat GISCO website.

3.3.1 Climate data on physical hazards and vulnerability

Climate modelling[48] started in the early 1960s, but has come on leaps and bounds since then due to the relentless improvements in high-performance computing. The highly complex climate models we have nowadays do not only include information about atmospheric movements across the planet, but also display the global hydrosphere, biosphere and cryosphere, and the interactions between them. These climate models can be used for simulations of the climate system. The shorter the time horizon, the larger the influence of current climate conditions. For longer time horizons, the effect of other components such as planetary position or greenhouse gas emissions becomes more significant (DWD, 2021).

Climate models have been shown to be fairly reliable and accurate. In a study by Hausfather, Henri, Abbott, & Schmidt, the authors showed that even for models developed in the 1970s, the outcome did not diverge significantly from the historical climate observations (Hausfather, Henri, Abbott, & Schmidt, 2019). Naturally, increasing computer power and the complexity of the climate models increases their accuracy. Moreover, their foundation on physical principles in the earth system solidifies the confidence of the scientific community in the predictions of changes in the climate due to greenhouse gas emissions and biodiversity decline (Columbia Climate School, 2018).

While the physical principles used in the climate models remain constant over time, human behaviour (individually and collectively) is much more difficult to predict. However, the collective path, in terms of GHG emissions pathways, that humanity chooses in the coming decades will be one of the key elements shaping future climate and extreme weather events. ESCB climate indicators on physical risk include hazard projections for both current and forward-looking periods. Given the interest in the portfolios of financial institutions – which can be rebalanced in the medium term – the indicators are presented mainly for the period up to the mid-century. Where available, two scenarios are considered under what are known as representative concentration pathways (RCPs), more precisely RCP 4.5 and RCP 8.5. The RCPs were developed for the Fifth Assessment Report (AR5) and allow us to evaluate climate change risks for different amounts and concentrations of emissions in the atmosphere, while also helping to inform climate policies and necessary mitigation strategies (IPCC, 2010). The scenarios are expressed in terms of radiative forcing (4.5 and 8.5 W/m² respectively) by 2100. RCP 4.5 is considered as a moderate mitigation scenario, on the assumption that policies will be implemented to reduce GHG emissions, though without taking extreme measures to limit emissions. Meanwhile, RCP 8.5 assumes a high GHG emissions scenario, frequently referred to as a “business as usual” scenario, where no significant actions are taken to mitigate climate change.

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48 Climate predictions differ from weather forecasts in terms of both the level of detail and the forecasting period. While climate predictions provide some approximations to climate trends for coming months or years, weather forecasts aim to provide a detailed picture about the weather conditions in the coming hours or days. In contrast, climate projections take a long-term time horizon of several years or decades into consideration (DWD).

RCPs were later extended to account also for societal variables that can further influence the projections (e.g. population, education, or government policies on climate targets), which are known as Shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2014). Thus, every SSP scenario is defined by two factors: the level of societal steps taken towards climate change mitigation, and the assumption regarding the level of greenhouse gas emissions. SSPs allow us to incorporate the impact of socio-economic choices in the resulting magnitude of climate change and were prominently utilised in the IPCC Sixth Assessment Report (AR6) starting in 2021.

The indicators presented in this publication rely mostly on climate projections developed for the European continent – European Coordinated Regional Downscaling Experiment (EURO-CORDEX) – and are based on earlier models expressed in RCPs.[49] The primary goal of EURO-CORDEX is to provide detailed climate projections for Europe by downscaling global climate models to a finer regional scale, thus providing a clearer understanding of climate impacts at a more localised level.[50]

The physical hazard data used for this publication were retrieved entirely from public sources, which has several advantages: transparent methodology, no restrictions in data sharing, regular updates and steady stream of new data from established portals such as Copernicus[51] and the European Commission DRMKC RDH[52] developed and maintained by the Joint Research Centre (JRC).

The hazard maps provide almost full coverage across the EU (the overseas territories of France and the Netherlands, as well as the Canary Islands, Madeira and the Azores are excluded). In terms of entities covered in the financial dataset, at least 95% of RIAD entities registered in the EU are covered for each hazard type.

This section elaborates on the data sources and methodology for climate data – the foundation for the ESCB physical risk indicators. We cover a wide range of natural hazards. Information on floods is the most comprehensive source and includes not only flood severity for both coastal and river floods, but also estimates of monetary damage, along with data on adaptation measures in the form of flood defences. Frequency, intensity and damage are also available for windstorms, while for landslides and subsidence, data are available only as risk scores and moreover climate projections are not available for those particular hazards. The indicators also include hazards relating to an increase in temperatures: wildfires, water stress and droughts. In particular, we present two metrics developed for the purpose of IPCC

49 An IPCC assessment cycle typically spans five to seven years and involves extensive collaboration among hundreds of experts worldwide. Such a lengthy period is necessary in order to thoroughly review and integrate a vast amount of scientific research across various climate change aspects. In 2021, with the release of the IPCC AR6 report, which integrated the SSP scenarios for the first time, a EURO-CORDEX community held a workshop on prioritisation of the use of SSPs for downscaling the global projections. Only after the regional models are fully developed and validated – a process that can take several years – can specific hazard models be updated to incorporate the latest climate projections.

50 See EURO-CORDEX on the Climate-ADAPT platform and EURO-CORDEX Guidelines, Version 1.1 – 2021.02.

51 For more information, see https://www.copernicus.eu/en.

52 The Disaster Risk Management Knowledge Centre (DRMKC) Risk Data Hub (RDH): https://drmkc.jrc.ec.europa.eu/risk-data-hub.

AR6: consecutive dry days, which aims to capture drought conditions; and the standard precipitation index, which measures both extremes – dry and wet conditions – and links them to droughts and floods.

In the following sections, we elaborate on each type of hazard, covering also climate projections where available. The section on floods accounts for a wide range of aspects and is the most extensive. Wildfires are also described in greater detail, as the modelling was conducted internally by ESCB statisticians. For other hazards, where we rely directly on measures and methodology, references to the original sources are provided.

Lastly, a separate box is dedicated to additional metrics measuring the impact of heat on human health – Wet Bulb Globe Temperature and Heat Index. Those measures are not linked with financial portfolios, given the challenges in capturing the heat-stress spillovers to the financial system; instead, we elaborate extensively on the potential impact and channels of heat on economic activity (see Box 1).

Table 1 below presents an overview of the most relevant characteristics and data sources for physical hazards used for the physical risk indicators. Further technical details on hazards and data sources, including reference to geospatial datasets, are presented in Table 4 (see Section 3.2.2).

Table 1 – Overview of physical hazards data used

Hazard	Source	Methodology/original unit	Resolution	Time period	Climate scenario
Coastal flooding	Delft University of Technology (TUD)	Water level rise (m) based on the extreme events intensities (per return period)	100 m	1971-2000 (baseline) 2021-2050 2071-2100	RCP 4.5 RCP 8.5
River flooding	Delft University of Technology (TUD)	Water level rise (m) based on the extreme events intensities (per return period)	100 m	1971-2000 (baseline) 2021-2050	RCP 4.5 RCP 8.5
Windstorms	Own calculations, based on Copernicus WISC	Wind gust speed (m/s) based on the extreme events intensities (per return period)	NUTS3	1979-2020	-
Landslides	DRMKC RDH (JRC)	Score (1-5) based on characteristics of the terrain combined with daily maximum precipitation (per return period)	200 m	-	-
Subsidence	DRMKC RDH (JRC)	Score (1-5) based on soils' clay content	100 m	-	-
Wildfires	Own calculations, based on Copernicus	Probability of a fire event based on Fire Weather Index, land cover and burned areas	2.5 km	2001-2022 (baseline) 2023-2050	RCP 4.5 RCP 8.5
Water stress	Aqueduct WRI	Ratio of water demand and water supply	Hydrological sub-basins (5 arc-minute)	1960–2014 (baseline) 2030-2050	SSP2 RCP 4.5 SSP3 RCP 8.5
Consecutive dry days	IPCC	Maximum number of consecutive dry days (with precipitation < 1mm per day)	12.5km (11 arc-minute)	1986-2005 (baseline) 2021-2040 2041-2060	RCP 4.5 RCP 8.5
Standardized Precipitation Index (SPI-6)	IPCC	Index comparing cumulated precipitation for 6 months with the long-term precipitation distribution	12.5km (11 arc-minute)	1986-2005 (baseline) 2021-2040 2041-2060	RCP 4.5 RCP 8.5

Notes: RCP stands for Representative Concentration Pathways. RCP 4.5. corresponds to radiative forcing of 4.5 W/m² by the end of the century and is considered a moderate scenario. RCP 8.5 assumes a high GHG emissions scenario, leading to radiative forcing of 8.5 W/m² by 2100, and is considered a worst-case scenario.

3.3.1.1 Coastal and river floods

Flooding in Europe could rise to unprecedented levels due to increased precipitation (Tabari, 2020) and melting arctic ice shields (Hansen, 2016), both phenomena caused by climate change. Flood damage might also increase due to continued urban development in flood-prone areas. Flood management has a long history in the EU, which has a legal and early warning system framework[53] in place for assessing the negative consequences of flooding on population, environment and economic activity. As a result, there is more data available for flooding than for other natural catastrophes, thus benefiting our climate indicators in several areas: accounting for flood defences, expected loss, and projections under different climate scenarios.[54] In this paper, we use scientific datasets that offer harmonised historical data and projections under different climate scenarios and that were developed within the framework of the RAIN project (Groenemeijer et al., 2016) undertaken at the Delft University of Technology (TUD) by its Faculty of Civil Engineering and Geosciences, Department of Hydraulic Engineering.

Coastal floods

The modelling of coastal flood hazards incorporates several short- and long-term factors: (i) storm surges, which depend on meteorological conditions such as air pressure and wind; (ii) tides; (iii) sea level rise; and (iv) coastline changes due to erosion or uplift (Whitehouse, Pippa L., 2018). Under future projections, those forces may act in opposite directions. For Europe, Paprotny, Morales-Nápoles, & Jonkman (2017) estimate that between 2021 and 2050, on average 100-year surges would decrease slightly; also the uplift of land surface would help to lower relative water levels. According to the models, the overall trend reverses by end-century due to sea level rise, resulting in an increase in extreme water levels compared to the historical baseline. These developments are presented at regional level in **Figure 18**, which shows that the regions in the North and Baltic Sea areas are the most at risk. It is also worth noting the extent of flood risk: while on average the highest extreme water levels are estimated for the German coastline, the Netherlands experience both high water levels and a large country area at risk (over 40%), followed by Belgium (5%). In the Mediterranean region, Italy is also at relatively high risk. However, these estimates do not consider flood defences, which are currently the highest in Northern Europe (see **Figure 18**).

53 Floods Directive (2007/60/EC) mandating a Water Information System for Europe (WISE) and a European Flood Awareness System (EFAS) and its global extension GloFAS.

54 The historical flood maps of the European Commission Joint Research Centre (JRC) were used in the first release of the indicators. However, as the projections under different climate scenarios were not available for all dimensions at the time of this publication, changes have been made to the data sources that are used. An overview of the models and of the differences between them is provided in Paprotny, 2019, Table 1.

The authors highlight several uncertainties in the modelling (e.g. low spatial resolution and accuracy of input data, influence of local factors), although it should be noted that other large-scale pan-European models are not immune to these problems either. Paprotny conducts a comprehensive study of the accuracy of pan-European coastal flood maps, including TUD and JRC analysis (Paprotny, 2019). The results were validated using past observations, as well as high-resolution regional maps, indicating good model performance overall, albeit with some disparities between countries. With respect to projections of future changes, assumptions regarding flood protection levels have a considerable impact on the results and might lead to underestimation of risks, if the defences prove unreliable. The authors conclude that at the current stage, continental models are unable to replace local assessment and expert judgement, though they do allow for a broader analysis based on a harmonised approach – which offers advantages also for our analysis at the euro area level.

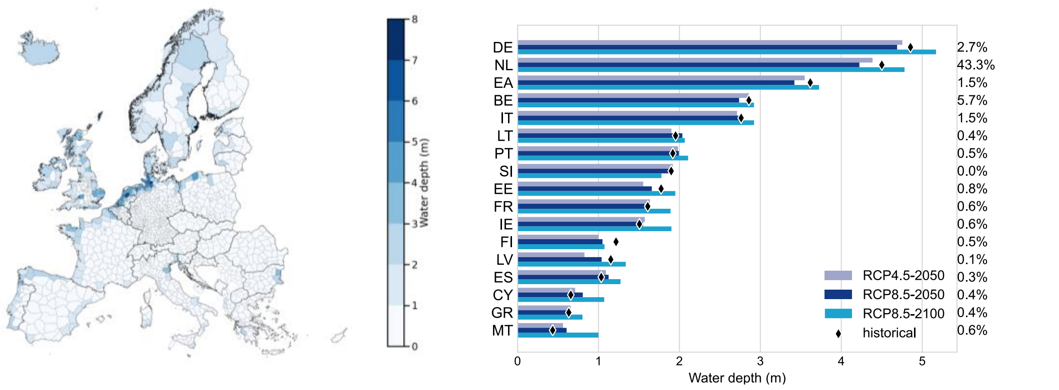
Figure 18
Coastal flooding

a) Regional (NUTS3) flood severity

Water depth (m), 1971-2000 median, 100-year flood, no flood protection

b) Flood severity by country, climate scenarios RCP 4.5, RCP 8.5 and historical baseline

Water depth (m), median within area at risk, 100-year flood, no flood protection



Source: Delft University of Technology.
Notes: Data are aggregated at NUTS3 (panel a) and country level (panel b) by taking weighted averages across the areas affected. Panel b: share of area affected is indicated on the right-hand scale.

River floods

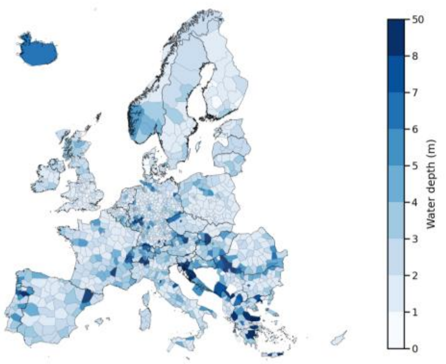
River floods can be caused by heavy rainfall, snowmelt and increased sea water levels. Limited absorption of soil during lengthy periods of rainfall is an important factor affecting the severity of the flooding. The risk is more pronounced in urban areas with limited water drainage within artificial surfaces. River flood risk maps are also based on the TUD study. The model estimates extreme river discharges based on: (i) catchment area and its steepness; (ii) fraction of land covered by water bodies and urban areas; and (iii) propensity to runoff, precipitation and snowmelt. The latter variables have been taken from the regional EURO-CORDEX climate model and are applied for projections under climate scenarios, while it is assumed that there are no changes in the land cover (Groenemeijer et al., 2016).

Figure 19 shows a heterogeneous picture of river flooding in the euro area. Looking at those countries with large rivers, Germany and France will experience an increase in river flood risk, as already shown in mid-century scenarios. Finland is on the other side of the spectrum – as Scandinavian countries will experience a decrease in risk due to lower snowfall and subsequently lower snowmelt.

Figure 19
River flooding

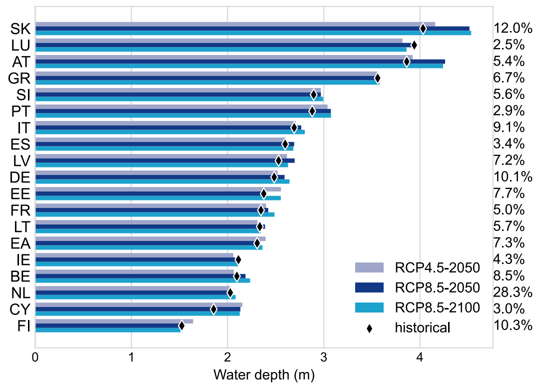
a) Regional (NUTS3) flood severity

water depth (m), 1971-2000 median, 100-year flood, no flood protection



b) Flood severity by country, climate scenarios RCP 4.5, RCP 8.5 and historical baseline

Water depth (m), median within area at risk, 100-year flood, no flood protection



Source: Delft University of Technology.
Notes: Data are aggregated at NUTS3 (panel a) and country level (panel b) by taking weighted averages across affected areas. Panel b): Share of area affected is indicated on the right-hand scale.

Groenemeijer et al. (2016) highlights high uncertainties surrounding precipitation predictions in the climate modelling, omissions of smaller catchments, and floods caused by ice blocking of river flow, which might be relevant in Northern Europe. Similar to coastal flooding, assumptions regarding flood defences might have large impact on the risk assessment, as described in the following section.

Adaptation measures for floods

As floods are one of the most common and costly natural disasters in Europe, European countries have developed effective flood adaptation strategies that will need to be strengthened as flood risk intensifies in the future and as economic development expands in flood-prone areas. Dottori et al. (2023) investigates four adaptation strategies that can be effective in limiting river flood damage: (i) detention areas that can be flooded in a controlled manner; (ii) dyke systems that elevate river banks and control the streamflow; (iii) flood proofing of individual buildings; and (iv) relocation to safer areas. Detention area appear to be the most cost-effective, with the ratio of benefits (in terms of damage avoided) to investment estimated at 4.2 for the EU plus the United Kingdom under the 3 ºC warming scenario by 2100.

Thus, the incorporation of flood defences is an important element when assessing flood risk. In our analysis, we rely on a map of flood protection standards for European countries created by the Joint Research Centre (JRC) (Bianca et al., 2022). The map was crafted through multiple stages, utilising diverse information sources and modelling. The selection of appropriate protection levels for each country was informed by prioritising data on design protection levels, which incorporates empirical information detailing the actual standard of existing protection infrastructure, as well as the standards defined by engineers when designing and implementing current river and coastal flood protection systems. This information was gathered as part of the Flood Protection Standards (FLOPROS) project[55] (Scussolini et al., 2016), sourced from official reports, technical documentation, and scientific publications, and quantifies protection standards in terms of the flood return period in years. Where literature information was unavailable, the JRC’s map relies on estimates, where the level of flood defence was determined based on the closest match between modelled and observed losses. Given that the flood losses are largely reported at national level, the results show uniform protection standards for several countries (see **Figure 20**).

The dataset aims to capture present conditions of flood protection levels across Europe. For the climate scenarios, our approach follows the RAIN project methodology (Groenemeijer et al., 2016), assuming that the current flood defences will be able to withstand the same water levels in the future (see Annex 6.4.1).

As pointed out in the previous section, loss estimates are contingent on the reliability of the protection standards assumed. The data are partially based on modelling, legal or design requirements, which might diverge from the actual defence structures. Existing infrastructure is also expected to evolve. For instance, future investments in adaptation measures might improve protection levels and reduce vulnerability to flooding. Meanwhile, flood defences, if not regularly maintained, might deteriorate.

Given the high level of uncertainty regarding flood protection, in this paper we elaborate on the results both with and without flood protection – and the latter can indicate potential losses when protective structures fail.

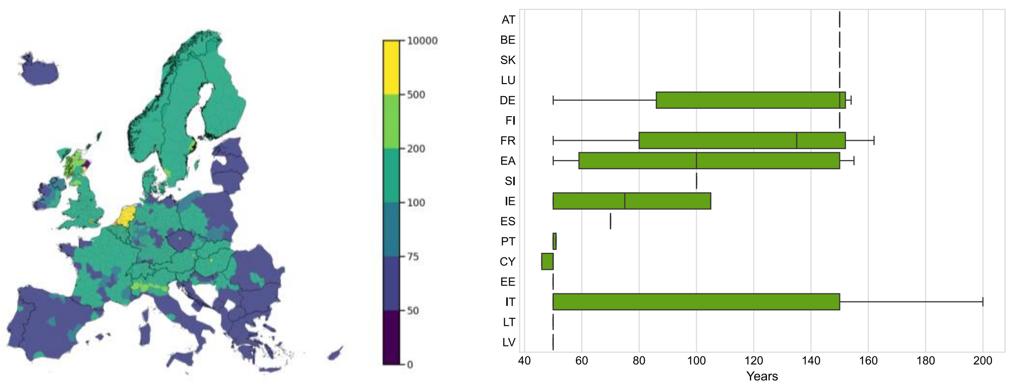
Figure 20
Distribution of flood protection levels across Europe

a) Regional (NUTS3) flood protection

Maximum return period of flood protection (years)

b) Flood protection distribution by country

Maximum return period of flood protection (years)



Source: Joint Research Centre (JRC), based on Dottori et al., 2022.
Notes: Values indicate the estimated return period of the design (in years) of local protection structures against floods. In panel b), the Netherlands was removed as an outlier. Whiskers show 5th and 95th percentiles; boxplot represents 25th, 50th and 75th percentiles.

55 For more information on the database and other aspects, see https://nhess.copernicus.org/articles/16/1049/2016/nhess-16-1049-2016-supplement.zip.

3.3.1.2 Windstorms

Wind damage primarily arises from gusts, which are brief, high-speed wind blasts, or through extended durations of strong winds.[56] The intensity of a windstorm is often gauged by its gust speed, defined as the peak wind speed reached during the storm. This peak speed is typically when the windstorm is at its most destructive. Consequently, gust speeds serve as a critical metric for assessing the potential damage caused by windstorms (Alduse, Pang, Tadinada & Khan, 2022).

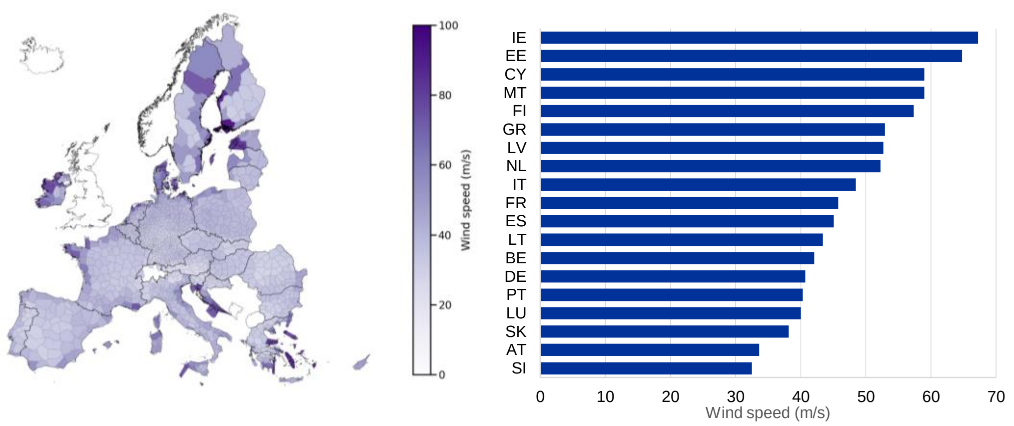
The impact of climate change on windstorm patterns is unclear, at least in Europe. The work of the Intergovernmental Panel on Climate Change (IPCC) does not find any increase in average annual wind speed, even in the worst-case scenario (IPCC, 2022). Still, windstorms are one of the most harmful hazards in Europe and their inclusion in the physical risk assessment is therefore crucial.

Expected damage is estimated by looking at gust speeds for designated return periods, alongside frequency analysis to ascertain the number of storms. The analysis employs storm footprint data, which provides a detailed representation of each storm's impact area. This approach combines meteorological data with statistical methods to estimate the likelihood and potential severity of windstorm-related damage over time.

Figure 21
Windstorms (wind speed, m/s)

a) Regional (NUTS3) wind speed
Wind gust speed (m/s), 1979-2000 median, 100-year return period

b) Wind speed by country, historical baseline
Wind gust speed (m/s), median within area at risk, 100-year return period



Sources: Copernicus WISC, ESCB calculations.
Notes: Data are aggregated at NUTS3 (panel a) and country level (panel b) by taking medians across affected areas. Windstorms as wind gust speed (m/s) based on extreme events intensities.

The final estimates of windstorm risk are based on ESCB calculations. The analysis was conducted with the aim of aligning the methodology with the existing framework for flood hazards and to estimate potential damages depending on hazard severity. Data at a granular level are applied to assess the impact of windstorms on a

56 See https://www.britannica.com/science/windstorm.

selected area, such as at country level (NUTS0) or at a more granular level (NUTS3).

A frequency analysis is performed to determine the occurrence of windstorms (officially classified as such) within a single year, and to spot any discernible trend in the frequency of occurrence. We use historical occurrence of classified storms per year from Copernicus and derive the frequency of storms per year for the whole dataset. A linear regression analysis is then performed on the recorded frequencies, to determine the trend within the dataset. Lastly, the results are back-tested using IPCC scenario analyses for windstorm occurrence.

Gumbel's method[57] is applied to determine return periods of gust speed as detailed in Kiyani, Kiyani & Behdarvand, 2021. This involves the use of the Gumbel distribution to compute a probability density function (PDF), which represents the probability of specific gust speeds occurring per storm and is used to determine the return period of a specific wind speed. By combining return periods and storm frequency, damage is determined using damage curves per type of land cover, as detailed in Koks & Haer, 2020, using an analogical method as for flood risk.

The resulting regional and country estimates are presented in **Figure 21.**

3.3.1.3 Landslides

A landslide is defined as the gravitational movement of a mass of rock, earth or debris down a slope. It can be triggered by various events: heavy or prolonged rainfall, earthquakes, volcanic eruptions, rapid snow melt, slope undercutting by rivers or sea waves, permafrost thawing, land use changes (e.g. deforestation), rapid reservoir drawdown, irrigation, blasting vibrations or water leakage from utilities.[58]

The data are sourced from the DRMKC RDH and are available for seven different return periods. The RDH landslide indicator is based on a matrix approach (Thiebes et al., 2017) and combines predisposition to landslide resulting from terrain characteristics with probabilistic daily maximum precipitation. The risk scores computed for the purpose of our climate indicators incorporate several return periods and follow the derivation of the risk scores for floods (see Section 3.3.2 and Annex 6.4.1). The geographical distribution of landslides in Europe is presented in **Figure 22**, panel a), below.

3.3.1.4 Subsidence

Subsidence refers to the sinking of a part of the earth's crust and can be man-made (e.g. underground excavations) or due to a natural process of soils shrinking and

57 A Gumbel distribution is a is a type of extreme value distribution that models the distribution of the maximum (or minimum) values of a sample from various underlying distributions. The Gumbel method is commonly used within civil engineering to determine design criteria of buildings, bridges and other structures.

58 See https://esdac.jrc.ec.europa.eu/themes/landslides.

swelling depending on soil moisture. Its probability increases with sea level rise (Nicholls, 2021) or drought (Charpentier et al., 2021) and subsidence can be also triggered by earthquakes. It can cause significant damage to buildings and infrastructure. For example, Corti et al. (2011) suggest that in France, financial cost of subsidence is comparable to flood damage, based on insurance claims (Corti, M., Bresch & Seneviratne, 2011).

Subsidence data are taken from the DRMKC RDH. Currently, the probability of a subsidence event happening is not available and susceptibility scores are largely based on soil clay content. Subsidence risk scores are presented in **Figure 22**, panel b), below.

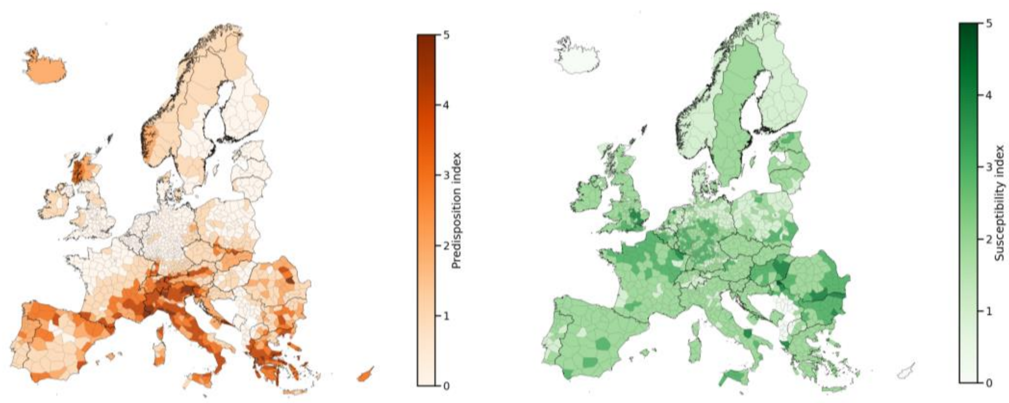
Figure 22
Landslides and subsidence risk scores

a) Regional (NUTS3) landslide predisposition

Predisposition index (1-5), median, 100-year return period

b) Regional (NUTS3) subsidence susceptibility

Susceptibility index (1-5), median



Source: DRMKC RDH (JRC).
Notes: Data are aggregated at NUTS3 level by taking medians across affected areas. Panel a): scores for: landslides 100-year return period from 1 (low) to 5 (extremely high). Panel b): subsidence in scores, 1 – Coarse (clay< 18% and > 65% sand); 2 – Medium (18% < clay < 35% and sand >= 15%, or clay > 18% and 15% < sand < 65%); 3 – Medium fine (clay < 35% and sand < 15%); 4 – Fine (35% < clay < 60%); and 5 – Very fine (clay > 60 %).

3.3.1.5 Wildfires

A wildfire is defined as an unplanned fire that burns in a natural area, not limited to forest fires. They are often caused by humans, directly or indirectly, or by natural phenomena. The recent past shows that wildfire is an increasing challenge in Europe. While in 2020, 340,000 hectares (ha) were burned by wildfire in the EU, this area exceeded 500,000 ha in 2021 and more than doubled in 2022, when an area comparable to the size of Montenegro (1,624,381 ha) suffered wildfire events. Wildfires not only lead to high economic and ecological damages but also increase CO2 emissions and accelerate climate change. In a recent study[59], the UN estimated

[59] See page 10 of United Nations Environment Programme (2022), *Spreading like Wildfire – The Rising Threat of Extraordinary Landscape Fires,* a UNEP Rapid Response Assessment, Nairobi.

that, in a moderate scenario for global warming, the likelihood of extreme, catastrophic fires could increase by up to a third by 2050 and up to 52% by 2100.

For the purpose of our statistical indicators, wildfire risk is expressed as a score indicator and is based on fire occurrence probability. The indicator uses three main sources: the Fire Weather Indicator (FWI), MODIS land cover data and MODIS burned area detection. The final estimates are the result of ESCB work and the modelling methodology, including input data sources, is described in more detail in Annex 6.4.4.

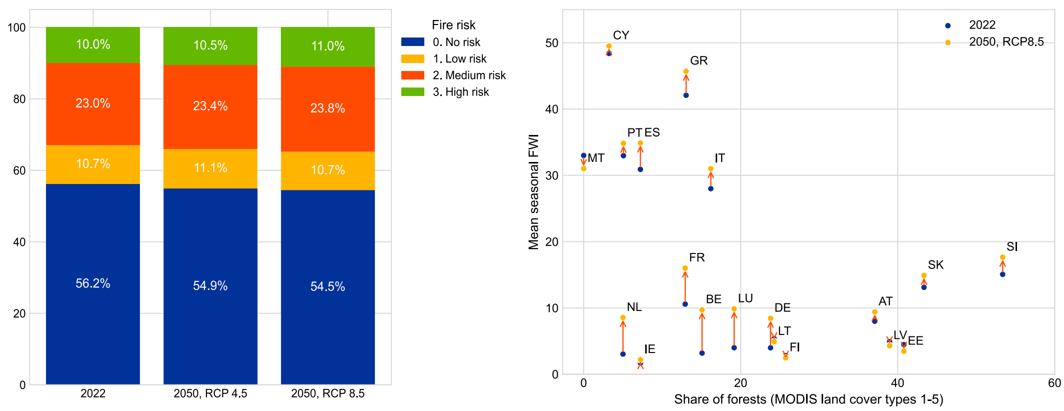
Figure 23
Wildfire risk

a) Fire risk by risk category

Predicted fire probability (%)

b) Fire risk changes by FWI and land cover by country

Share of forest as part of total land cover (%, x-axis), mean seasonal FWI (index, y-axis)



Sources: Copernicus and ESCB calculations, based on: (i) Copernicus Fire Weather Index; (ii) Copernicus land cover (distance to city, railway and road); and (iii) MODIS burned area and land cover.

The results are characterised by an increase in average fire probability over all grid cells, from 0.49% in 2022 to 0.51% in 2050 under the RCP 4.5 scenario, and to 0.53% under the RCP 8.5 scenario, which is also visible when looking at risk classes (see **Figure 23**, panel a). At the same time, while Portugal, Greece and Spain are expected to see a sharp increase in risk by 2050, compared to 2022 (see **Figure 24**, panel b), the Baltics region is likely to encounter lower maximum FWI values (thanks to warmer but more humid weather) and therefore similar, or possibly lower, fire risk.[60] The greatest relative change in fire risk under the RCP 8.5 scenario is expected in the Netherlands (+180%), Belgium (+69%) and Luxembourg (+54%), albeit from relatively low bases, while the median risk increases are more worrying

60 As a comparison, mean FWI is expected to increase under both future scenarios in Cyprus, while max FWI increases under the RCP 4.5 scenario but decreases under the RCP 8.5 scenario, compared to 2022. As a result, fire risk is higher under the RCP 4.5 scenario than under the RCP 8.5 scenario (see **Figure 24**, panel b). Baltics countries are predicted to experience a slight drop in their FWI mean values, as shown in **Figure 23**, panel b).

for Portugal (+9%), Greece (+36%), Italy (+7%) and Spain (+20%), all countries with already comparatively high risk values.

A deeper analysis of predicted fire probabilities reflects the advantage of incorporating land cover types in the model. A higher share of forests[61], for instance, reduces fire risk thanks to the moisture-preserving nature of trees. The highest forest shares are present in Slovenia, Slovakia and Estonia (over 40%), while the lowest shares are found in Malta, Cyprus, Portugal and the Netherlands, which in turn have an impact on fire risk (**Figure 23**, panel b).

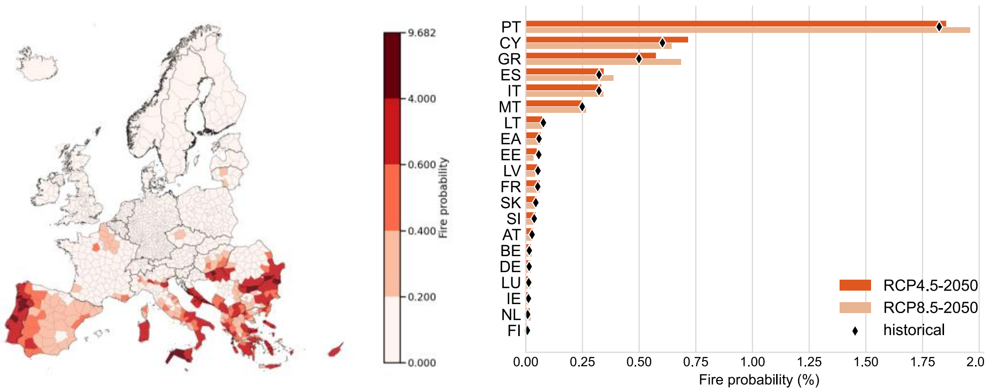
Figure 24
Wildfires – geographical distribution of risk

a) Regional (NUTS3) fire probability

Fire probability, 2001-2022 average

b) Fire probability by country, climate scenarios RCP 4.5, RCP 8.5 and historical baseline

Fire probability, median within area at risk



Sources: Copernicus, ESCB calculations.
Notes: Data are aggregated at NUTS3 (panel a) and country level (panel b) by taking medians across affected areas. Panel a) probability of a fire event based on the Fire Weather Index (FWI), land cover and burned area.

3.3.1.6 Water stress

Climate change, global economic development and population growth will alter the availability of, and competition for, water around the world. The global score data provided by the Aqueduct project of the World Resources Institute incorporates both climate change impacts on water supply and changes in socioeconomic demand for water. The variable considered for the physical risk indicators is water stress, the ratio between total water withdrawal, and available renewable surface water. It measures the level of competition for available water and estimates the degree to which freshwater availability is an ongoing concern. A higher ratio indicates fiercer competition among users. These ratios are then converted into risk scores ranging

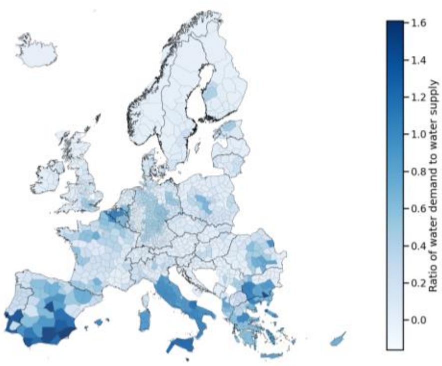
[61] Share of area covered by MODIS land cover types 1 to 5 (various forest types). This excludes cropland/natural vegetation mosaics.

from low water stress (<10%) to extremely high water stress (>80%). The overall water stress for Europe between 1950 and 2010 can be seen in **Figure 25**.

Figure 25
Water stress (ratio of water demand to water supply)

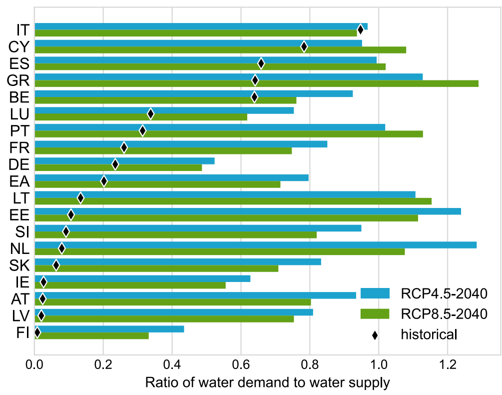
a) Regional (NUTS3) water stress

Ratio of water demand to supply, 1960-2014 average



b) Water stress by country, climate scenarios RCP 4.5, RCP 8.5 and historical baseline

Ratio of water demand to supply, median within area at risk



Source: Aqueduct WRI.
Notes: Data are aggregated at NUTS3 (panel a) and country level (panel b) by taking medians across affected areas. Due to the adoption of large-scale modelling techniques, the presentation of values for Malta is hindered by insufficient geographical resolution.

3.3.1.7 Droughts

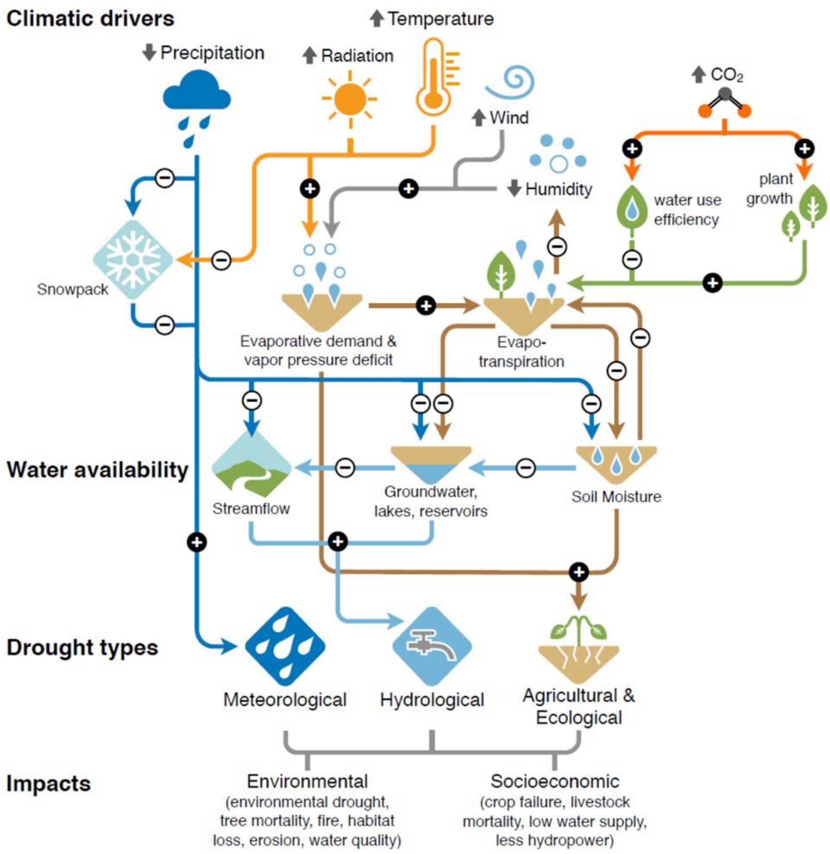
"Droughts refer to periods of time with substantially below average moisture conditions, usually covering large areas, during which limitations in water availability result in negative impacts for various components of natural systems and economic sectors" (IPCC, 2021, p. 1570).

Generally, droughts are not measured by a single variable, as they may involve different timescales, from quite sudden "flash droughts" to decadal rainfall deficits (Ault, 2014; Cook et al., 2016; Garreaud et al., 2017). Droughts can also take various forms, including meteorological (mainly precipitation deficits), agricultural (crop yield reductions or failure, often related to soil moisture deficits), ecological (related to plant water stress, which can cause tree mortality), or hydrological (water shortage in streams or storages such as reservoirs, lakes or groundwater) (IPCC, 2021, pp. 1513-1766).

As for many extreme weather events, the mechanisms behind droughts are a combination of thermodynamic and dynamic processes. Thermodynamic processes largely relate to heat and moisture exchange and can be affected by plant cover changes and greenhouse gas emissions. These can affect atmospheric humidity, temperature and radiation, which can in turn affect precipitation and evapotranspiration in some regions and time frames (see also **Figure 26**).

Meanwhile, dynamic processes are responsible for the variation in drought durations (IPCC, 2021, pp. 1513-1766).

Figure 26
Climatic drivers for drought



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Source: IPCC AR6, Chapter 8 (Fig 8.6).

In a first approximation to capture the drought phenomena in the climate risk indicators, the focus lies on meteorological droughts and thus on the measurement of precipitation deficits, as this is the most standardised measure for droughts and data availability is relatively high. We use two variables suggested by the IPCC: the Standardized Precipitation Index (SPI-6) and Consecutive Dry Days (CDD). As a further development of the climate risk indicators, we aim to include moisture deficits and evaporation effects to provide a full picture of drought drivers.

Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) is a widely used index to characterise meteorological drought on a range of timescales. In 2010, the World Meteorological Organization (WMO) selected the SPI as a key meteorological drought indicator to be produced operationally by meteorological services (European Drought Observatory). On short timescales, the SPI relates closely to soil moisture, while on longer timescales, the SPI can relate to groundwater and reservoir storage. It quantifies observed precipitation as a standardised departure from a selected probability distribution function (normally gamma distribution that is then transformed into a normal distribution) that models raw precipitation data. SPI-6 compares accumulated precipitation over six-months periods with the long-term precipitation distribution for the same location and accumulation period. The index is computed by follows: (i) a monthly precipitation time series (at least 30 years) is selected; (ii) the running average for the n-months window is computed; (iii) a Gamma distribution is used to fit the data (the fitting can be achieved through the maximum likelihood estimation of the Gamma distribution parameters); and lastly (iv) the values from this probability distribution are transformed into a normal distribution, so that the mean SPI for the location and desired period is zero and the standard deviation is 1 (Edwards & McKee, 1997).

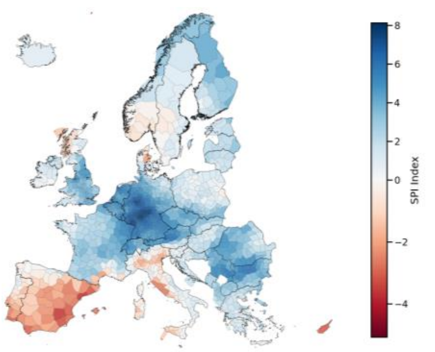
A drought event starts in the month when SPI falls below −1 and ends when SPI returns to positive values, for at least two consecutive months (Spinoni et al., 2014). In general, negative values indicate less rain and positive values indicate more rain. The advantage of the SPI is that it can be compared over different climate regions, while the disadvantage is that it fails to account for evaporation effects.

Figure 27 shows the expected deviation from the historical averages, which was close to zero across all EU countries. Future predictions show a larger divergence from this “normal” precipitation pattern. While in Northern Europe higher and more frequent amounts of rain are expected, Southern Europe runs the risk of experiencing further rain deficits over the coming decades.

Figure 27
Standardized Precipitation Index (SPI)

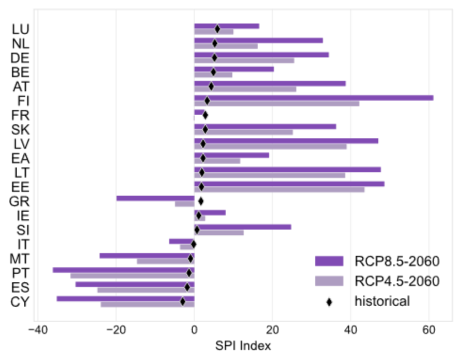
a) Regional (NUTS3) SPI

SPI index, 1986-2005 average, 100-year return period



b) SPI by country, climate scenarios RCP 4.5, RCP 8.5 and historical baseline

SPI index, median within area at risk, 100-year return period



Source: IPCC.
Notes: Data are aggregated at NUTS3 (panel a) and country level (panel b) by taking medians across affected areas. Index comparing accumulated precipitation over six months with the long-term precipitation distribution.

Consecutive dry days (CDD)

A day is counted as a consecutive dry day if it is at least the second day with a precipitation of less than 1 mm (Dunn et al., 2020). CDD can serve as an effective measure of extreme precipitation and seasonal droughts. However, the precise number of consecutive dry days that qualifies as a drought depends heavily on geographical location or “usual” climate conditions. For instance, while a week without rain in a tropical climate at the equator might already qualify as a drought, whole months without rain might not be considered as a drought in countries like Libya (NDMC).

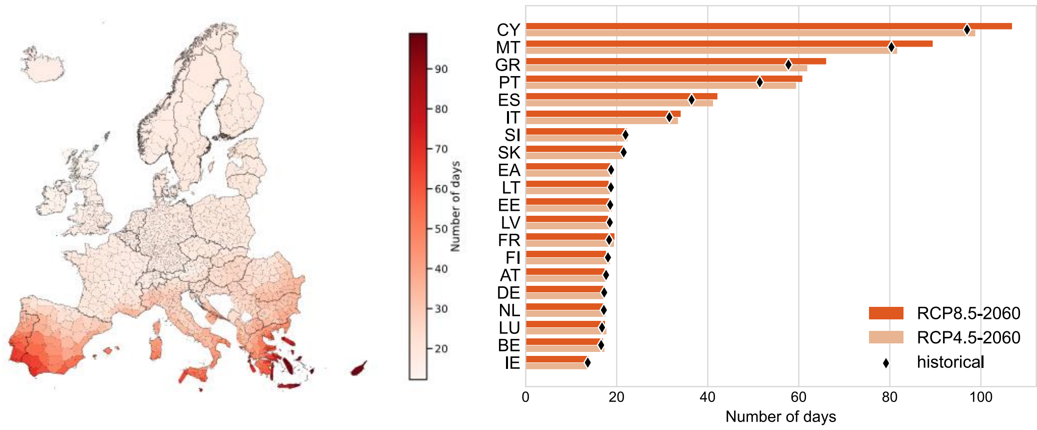
Figure 28
Consecutive dry days (number of days)

a) Regional (NUTS3) consecutive dry days

Consecutive dry days (days), 1986-2005 average, 100-year return period

(b) Consecutive dry days by country, climate scenarios RCP 4.5, RCP 8.5 and historical baseline

Consecutive dry days (days), median within area at risk, 100-year return period



Source: IPCC.
Notes: Data are aggregated at NUTS3 (panel a) and country level (panel b) by taking medians across affected areas. Defined as the maximum number of consecutive dry days with precipitation of no more than 1 mm per day.

Box 1 – Review of possible economic impacts of heat stress in Europe

Over the last two decades, heat-related mortality has become a significant concern in Europe, particularly following the 71,449 excess deaths recorded during the months of June, July, August, and September of 2003 (Ballester et al., 2023)**.** The summer of 2022 claimed the record for being the hottest season on record in Europe, witnessing 61,672 heat-related deaths between 30 May and 4 September of that year. Notably, Italy, Greece, Spain and Portugal experienced the highest heat-related mortality rates relative to their respective populations.

The escalating frequency and intensity of heat waves has become a major issue for various sectors of society. Heat stress levels, which are currently on the rise, significantly impair human productivity and occupational health. Heat stress is becoming more prevalent and is therefore expected to be one of the most severe consequences of future climate change, given the likely higher frequency and intensity of heat waves.

While workers across nearly every sector can be affected by rising temperatures leading to heat stress, outdoor workers in labour-intensive sectors are at particularly high risk, as are first responders and healthcare personnel (European Agency for Safety and Health at Work, 2023). Indoor workers are also at risk, particularly if they are employed in heat-intensive industries or engage in physically demanding tasks. Occupational risks related to heat stress vary, based on geographical location, and the severity of health issues may be influenced by factors such as age or pre-existing medical conditions.

Despite ample evidence demonstrating the adverse effects of heat on human health and well-being, there is a need for further investigation into the impact of heat exposure on labour productivity (Foster et al., 2021). Sectors such as agriculture, forestry, fisheries and construction are especially troubling, as indicated by estimates of heat-related productivity loss (Romanello et al., 2021). This study aims to explore the potential impact of heat stress on labour productivity in Europe, and its relevance when it comes to quantifying the economic impact on the real economy and the financial system.

Copernicus climate extreme indices and heat stress indicators

Heat stress is quantifiable through a range of methods that consider diverse physiological and environmental factors. This analysis focuses on the Heat Index (HI) and the Wet-Bulb Globe Temperature (WBGT), two indicators designed to measure the effect of heat on the human body and on labour productivity and to assess the health-related risks. These metrics guide the implementation of measures to safeguard individuals in various settings, from workplaces to outdoor activities, thus playing a crucial role in assessing the potential hazards posed by heat stress.

The Heat Index (HI) is a heat stress indicator employed by the US National Oceanic and Atmospheric Administration (NOAA) National Weather Service for issuing heat warnings. This indicator is also referred to as apparent temperature, and represents how the temperature is sensed by the human body depending on the relative humidity conditions.[62] It provides a simple way to communicate perceived temperature and potential heat stress to the general public. Table 2 below shows the risk classification based on the Heat Index (HI) and describes some of the potential effects that can be caused by temperature and humidity on the human body. The indicator is calculated using multiple linear regression based on daily maximum temperature and relative humidity, and expressed in °C (or °F).

[62] The comfort of the human body is significantly influenced by its ability to regulate temperature through perspiration. Sweating helps cool the body through the evaporation of moisture. However, in high relative humidity, where evaporation is hindered, the body struggles to dissipate heat effectively, resulting in a warmer sensation. Conversely, in low humidity, the body feels cooler as perspiration evaporates more rapidly. The heat index demonstrates a direct correlation between air temperature, relative humidity and perceived heat (see also NOAA National Weather Service).

Table 2 – Risk classification based on the Heat Index (HI) and potential effects on the human body

HI (°C)	Classification	Effects on human body
< 27	No risk	No effects for health
27-32	Caution	Fatigue possible with prolonged exposure and/or physical activity
32-41	Extreme caution	Heat stroke, heat cramps, or heat exhaustion possible with prolonged exposure and/or physical activity
41-54	Danger	Heat cramps or heat exhaustion likely, and heat stroke possible with prolonged exposure and/or physical activity
> 54	Extreme danger	Heat stroke highly likely

Source: US National Oceanic and Atmospheric Administration (NOAA) National Weather Service.
Notes: Classification labels may differ slightly, depending on the source of information used. Societal elements like adaptive capacity, degree of urbanisation, social processes or the existence of early warning systems might substantially improve the representation of community vulnerability at local level (see "Connecting people and place: a new framework for reducing urban vulnerability to extreme heat"). The reported effects on the human body are general and do not account for these components.

Wet-Bulb Temperature (WBT) is a heat stress indicator that measures the human cooling capacity through sweating. It is calculated from the equivalent potential temperature, based on daily maximum temperature and water vapour mixing ratio.[63] For this analysis, the Wet Bulb Globe Temperature (WBGT) from Copernicus has been used. This is a heat stress indicator expressed in °C (or °F) and computed as the weighted mean of wet-bulb temperature, globe temperature and daily maximum temperature. Similar to the HI, the WBGT can be used to outline a risk classification and identify the associated potential effects on human activity.

Table 3 – Risk classification based on the Wet-Bulb Temperature (WBT) and potential effects on human activity

WBT Index (°C)	Classification	Effects on human activity
< 27.7	Low	No effects for health
27.8–29.4	Moderate	Working or exercising in direct sunlight will stress the body after 45 minutes
29.5–31.0	Elevated	Working or exercising in direct sunlight will stress the body after 30 minutes
31.1–32.1	High	Working or exercising in direct sunlight will stress the body after 20 minutes
> 32.2	Extreme	Working or exercising in direct sunlight will stress the body after 15 minutes

Sources: US National Oceanic and Atmospheric Administration (NOAA) National Weather Service.
Notes: Classification labels may differ slightly depending on the source of information used. Societal elements like adaptive capacity, degree of urbanisation, social processes or the existence of early warning systems might substantially improve the representation of community vulnerability at local level (see "Connecting people and place: a new framework for reducing urban vulnerability to extreme heat"). The reported effects on the human body are general and do not account for these components.

The Copernicus Climate Change Service (C3S) provides a comprehensive set of climate extreme indices related to temperature and precipitation, as well as a selection of relevant heat stress indicators.[64] The HI and the WBGT have been downloaded for historical (from 1950 to 2010) and future (from 2011 to 2100, for the medium-emissions scenario SSP2-4.5 and the high-emissions scenario SSP5-8.5) climate projections included in the Coupled Model Intercomparison Project Phase 6 (CMIP6) and used in the 6th Assessment Report of the IPCC. In particular, data used for the analysis refers to the CMIP6 Earth System Model (ESM) EC-Earth3, and its ensemble member encoded "r1i1p1f1", which provides gridded data at a daily frequency and with a resolution of 0.7° x 0.7°.[65] The bias-adjusted version of the indicators has been considered so as to facilitate the usage of heat stress metrics in combination with absolute thresholds. Data are processed and statistics

[63] The Wet Bulb Temperature (WBT) also tends to factor in the influence of solar radiation and wind speed. These elements are not considered by Copernicus, and wet-bulb globe temperature is calculated as the weighted mean of wet-bulb temperature and the daily maximum temperature (neglecting globe temperature), thus representing indoor conditions.

[64] Data available from the Climate Data Store of the Copernicus Climate Change Service (C3S).

[65] For detailed information on EC-Earth3, please see the paper titled "The EC-Earth3 Earth system model for the Coupled Model Intercomparison Project 6".

are calculated to reduce the dimensionality of the dataset and provide information aggregated at NUTS-3 level for the countries of the European Union. In addition, all the analytics developed are computed for the summer period, this being the only time window in which heat stress is actually relevant in the European continent.

Copernicus indicators of heat stress are computed without considering the effects of solar radiation and wind, which could substantially influence the effect of high temperatures and humidity. In this setting, the indicators reflect indoor or outdoor shade conditions.

Historical trend and future projections of the Wet-Bulb Globe Temperature and Heat Index

Throughout history, Europe has been unevenly impacted by heat stress. **Figure 29** below takes as its reference period the summer of 2003, and shows that both WBGT and HI recorded high values, despite being largely associated with mild to medium risk classifications. In Europe, the WBGT peak values were associated mainly with conditions of moderate risk, except for the south of Portugal and Spain, the south of France and west coastal regions in Italy, where the risk was elevated (WBGT > 29.5 °C) or high (WBGT > 31.1 °C). Meanwhile, the HI signalled that extreme caution (HI > 32 °C) was required across all of Western-Central Europe and Mediterranean regions, with some scattered cases of danger alerts (HI > 41 °C) in Spain, France and Italy. These results are consistently in line with the events observed over the same period, where excess mortality also peaked.

Episodes of heat stress have been recorded more frequently since 1950, and are expected to increase substantially, especially when analysing more adverse global warming scenarios. More extreme conditions are expected to grow over time, with more substantial impacts concentrated in the Mediterranean (+4.6 °C and +13.5 °C at the end of the century compared to 2010, for SSP2-4.5 and SSP5-8.5 respectively) and Western-Central Europe (+5.0 °C and +11.4 °C at the end of the century compared to 2010, for SSP2-4.5 and SSP5-8.5 respectively) regions, leaving Northern Europe (NEU) virtually unaffected. **Figure 31** further below displays the number of days in a year in which the WBGT and HI lie above the respective no-risk thresholds (as reported in Table 2 and Table 3). Substantial differences across scenarios and regions can be observed, and interpreted as an indication that timely and effective introduction of climate policies is especially relevant in limiting adverse conditions. The HI in particular is more likely to signal prolonged situations over the year in which at least some caution is required when carrying out economic and human activities.

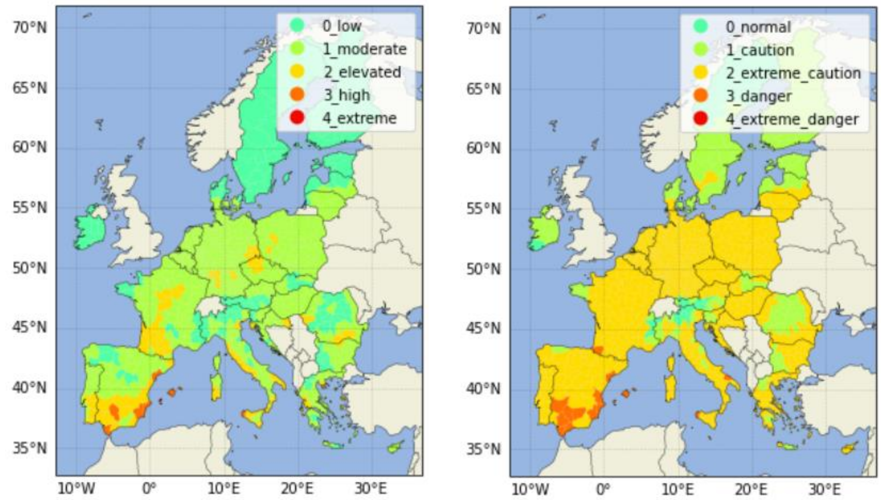
By the end of the century heat stress risk could become significantly worse, when looking at both WBGT and HI. Extreme risk events are likely to occur over the summer in coastal areas of Spain and Italy, south France, Malta, Greece and Cyprus (**Figure 30**). Continental areas and Eastern Europe will also be affected by situations of elevated and high risk, where extreme caution and danger alerts might be issued. Northern Europe is still not affected or affected only mildly, mainly as a result of an average lower temperature even in the hottest months of the year.

Figure 29

Historical heat stress risk derived from WBGT and HI recorded during July and August 2003

a) Wet-Bulb Globe Temperature Index (WBGT) | b) Heat Index (HI)

(Heat stress risk) | (Heat stress risk)



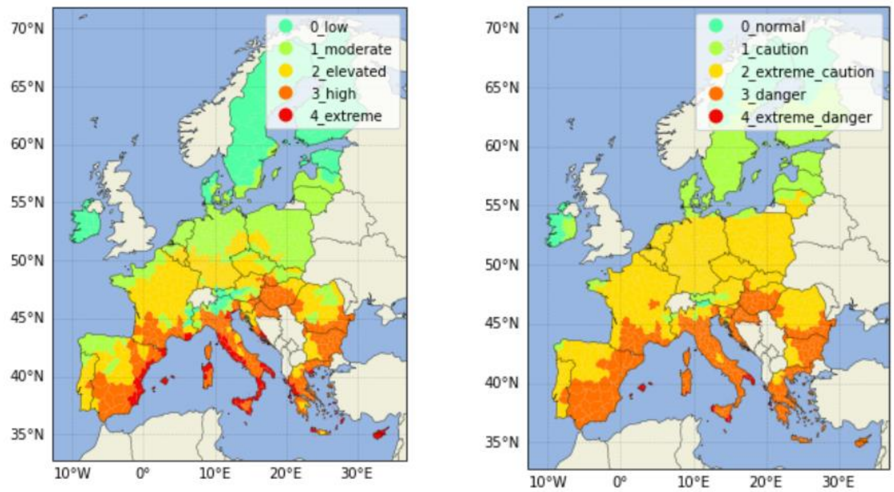
Sources: Sandstad, M. et al., (2022), *Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections*, Copernicus Climate Change Service (C3S) Climate Data Store (CDS); ECB calculations.
Notes: Daily observations and projections are derived from the Earth System Model (ESM) EC-Earth3 and its ensemble member encoded as r1i1p1f1. Data refer to the maximum values recorded over the time window between July and August.

Figure 30

Projected heat stress risk derived from WBGT and HI for July and August 2100 and SSP-5 RCP-8.5 scenario

a) Wet Bulb Globe Temperature Index (WBGT) | b) Heat Index (HI)

(Heat stress risk) | (Heat stress risk)



Sources: Sandstad, M. et al. (2022), *Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections*, Copernicus Climate Change Service (C3S) Climate Data Store (CDS).
Notes: Daily observations and projections are derived from the Earth System Model (ESM) EC-Earth3 and its ensemble member encoded as r1i1p1f1. Data refer to the average values projected over the time window between July and August.

Figure 31

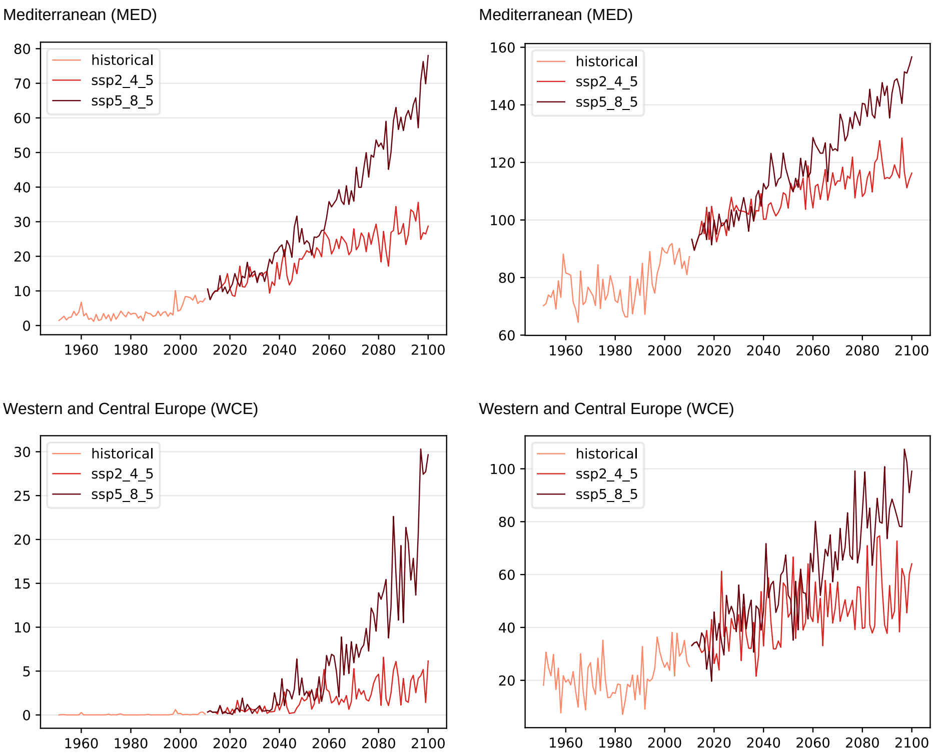
Number of days with WBGT and HI over no-risk thresholds, historical and projected data from 1950 to 2100

a) Wet-Bulb Globe Temperature Index (WBGT)

(y-axis: number of days per year)

b) Heat Index (HI)

(y-axis: number of days per year)



Sources: Sandstad, M. et al. (2022), *Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections*, Copernicus Climate Change Service (C3S) Climate Data Store (CDS). Iturbide, M. et al. (2020), *An update of IPCC climate reference regions for subcontinental analysis of climate model data: definition and aggregated datasets*, Earth Syst. Sci. Data, 12, 2959-2970; ECB calculations.
Notes: Daily observations and projections are derived from the Earth System Model (ESM) EC-Earth3 and its ensemble member encoded as r1i1p1f1. Data for Northern Europe (NEU) are not displayed due to low relevance of heat stress in this geographic region.

Potential impacts of heat stress on labour productivity

Europe happens to be the global region least affected by heat exposure, primarily due to its low rates of agricultural employment, relatively low Wet-Bulb Globe Temperature (WBGT) values, and high adaptive capacity. However, subregional variations reveal distinct vulnerability levels. Northern, Central, and Eastern Europe exhibit lower vulnerability, while Southern Europe is expected to experience at least marginal effects from heat stress. Despite these regional differences, the increasing frequency and intensity of heatwaves across Europe pose significant health and productivity challenges (Venugopal et al., 2019).

In Southern European countries particularly, the elderly, outdoor workers, and indoor workers engaged in physical activities without air conditioning are susceptible to heat-related illnesses and injuries. Sectors with heightened exposure, such as agriculture and construction (NACE sections A and F), face difficulties in implementing effective mitigation measures against heat and its impact on labour productivity. According to Eurostat and as of 2023, over 23 million people were employed in these sectors in Europe.[66]

Existing models in this field of research commonly use the WBGT index for workplace applications, as it combines temperature and humidity effects and is endorsed by the International Organization for Standardization (ISO) as an occupational heat stress index (Morabito et al., 2021). Therefore, the remaining part of this analysis focuses on this indicator. More precisely, the study conducted by Venugopal (2021), which investigates the influence of heat stress on labour capacity for heavy and moderate work (Venugopal et al., 2021), has been taken as the reference point. The authors introduced the Labour Capacity Loss (LCL) metric, an easily interpretable measure that addresses the negative impact of increased workplace heat stress on health and productivity.

The LCL metric was established by linking labour capacity to the WBGT, based on the Threshold Limit Value (TLV). Labour Capacity (LC) was derived using Dunne's (Dunne, Stouffer & John, 2013) empirical formula, encompassing light, moderate and heavy labour into a single metric:

$$\text{Labour Capacity (LC)} = 100 - 25 * \text{MAX}\,(0, \text{WBGT} - 25)^{2/3}$$

Subsequently, LCL is calculated by subtracting the projected future LC from the baseline LC obtained from historical values. From the formula, full labour productivity is achieved when the WBGT is ≤ 25 °C, while labour productivity drops to zero when WBGT is ≥ 33 °C.

For future projections of LCL, the year 2050 has been selected, as it strikes a balance between foresight and uncertainty. This time frame is less affected by uncertainties associated with natural climate variability, thus providing clearer signals compared to near-term projections. Simultaneously, it encounters less uncertainty related to mitigation pathways than late-21st century periods, where uncertainties steadily increase over time (García-León et al., 2021).

In panel a) of **Figure 32**, the average projected labour capacity loss for the adverse scenario SSP5-RCP 8.5 in 2050 is presented, contrasting with the baseline labour capacity calculated historically from 1950 to 1990. Substantial anticipated losses in labour capacity are foreseen in Mediterranean regions (Portugal, Spain, Italy, Greece, Malta and Cyprus) and, to a more limited extent, in Bulgaria, Romania and France. Panel b) of **Figure 32** illustrates the distribution of potential losses for the affected countries in the euro area, excluding regions where the loss is projected to be zero. The impact of a higher Wet-Bulb Globe Temperature varies both across and within countries, with peak losses exceeding 50% in specific regions of Greece, Spain, Italy and Malta.

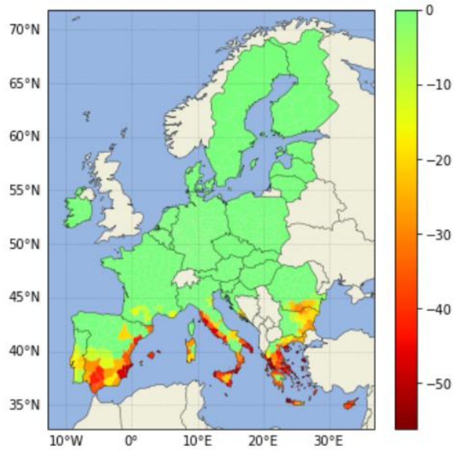
[66] Eurostat, "Employment by NACE, Rev. 2 – thousand persons", https://ec.europa.eu/eurostat/databrowser/product/page/tec00109.

Figure 32

Labour capacity loss (LCL) due to increase in Wet-Bulb Globe Temperature (WBGT)

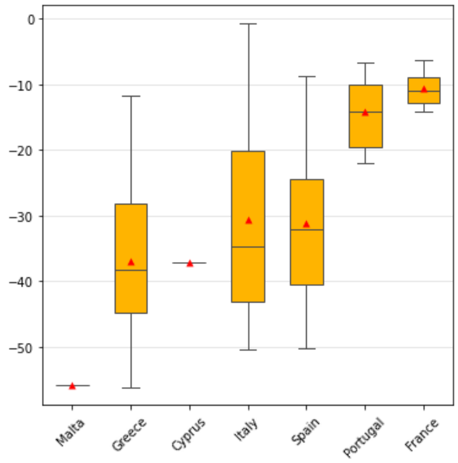
a) Average potential labour capacity loss in 2050 and for scenario SSP5-8.5, compared to baseline (1950-1990 average), by NUTS3 region

(Percentage points)



b) Distribution of average potential labour capacity loss by NUTS3 region in 2050 and for scenario SSP5-8.5, compared to baseline (1950-1990 average), by EA country affected

(y-axis: percentage points)



Sources: Sandstad, M. et al., (2022), *Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections*, Copernicus Climate Change Service (C3S) Climate Data Store (CDS).
Notes: Daily observations and projections derived from the model EC-Earth3 and ensemble member r1i1p1f1. Panel b): Regions for which the loss is zero are excluded to improve readability of the results. Red triangles represent the average. Whiskers are defined as ± 1.5 * IQR from the nearest hinge.

Conclusions and future research

Exposure to heat stress diminishes both physical capacity and productive working time. Accurate equations that establish a connection between human physical work capacity and various heat stress indicators are essential to precisely assess the impact of environmental heat.

In order to gain initial insights into how heat stress influences labour productivity, the Labour Capacity Loss (LCL) measure has been calculated, using data related to historical and projected Wet-Bulb Globe Temperature from the Copernicus Climate Change Service. Substantial heterogeneity across and within countries can be observed in Europe. Evidence suggests that Southern European countries will be more likely to experience the most significant economic repercussions due to excessive heat in the future.

For future research endeavours, the recommendation is to explore already published metrics that account for heat-related productivity loss. Key inputs might include indicators that consider the number of employees and other economic variables (e.g. Gross Domestic Product or Gross Value Added) that are available with a sufficient degree of frequency and granularity. Incorporating sectoral breakdowns (to focus on highly exposed sectors such as agriculture, manufacturing, tourism, transportation and construction) will be crucial. Examining distinct seasonal periods can also be source of additional insights.

3.3.2 Methodology for the construction of indicators

This section details how climate data, as summarised above, is integrated with financial datasets to assess physical risk within the portfolios of euro area financial institutions. It introduces physical risk scores and expected loss (EL) indicators, then investigates how financial aspects such as term to maturity and collateral – recorded at the loan level – can help to assess and reduce risk. We conclude with an overview of insurance data and how it is linked to our indicators to capture shifts in country risk profiles upon accounting for insurance as a key financial mitigant of damage caused by natural catastrophes.

Four types of physical hazard indicators are developed for the portfolios of financial institutions toward non-financial corporations. Two of these indicators are based on physical risk level categories: risk scores (RS) and potential exposure at risk (PEAR), while the other two – normalised exposure at risk (NEAR) and collateral-adjusted exposure at risk (CEAR) – are based on estimates of expected losses. All metrics are presented as a percentage of the portfolio and in monetary values (serving as a numerator in the respective formulae), i.e. a portfolio value classified in each risk category in the case of risk scores, or potential financial loss in the case of expected loss indicators.

Physical risk scores cannot be compared directly across different hazard types because the methodologies[67] and data sources used are different in each case. However, they do provide valuable insights for assessing relative risk levels across countries, climate scenarios, and variations within the same hazard type, such as comparing flood risks with and without flood defences.

Conversely, EL indicators quantify risk in monetary terms, thus allowing for comparisons across different hazards. However, they also happen to suffer from data limitations and require assumptions as to how hazard intensities convert into physical and monetary damage for affected companies and how they subsequently propagate into the financial system. If these businesses hold debt with financial institutions, the resulting damage at the company level could impair their repayment ability. This, in turn, may lead to financial losses for those banks exposed to the debtors affected by the natural disaster. Similar to the risk scores, while the absolute values might be sensitive to various assumptions, the process of compiling the indicators follows a consistent methodology and relies on harmonised sources. This enables comparisons across different specifications and countries, thus ensuring a coherent analytical framework.

First, **physical risk scores (RS)** denote both the value and the percentage of the portfolio associated with debtors located in areas of varying physical risk from 0 (no risk) to 3 (high risk):

- $RS_{j\in[0,3]} = \frac{\sum_{i=1}^{N}(EXPOSURE_i|SCORE_{i,j})}{\sum_{i=1}^{N}(EXPOSURE_i)}$

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67 Except for floods and windstorms that are based on damage functions and incorporate aspect of expected loss (see Section 6.4.1).

where *j* is the risk score and $EXPOSURE_i$ is the exposure volume for a specific portfolio (loans, debt securities and equities) towards company *i* (single entity level).

The risk scores are computed at debtor level for each hazard separately and different types of hazards are not additive. A company may be exposed to several risks, which could result in the counting of exposures multiple times, especially in the case of correlated risks, such as water stress and wildfires.

Table 1 above provides an overview of the hazards used in this publication, while more technical details, including the exact thresholds used for the risk scores, can be found in Table 4 below.

Table 4 – Methodology and technical details for physical hazard risk scores

Hazard	Return period	Damage function	Score calculation method	Data sources (download)
Coastal flooding	10,30,100,300, 1000	Based on intensity and area type	Based on the damage functions/return periods	Geospatial data (Paprotny, 2020)[68]
River flooding	10,30,100,300, 1000	Based on intensity and area type	Based on the damage functions/return periods	Geospatial data (Paprotny, 2016) [69]
Windstorms	10, 50, 100, 500	Based on intensity by NUTS3 and area type	Based on the damage functions/return periods	Based on Copernicus WISC[70] geospatial data
Landslides	10, 50, 100, 500	Not available	Based on original scores/return periods	Available from DRMKC RDH contact point
Subsidence	-	Not available	Original score rescaled: No risk: Coarse soil texture (clay < 18% and sand > 65%) Low risk: Medium (18% < clay < 35% and sand >= 15%, or clay > 18% and 15% < sand < 65%) Medium risk: Medium fine (clay > 35% and sand < 15%) High risk: Fine (35% < clay < 60%) and Very fine (clay > 60%)	Available from DRMKC RDH contact point
Wildfires	-	Not available	Based on the probability of a fire event: No risk: <0.001 (frequency less than every 1,000 years) Low: 0.001-0.002 (between 500 and 1,000 years) Medium: 0.002-0.004, 0.004-0.01 (between 500 and 100 years) High: 0.01-0.02, >0.02 (more frequent than every 50 years)	Own calculations[71] based on: (i) Copernicus Fire Weather Index; (ii) Copernicus land cover (distance to city, railway and road); and (iii) MODIS burned area and land cover
Water stress	-	Not available	Based on original score: No risk: Arid and low water use, ratio of water demand to water supply <10% Low: 10-20% Medium: 20-40%, 40-80% High: >80%	Geospatial data (version 3.0, 2019)[72] Methodology
Consecutive dry days	-	Not available	Thresholds based on the number of days: No risk: < 15 days Low: 15-20 Medium: 20-30, 30-40 High: 40-50, >50 days	Geospatial data (IPCC Interactive Atlas) [73]
Standardized Precipitation Index	-	Not available	Based on index thresholds: No risk: -1 to 1 Low: (-1.5 to -1), (1 to 1.5) Medium: (-2 to -1.5), (1.5 to 2) High: <-2 (extremely dry), > 2 (extremely wet)	Geospatial data (IPCC Interactive Atlas)

Notes: The "return period" is a statistical concept used in hydrology and disaster risk assessment and represents the average interval of time between events of a certain intensity. The original scores are usually available on a scale of 0-5. For the purpose of the statistical climate indicators, they were rescaled to 0-3 and the column "Scores calculations" shows the individual original categories assigned to each risk score.

68 Dominik Paprotny, O. (Oswaldo) Morales Nápoles (2020), *Pan-European data sets of coastal flood probability of occurrence under present and future climate* – Version 2, 4TU.ResearchData, dataset: https://doi.org/10.4121/uuid:e06ca666-90e2-4a2c-a1d0-4c39f815b04d.

Second, **the potential exposure at risk (PEAR)** indicator is formulated as a sum of positive risk scores (categories from 1 – Low risk to 3 – High risk) and reveals financial exposure to debtors in at-risk areas regardless of the intensity or frequency of the hazard:

- $$PEAR \quad = \frac{\sum_{i=1}^{N}\left(EXPOSURE_i | RS_{i,j}(j>0)\right)}{\sum_{i=1}^{N}(EXPOSURE_i)}$$

In can be considered as a measure of the prevalence of a natural phenomenon, encompassing all exposures but without considering the vulnerability of affected debtors should an event occur. Thus, coastal floods, with their limited geographical extent, tend to have lower PEAR exposure levels compared to more widespread hazards like heat stress, even though coastal floods may result in significantly higher physical damage.

Third, **normalised exposure at risk (NEAR)** provides an estimate of the anticipated losses in a financial institution's portfolio if debtors are unable to honour their repayment obligations in the wake of a natural disaster. It is assumed that the company's debt to financial institutions will be impaired in proportion to the expected losses to the debtor's physical assets relative to its total assets.

[69] Dominik Paprotny, O. (Oswaldo) Morales Nápoles (2016), *Pan-European data sets of river flood probability of occurrence under present and future climate* – Version 1, 4TU.ResearchData, dataset: https://doi.org/10.4121/uuid:968098ce-afe1-4b21-a509-dedaf9bf4bd5.

[70] Copernicus WISC (Windstorm Information Service): https://climate.copernicus.eu/windstorm-information-service.

[71] Burger C., Herzberg, J., Nuvoli, T., *Explainable AI in fire risk estimations*, forthcoming.

[72] WRI Aqueduct: https://www.wri.org/aqueduct.

[73] Gutiérrez et al., 2021: Atlas. In Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. In Press. Interactive Atlas available here.

- $$NEAR = \frac{\sum_{i=1}^{N}(FINANCIAL\ RISK\ RATIO_i \cdot EXPOSURE_i)}{\sum_{i=1}^{N}(EXPOSURE_i)};$$

where the financial risk ratio is a proportion of expected physical losses to total assets at entity level:

- $$FINANCIAL\ RISK\ RATIO_{i,Total\ assets} = \frac{Tangible\ fixed\ assets_{Orbis,\,i}}{Total\ assets_{Orbis,\,i}} \cdot EL_i(m)$$

The term $\mathrm{EL_I(m)}$ is the expected loss (expressed as a share in the value of the exposed asset) over the remaining maturity of an instrument.

This indicator incorporates an estimation of monetary losses and allows for aggregations across hazards. At the current stage, the quality and availability of the underlying data are not always sufficient to calculate EL-based indicators for all hazards and the estimates are currently only available for windstorms and for coastal and river flooding.

Fourth, **the collateral-adjusted exposure at risk (CEAR)** indicator, similar to the NEAR metric, offers an estimate of expected losses within a financial institution's portfolio and also considers the mitigating effect of collateral pledged with a loan commitment. In physical risk assessments, the type of collateral must be taken into account. Financial protection is included in the full amount. However, when evaluating physical collateral, it is crucial to factor in the potential reduction in collateral value due to the destruction of physical assets by natural hazard – and notably these aspects are reflected in the CEAR indicator.

- $$CEAR = \frac{\sum_{i=1}^{N}\max\,[0, FINANCIAL\ RISK\ RATIO_i \cdot EXPOSURE_i - CV_i]}{\sum_{i=1}^{N}(EXPOSURE_i)},$$

where CV_i is the collateral allocated to each creditor-debtor-instrument combination.

We discuss collateral at greater length and explain how it is included in the calculations in the following section.

The two EL-based indicators follow the same methodology, which allows for a comparison of expected losses under NEAR with those under CEAR, reduced by the value of collateral, thus illustrating the effect of collateralisation. To facilitate this benchmarking exercise, the current indicators are compiled only for loans, as collateral is not available for securities. The expected damage is calculated over the instrument's maturity, capturing potential differences in the maturity structure of banks' portfolios. Moreover, the indicators are presented on the basis of expected annual loss to enable a comparison with estimates of natural disasters found in the literature, which are usually expressed on an annual basis.

Further information on the technical aspects of the indicators can be found in the Annex. Annex 6.4.1 explains the methodology employed to compile the risk scores and EL-based indicators. The estimation of the tangible fixed assets to total assets ratio is included in Annex 6.4.2. Lastly, we present a comparison of the current ESCB indicators[74] with their earlier versions in Annex 6.4.3.

All indicators are based on financial variables from AnaCredit, SHS and RIAD, refreshed with reference to December 2022.

Accounting for collateral

To develop the new physical risk indicator accounting for collateralisation in the loan portfolio (CEAR), we use the AnaCredit dataset, which offers several attributes describing the value and characteristics of all the protection items securing each instrument: collateral type, provider, value allocated to each of the loans it secures and, in case of physical collateral, its location.

The richness of the information also poses analytical complexity, especially due to the multiple relationships existing among instruments, creditors, debtors and collateral. Each instrument might have multiple counterparties, both creditors and debtors, and it might be collateralised or secured by one or more protection items. In turn, each collateral might secure one or multiple instruments. Of the outstanding nominal amount of the instruments in our scope, 31% is not secured by any collateral, 31% by a single collateral and 38% by multiple collateral.

In our analysis, the relevant monetary amounts (outstanding nominal amount and collateral value) must be carefully assigned at loan level and split into parts: the part secured by physical collateral, the part secured by financial collateral, and the remaining unsecured portion of the loan. When we consider also this unsecured portion of partly secured loans, the uncollateralised portion of the NFC loan portfolio among the euro area creditors increases to 47%.

There is high heterogeneity across countries with respect to type and share of collateralisation (see **Figure 33**). Loans to NFCs in Baltic countries are highly collateralised (at least 80% of loan volumes), with Ireland and Belgium lying on the other side of the spectrum (less than 40% of loan volumes secured). From the physical risk perspective, it is worth noting the relatively high share of real estate collateral (over 40%) in Estonia, Cyprus, Finland and Austria.

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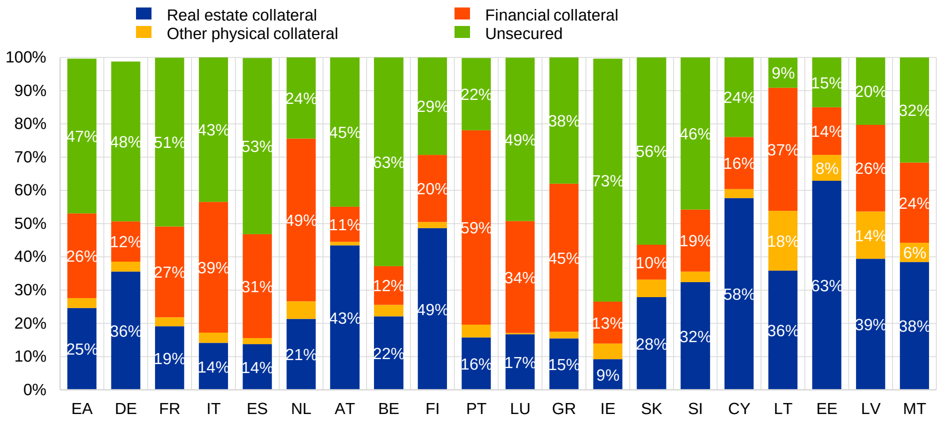
74 Please see https://www.ecb.europa.eu/stats/ecb_statistics/sustainability-indicators/html/index.en.html.

Figure 33
Loan volumes by types of collateral and creditor country

Outstanding nominal amounts (%)

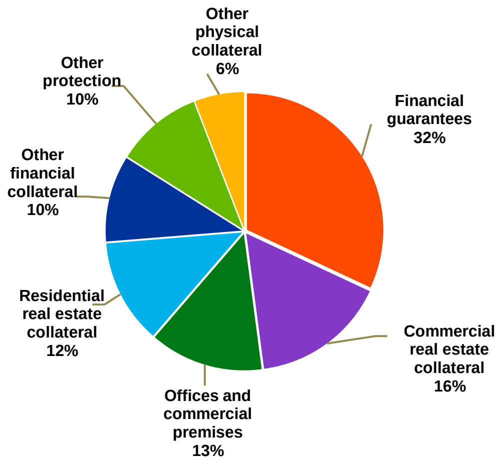


Notes: Own calculations based on AnaCredit, loan portfolio of euro area creditors towards the NFC sector, December 2022 reference period.

In terms of protection value, real estate collateral represents 41% of the total protection provided to euro area creditors, with an additional 6% stemming from other types of physical collateral (see **Figure 34**).

Figure 34
Financial and physical collateral by category

Protection value (%)

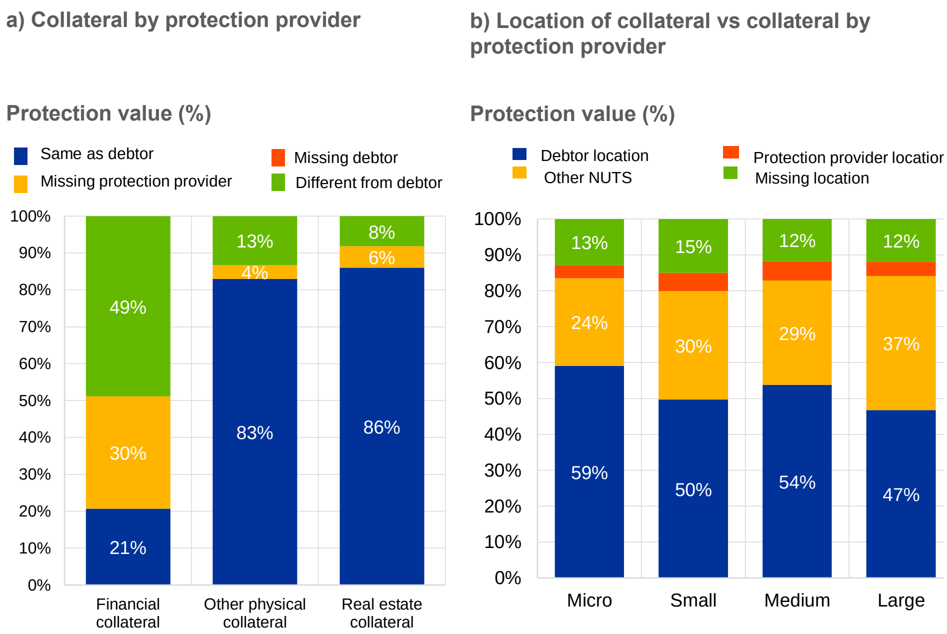


Notes: Own calculations based on AnaCredit, loan portfolio of euro area creditors towards the NFC sector, December 2022 reference period. "Financial guarantees" includes financial guarantees other than credit derivatives. The "Other financial collateral" includes *Life insurance policies pledged, Credit derivatives, Securities, Gold, Currency and deposits, Loans, Trade receivables and Equity and investment funds shares*. The "Other physical collateral" follows the definition in Regulation (EU) No 575/2013 and includes e.g. commercial equipment, machines and vehicles. The "Other protection" covers protection items that are not included in the other categories.

Since physical risk is linked to geography, the location of real estate collateral is key to assessing the corresponding risk. While debtors and protection providers are identified with an address level, reporting of real estate collateral location is required only at the level of NUTS3 regions. We checked whether the NUTS3 regions of the protection provider coincide with the location of the physical collateral, and whether one could assume that the real estate is located at the same address as the entity that pledged it, thus achieving more precise information for the purpose of identifying the hazards. First, for the vast majority of real estate, the collateral is provided by the debtor, while for financial collateral around 50% of the total collateral value is provided by some other entity (**Figure 35**, panel a). Guarantees are the most common type of collateral provided (60% of the financial collateral value) and must naturally be provided by an entity other than the debtor.

Second, real estate collateral is predominantly reported in the same region as the debtor and, as might be expected, collateral pledged by larger firms is more often found at a different location than the registered address of the debtor (**Figure 35**, panel b). For around one third of real estate, the location of the collateral cannot be deduced from the address of the protection provider (indicated by the "Other NUTS" category in **Figure 35**, panel b). In addition, it should be noted that even where the NUTS3 region of the collateral and the address of its provider match, the location may not be the same. While a mixed approach of using the address for a sub-sample was considered, different treatments across entities and countries could introduce bias and lead to lack of comparability. Therefore, in the current compilation of the indicators, expected damage to physical collateral is based on a harmonised approach applying NUTS3 risk profiles.

Figure 35
Financial and physical collateral by protection provider

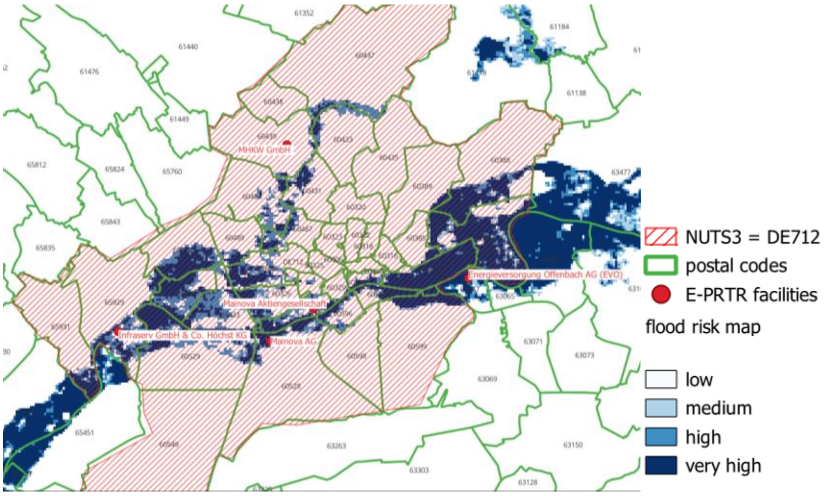


Notes: Own calculations based on AnaCredit, loan portfolio of euro area creditors towards the NFC sector. December 2022 reference period.

Figure 36 below shows the resolution of postal codes versus NUTS3 for the Frankfurt area. While for flood risk, the address would be preferable, the postal code can offer a much better approximation for the risk assessment than broader administrative boundaries. Collateral location for some countries is already reported at postal code level and several national central banks (NCBs) have initiated work towards the provision of more precise information. Further work is envisaged to enhance the physical risk assessment for real estate once improvements are made in terms of data availability.

Figure 36

Flood risk in the Frankfurt area – Illustration of postal codes vs NUTS3 region



Source: Flood risk based on JRC DRMKC European flood map, 100-year return period. NUTS3 boundaries are based on Eurostat GISCO portal. Postal codes for Germany are available from Deutsche Post Direkt GmbH and Bundesamt für Kartographie und Geodäsie (BKG).

Accounting for insurance

Insurance is one of key relief elements in the aftermath of a natural catastrophe. It accelerates the path to recovery by mitigating direct losses to assets and can diminish indirect losses stemming from business interruptions that also are insurable. Overall, as discussed in Fache Rousová et al. (2021), insurance has significantly mitigated the macroeconomic impact of natural catastrophes in the past. As the frequency and intensity of natural catastrophes are expected to increase in the future, insurers might be hesitant to provide protection against certain perils in the most vulnerable regions or might be tempted to raise premium payments to prohibitive levels, thus driving down insurance coverage (Mills, 2005; Maynard, 2008; Johnson, 2015). For instance, according to the European Commission (2021) , the expected increase in the frequency of flooding and drought events the future would make insurance coverage for those natural disasters increasingly unaffordable.

Insurance coverage is a challenge when it comes to physical risk assessment, as this risk-transfer and risk-pooling mechanism faces strong data availability constraints, especially at firm-level – yet a firm-level approach would give the most accurate view of how the losses incurred by an economic agent are mitigated. We thus use country hazard-level information on insurance coverage, based on the approach of the EIOPA protection gap dashboard[75]. This data allow us to define country hazard-level insurance coverage using two complementary concepts that serve to build net-of-insurance indicators:

- **The historical share of insured losses** uses information on economic and insured losses recorded for natural catastrophe (Nat Cat) events in the CATDAT[76] and EM-DAT[77] databases – weighting both equally when both are available – as well as complementary data sources for certain perils/countries. For both variables, no distinction is made in those databases between losses associated with residential and commercial infrastructure. Economic losses are generally broader in scope than insured losses. For example, damage to public infrastructure is included in CATDAT economic losses. This historical approach is likely to be a lower bound for insurance coverage, even though the share of insured losses could also retreat from historical levels in the future.

- **Estimated current insurance penetration** is defined as insured amount over replacement value. It largely relies on expert judgment from European Economic Area (EEA) supervisors and comes in four brackets, with thresholds at 25%, 50% and 75% (for our analysis we apply the mid-point of a bracket). Estimated insurance penetration is generally higher than the historical share of insured losses and is a likely upper bound for insurance coverage.

One should keep in mind that even on an aggregate level, methodological issues can affect the granularity, accuracy and comparability of economic loss and insured loss data.[78] The two main databases used by the EIOPA dashboard suffer from quality issues and limited coverage. The EM-DAT database is open source and developed by the University of Louvain. While most records include details about fatalities, missing people and those otherwise affected, approximately 70% of recorded events include no information on economic losses (European Commission, 2021). The CATDAT database on economic losses and fatalities from weather- and climate-related events is not publicly accessible[79], apart from the aggregate figures published with the EIOPA protection gap dashboard. Information on economic losses has better coverage than in the EM-DAT dataset.

For our statistical climate indicators, we derive the share of uninsured losses factors through the approach based on historical losses and current insurance penetration, which constitute upper and lower bounds for the net-of-insurance estimated losses. We assume that losses fall in proportion to insurance coverage and apply the factors to the aggregated NEAR indicator – since insurance intervenes before collateral (and may reduce the need for it). To ensure consistency with the published results in the analysis presented, we do not exclude foreign debtors, even though insurance

75 Dashboard on insurance protection gap for natural catastrophes (europa.eu).

76 Economic losses and fatalities from weather- and climate-related events in Europe – European Environment Agency (europa.eu).

77 EM-DAT – The international disaster database (emdat.be).

78 European Commission staff document related to the data gaps affecting the measure of the climate protection gap.

79 The CATDAT database is developed by RiskLayer GmbH and is received by the European Environment Agency (EEA) under institutional agreement, extended to EU institutions.

coverage of creditor country would not apply in their case. However, the calculations restricted to domestic transactions show consistent results.

Having accounted for those restrictions, we compute the net-of-insurance NEAR indicator for loans at country-hazard (i,j) breakdown level:

$$Net\_NEAR_{i,j} = NEAR_{i,j} \times (1 - Insurancecoverage_{i,j})$$

Regarding the scope of hazards, the EIOPA dashboard considers windstorms and coastal floods in a way that is consistent with the ESCB statistical indicators. However, river floods are not distinguished from flash floods in the EIOPA dashboard. This should be taken into account when interpreting net-of-insurance indicators for river floods (see Section 3.3.3).

Accounting for maturity in the loan portfolio

In this paper we present two versions of indicators based on expected losses: annual loss estimates and losses calculated over the remaining maturity of a financial instrument. Given the long-term nature of climate change risks, incorporating maturity into the analysis enhances the understanding of these risks within bank portfolios.

To account for maturity, the first step involved assessing the data quality of the maturities reported and applying statistical treatment for the missing values. Table 5 provides an overview of loan instruments, showing the reporting practices for remaining maturities.

Observations with negative values for remaining maturities were minimal, accounting for 1% of the outstanding amounts. For these instances, we assigned a standardised duration of one year. On the opposite end, observations indicating exceptionally long maturities, which could suggest data quality issues, were capped at 40 years.

To address missing maturities, we adopted the method utilised in other statistical collections such as the Balance Sheet Items (BSI) statistics.[80] In this approach, instruments of a revolving nature with flexible credit arrangements are categorised as short-term and consequently assigned a remaining maturity of one year. These include overdrafts, credit card debt, trade receivables and revolving credit and are characterised by a high share of missing values. For other instruments, such as standard loans and credit lines, the proportion of missing values is negligible, not exceeding 1% of the outstanding amounts. These were assigned a maturity of 10 years, based on the mean value observed in the reported data. A longer maturity was also applied in the case of financial leases to ensure consistency with BSI statistics.

80 For details on methodology and compilation methods of Balance Sheet Items (BSI) statistics, please see the Manual on MFI balance sheet statistics.

The impact of accounting for maturity in the loan portfolios of euro area banks is presented in the next section.

Table 5 – Remaining maturities for loans by instrument type

Instrument type	Share of instrument type (outstanding amounts)	Negative values	Not applicable values reported	Share of not applicable values reported (outstanding amounts)	Remaining maturity (years, mean)	Remaining maturity (years, median)	BSI statistics approach	Number of years assigned
	amount	amount	count	amount	mean	median	original maturities	years assigned
overdrafts	5%	1%	68%	51%	81.3	0.8	Up to 1 year	1
credit card debt	0%	0%	85%	86%	11.8	1.0	Up to 1 year	1
trade receivables	4%	1%	32%	46%	1.1	0.2	Up to 1 year	1
financial leases	3%	1%	0%	0%	3.2	2.4	Above 5 years	10
revolving credit	6%	1%	21%	20%	1.2	0.5	Up to 1 year	1
credit lines	35%	0%	1%	1%	9.8	3.5	Up to 1 year	10
other loans	46%	1%	1%	1%	9.3	3.4	Above 5 years	10
Total	**100%**	**1%**	**16%**	**7%**	**9.3**	**2.7**		

Notes: Own calculations based on AnaCredit; December 2022 reference period.

3.3.3 Results

In this section we present the key findings, elaborating on various aspects and their impact on the physical risk assessment. First, we focus on the risk score indicators applicable to all hazards covered in this publication. When available[81], baseline indicators derived from historical data are contrasted with climate projections under the adverse RCP 8.5 scenario. In the specific case of flooding, the analysis is broadened to include the effectiveness of flood adaptation measures, illustrating the heterogeneity in flood protection standards across euro area countries.

We then evaluate expected loss indicators for floods and windstorms, calculated for loan portfolios. While risk scores are presented for different types of instrument, these indicators are calculated for loan portfolios where both maturity and collateral are relevant attributes. Applying certain assumptions, the indicators could also be derived for debt securities and equities. However, focusing on loan portfolios allows us to disentangle various aspects under study, thus making it easier to interpret the newly applied methodology – a desirable feature in the experimental phase of indicator development. The results for expected loss estimates are first presented for the euro area, with a subsequent examination of different indicator specifications on country distributions. We also compare our findings with other estimates of natural

81 Climate projections are not available for landslides, subsidence and windstorms.

disaster losses and conclude with the role of national insurance practices as a means of mitigating the financial impact.

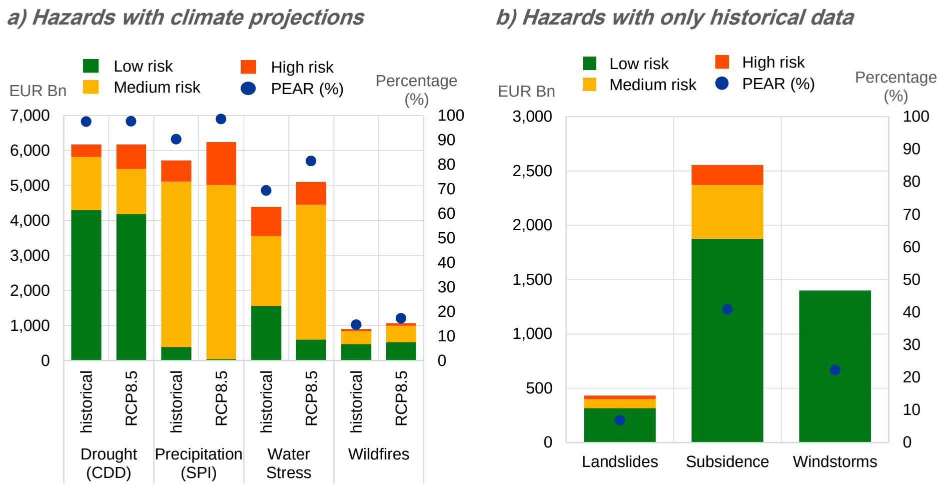
3.3.3.1 Risk scores indicators

Exposure among financial institutions to the physical risk examined, as measured by risk scores, broadly reflects the geographical prevalence of the hazards.

For temperature- and precipitation-related hazards, almost the entire portfolio of financial institutions exhibits a positive risk profile both for the historical baseline as well as under the pessimistic climate scenario (**Figure 37**, panel a). In the case of the Consecutive Dry Days (CDD) indicator, which aims to capture droughts, the majority falls into the low risk category, i.e. number of consecutive days without rain of between 15 and 20 days within a year. As for the Standardized Precipitation Index (SPI), which captures the dual risks of excessively dry and overly wet conditions, the exposures fall predominantly into the medium risk category. This is also the case for water stress, indicating that financial exposure is the greatest among non-financial corporations located in the areas exposed to the medium risk, measured in terms of water demand to supply ratio. Lastly, for wildfires, the positive risk is established using thresholds of fire frequency once every 1,000 years, with around 15% of the portfolio affected for the historical baseline, rising to 17% for the RCP-8.5 climate scenario for the 2050 time horizon. Across all these hazards, the outcomes derived from a pessimistic climate scenario indicate an escalated risk compared to the baseline, manifested by greater total exposures at risk or a higher proportion of exposures in the most severe risk categories.

The forward-looking measures are not currently available for three types of hazards: landslides, subsidence and windstorms. While the share of the portfolio affected might be sizeable (7% for landslides, 41% for subsidence and 22% for windstorms), most of it is considered low risk. In the specific case of windstorms, where, similar to floods, risk scores are determined based on expected losses (for more information, see Annex 6.4.1), the notable predominance of low risk categories can be attributed in part to the robustness of building designs in Europe, which contrasts with the potentially more severe damage caused by flooding (see **Figure 38**).

Figure 37
Exposures to different hazards by risk score

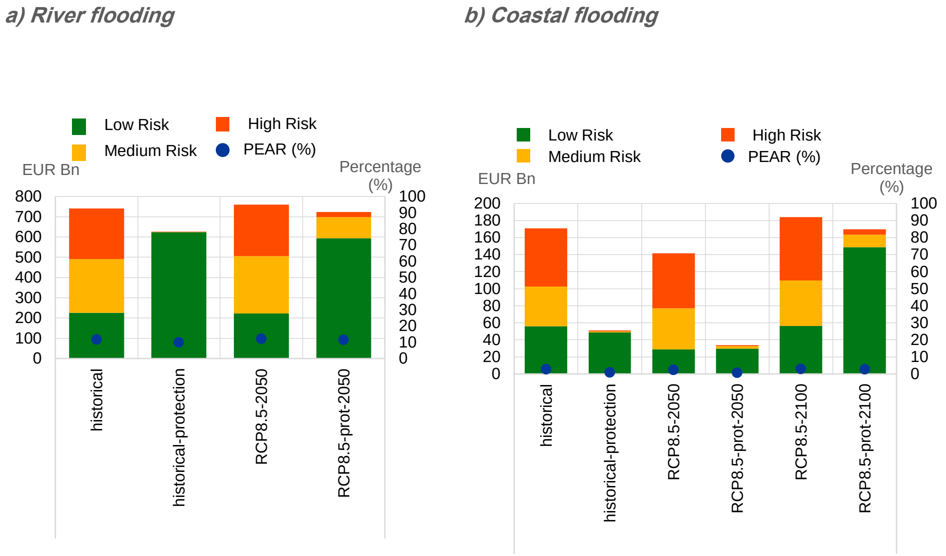


Sources: ESCB calculations based on AnaCredit, RIAD, SHSS, IPCC Interactive Atlas, World Resource Institute (WRI), Joint Research Centre (JRC), and Copernicus.
Notes: Aggregate scores for all EA countries, for Deposit-taking corporations except central banks (S122), Non-money market fund investment funds (S124), Insurance corporations and Pension funds (S128, S129) and all instruments (Debt securities, Equities, Loans). Risk scores are not comparable across hazard types as they rely on different methodologies and sources: windstorms (scores based on expected annual losses – own calculations based on expected wind speed at return periods of 10, 50, 100 and 500 years); landslides (based on JRC DRMKC RDH original scores and adapted according to the return periods of 10, 50, 100 and 500 years); subsidence (scores from JRC DRMKC RDH based on the percentage of clay and sand in the soil); water stress (scores derived from the WRI based on the ratio between water demand and water supply); wildfires (scores derived from probability of fire event – own calculations based on Fire Weather Index of Copernicus and MODIS land cover); drought (score thresholds based on consecutive dry days from the IPCC); and precipitation (score thresholds based on the IPCC Standard Precipitation Index, 6-months).

Floods warrant a more detailed examination encompassing outcomes under different climate scenarios, as well as accounting for flood defences. The affected part of the portfolio remains relatively small, reflecting the limited geographical scope of floods under the historical baseline: 11.7% for river flooding and 2.7% for coastal flooding. Under adverse climate scenarios, this affected proportion is projected to rise to 10.3% under RCP 4.5 and 11.9% under RCP 8.5. Notably, when accounting for existing flood defences the risk for coastal floods initially drops to 0.5% of the portfolio under RCP 8.5 by 2050 (from 0.8% for the historical baseline) but is expected to rise to 2.7% towards the end of the century – a pattern that mirrors climate data trends (for more information, see Section 3.3.1.1).

Figure 38

Exposures to flooding hazards by risk score



Sources: ESCB calculations based on AnaCredit, RIAD, SHSS, and Delft University of Technology (TUD).
Notes: Aggregate scores for all EA countries, for Deposit-taking corporations except central banks (S122), Non-money market fund investment funds (S124), Insurance corporations and Pension funds (S128, S129) and all instruments (Debt securities, Equities, Loans). Risk scores are not comparable across hazard types as they rely on different methodologies and sources. For river and coastal flooding, scores are based on expected annual losses – own calculations based on expected water depth of flooding in return periods of 10, 30, 100, 300 and 1,000 years.

Flood protection is an important aspect when it comes to disaster risk management. First, financial exposure is lower because a smaller geographical area will be affected thanks to the flood protection, albeit with a more pronounced impact in the case of coastal floods: from 11.7% to 9.9% for river floods, and from 2.7% to 0.8% for coastal floods as the historical baseline (see **Figure 38**). Second, the most severe risk categories are re-classified to lower risk, due to the methodology of scoring based on expected losses. Flood defences protect against floods of lower intensity, thus setting expected losses to zero. The calculations still factor in more severe floods, albeit of lower frequency (dependent on prevailing flood protection standards in the region), leading to an overall reduction in expected losses and subsequently, lower risk scores.

Looking at the impact of flood protection across countries under the benchmark RCP 8.5 climate scenario in 2050, **Figure 39** shows the level of risk reduction stemming from flood protection in terms of the PEAR indicator, which combines positive risk scores (scores from 1 – Low to 3 – High risk). Among the countries most exposed to river flooding, the highest reduction is observed in the Netherlands, with a 16% decrease in PEAR when accounting for flood defences, followed by Austria at 8%, and both Germany and Italy registering a 5% reduction.

As observed at the euro area level, flood defence standards in coastal areas demonstrate greater efficiency than those implemented for river floods, with a notable example being the Netherlands, where financial exposure is reduced by over 90%. This moves the Netherlands from its initial top position to third place, behind

Germany and Finland, once the impact of flood defences is considered in the PEAR indicator.

Examining outcomes under different climate scenarios and time horizons reveals that without further strengthening, existing flood defences may be inadequate in coping with the anticipated intensification of floods. This is especially visible for coastal floods under RCP 8.5 projections in 2100[82] (see **Figure 38**, panel b), as reflected in an increase in PEAR from 0.5% of the portfolio under RCP 8.5 in 2050 to 2.7% by the end of the century.

In the following section, we elaborate on the expected losses indicator, which sheds more light on risks stemming from floods and windstorms.

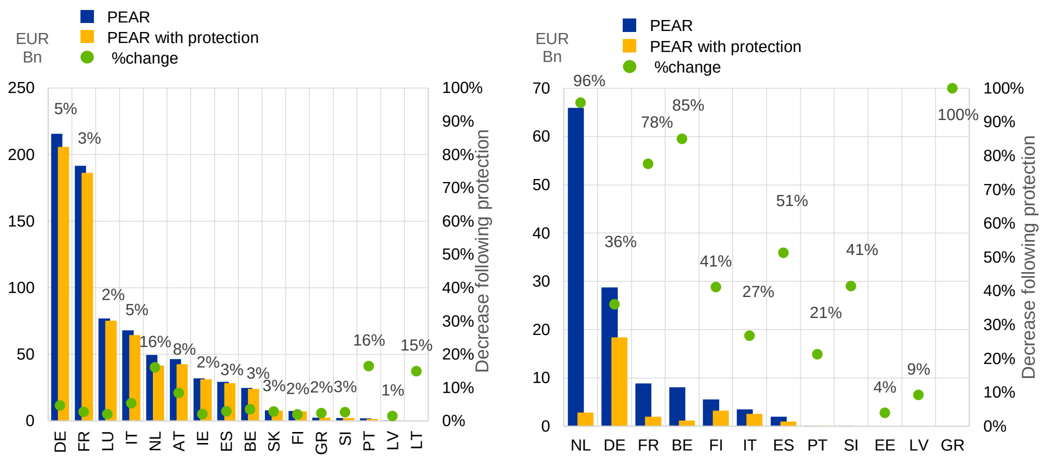
Figure 39
Effect of adaptation measures on floods

a) PEAR for river flooding with and without protection by country

RCP 8.5 projections for 2050 with and without protection; loans, debt securities and equities portfolio of euro area financial institutions

b) PEAR for coastal flooding with and without protection by country

RCP 8.5 projections for 2050 with and without protection; loans, debt securities and equities portfolio of euro area financial institutions



Sources: ESCB calculations based on AnaCredit, RIAD, SHSS, Delft University of Technology (TUD), Joint Research Centre (JRC).
Note: Includes Deposit-taking corporations except central banks (S122), Non-money market fund investment funds (S124), Insurance corporations and Pension funds (S128, S129) and all instruments (Debt securities, Equities, Loans). Panel b) shows the percentage decrease in total PEAR after accounting for protection. For river flooding: Cyprus and Malta removed due to confidentiality issues. For coastal flooding: Cyprus, Ireland, Malta and Lithuania removed due to confidentiality issues.

3.3.3.2 Expected loss-based indicators

The two indicators –normalised exposure at risk (NEAR) and collateral-adjusted exposure at risk (CEAR) – aim to quantify the damage inflicted on non-financial

[82] The year 2050 was selected as a default time horizon for presenting the indicators, on the understanding that it is more relevant than longer time periods when measuring the exposures of financial institutions to physical risk. However, for coastal floods we extend our analysis to 2100 to demonstrate the stark increase in risks in comparison to earlier decades, while the risks for other hazards are evident sooner.

companies by natural disasters and show how these impacts are transmitted to the financial system. The indicators provide an estimate of expected losses in the portfolios of financial institutions in monetary values and as a percentage of the portfolio. Currently, they are calculated for loans, a financial instrument where maturity and collateral are relevant attributes.

It should be noted that the indicators have been formulated on the basis of statistical concepts and probabilities of hazards occurring on average within a certain period (annually, for the remaining maturity of an instrument). The method does not take into account spatial and temporal correlations and their repercussions, such as when a lending institution has a substantial exposure in a region struck by a major catastrophic event. These events can trigger significant destabilising effects that are not adequately represented by applying metrics based on an average risk.

Despite these limitations, they offer an invaluable tool for comparing climate impact across various hazards, climate scenarios and countries, applying a consistent methodology (see **Figure 40**). When factoring in maturity effects, expected losses from river flooding surpass 1% of the loan portfolio, significantly exceeding those from other hazards. Coastal flooding reaches 0.4% for the baseline scenario, while windstorms register the smallest impact at 0.1% of the total portfolio (see **Figure 40**, panel a).

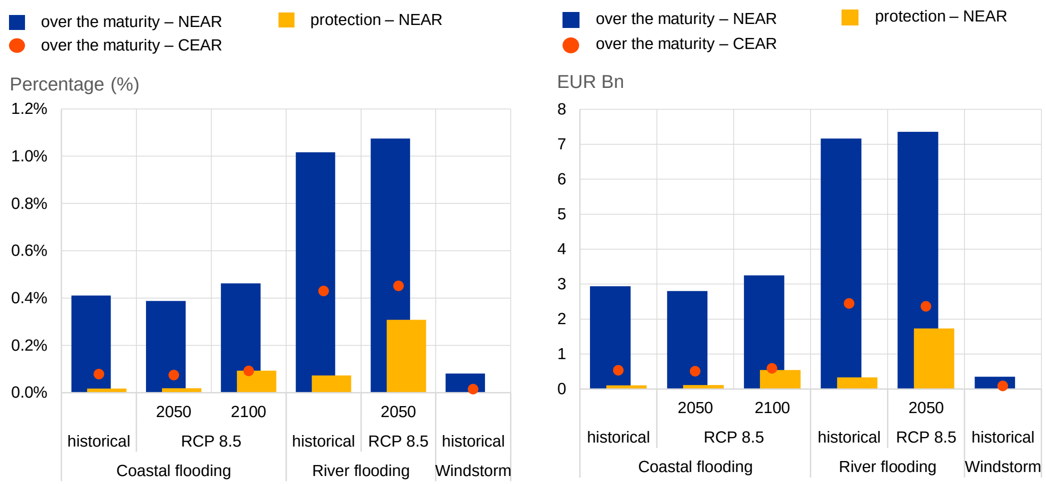
In line with the risk score results, we can observe significant benefits of the adaptation measure in the form of flood defences – expected losses incurred by bank loan portfolios drop by over 90% for both river and coastal floods. Flood defences will become less effective under future climate scenarios – for river flooding manifesting already in 2050 in the case of the adverse climate scenario, while for coastal floods the effects will take longer, with expected losses increasing fivefold in comparison to the historical baseline unless current defences are strengthened. Again, these trends corroborate the findings based on the risk score indicators.

The CEAR indicator introduces a new aspect when estimating damages, demonstrating how collateral pledged with loans serves as a mitigant for potential losses in bank portfolios. For river floods, collateral more than halves the expected losses (58% reduction at the euro area level). For coastal floods and windstorms, the effects are even stronger, with a reduction of over 80% in losses estimated over the remaining maturity of the portfolio (see **Figure 40**, panel b).

Figure 40
Expected-loss indicators: NEAR and CEAR for loan portfolios of euro area banks

a) NEAR and CEAR over the maturity of the loan, % of portfolio

b) NEAR and CEAR annual expected losses, EUR billions



Sources: ESCB own calculations based on AnaCredit for collateral; for coastal and river flooding calculations based on data from the Delft University of Technology (TUD), for flood protection standards Joint Research Centre (JRC), for windstorms based on Copernicus.

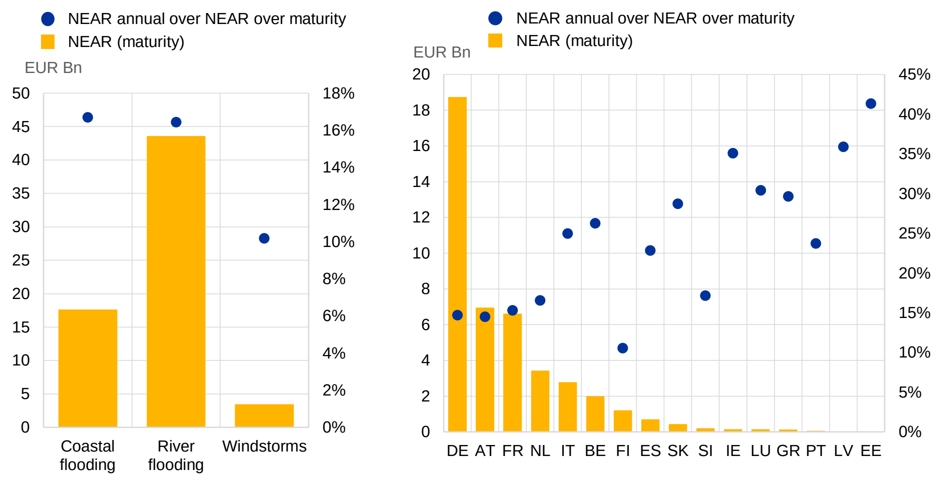
In the following section, we perform a closer analysis of the expected loss indicators, looking at the effects across countries.

Maturity effects

Figure 41
NEAR over maturity versus annualised losses

a) NEAR over the loan maturity and annualised losses, EA aggregates

b) NEAR over loan maturity and annualised loss due to river flooding, by country



Sources: ESCB calculations based on AnaCredit, RIAD, for coastal and river flooding calculations based on data from the Delft University of Technology (TUD); windstorm data based on Copernicus.
Notes: Panel b): countries excluded due confidentiality issues are Cyprus (CY), Malta (MT) and Lithuania (LT). Includes Deposit-taking corporations except central banks (S122) and Loans. Values plotted show the baseline scenario without flood protection.

We demonstrate the effect of maturities by presenting NEAR on both an annual basis and over the entire maturity period, representing the total expected loss from a specific hazard. At the euro area level, annual losses constitute around 16% of total flood damage when accounting for maturity within bank loan portfolios. For windstorms, the gap is even larger, and the NEAR indicator calculated over the maturity is ten times higher (see **Figure 41**, panel a). Looking at the distribution across countries in the case of river floods (see **Figure 41**, panel b), Finland presents the lowest share of annual to total expected losses, mirroring the higher share of longer-term instruments in the portfolios of Finnish banks. At the other end of the spectrum, in the Baltics and other smaller countries, annual expected losses account for over one-third of total losses, indicating a predominance of shorter remaining maturities.

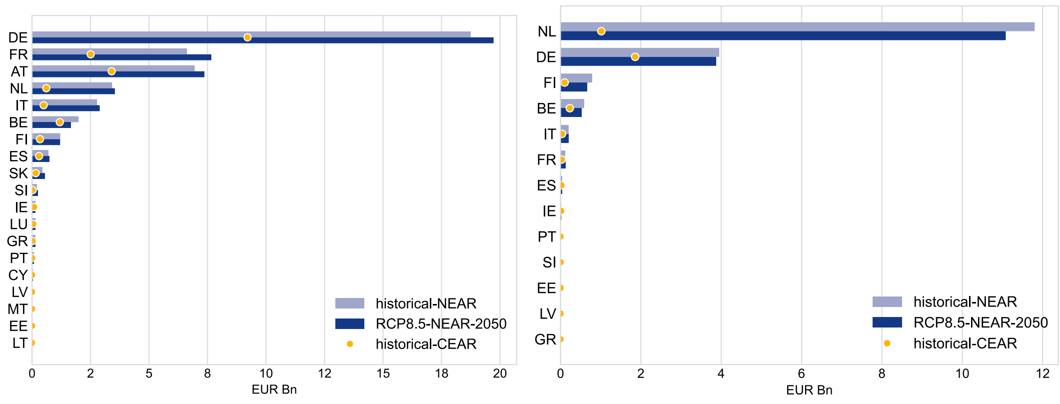
Country breakdown – NEAR indicator

The calculation of expected loss indicators combines climate risks, the physical assets of companies exposed to these risks and the composition of the portfolios of financial institutions. Thus, the distribution of the NEAR indicator across countries is determined by three factors: the country-specific risk as reflected in the risk scores (see Sections 3.3.1 and 3.3.3.1), the proportion of physical assets to total assets at the debtor level (see Annex 6.4.2), and lastly size and maturity effects in the bank portfolios.

For river floods, Germany and Austria ranks relatively highly across countries in relation to national climate risk in terms of total expected losses, given strong maturity effects and longer term portfolios (see **Figure 42**, panel a). For Finland, the higher level of the NEAR in comparison to the risk score ranking also stems from longer maturities, and a high share of tangible fixed assets in the sector of non-financial corporations. Meanwhile, flood risk in Ireland is relatively high, though expected losses rank lower, due to shorter maturities and lower on average fixed assets. For coastal floods, Italy happens to rank lower than expected based on the climate risk ranking, again due to lower fixed assets (see **Figure 42**, panel b). The fact that the Netherlands tops the table for coastal floods is a result of extremely high risk, long maturities and high fixed assets. However, as noted earlier, climate-related risk is drastically lower when accounting for flood defences, although the other forces are still at play.

Figure 42
NEAR and CEAR by creditor country – coastal and river flooding

a) River flooding, EUR billions, over maturity **b) Coastal flooding, EUR billions, over maturity**



Sources: ESCB calculations based on AnaCredit, RIAD; for coastal and river flooding calculations based on data from the Delft University of Technology (TUD).
Notes: Includes Deposit-taking corporations except central banks (S122) and Loans. Plotted values do not account for protection. Panel b): countries excluded due to confidentiality issues are Cyprus (CY), Lithuania (LT) and Malta (MT).

Country breakdown – CEAR

Country rankings for the CEAR indicator are influenced not only by those factors driving NEAR, but also national practices regarding collateral: proportion of unsecured loans as well as type of collateral pledged. Specifically, a high share of physical collateral reduces its effectiveness as a financial mitigant, as the value of real estate pledged can depreciate in the event of a natural disaster.

To illustrate these effects in the case of river floods, a high share of loans in Belgium and Ireland are unsecured (over 60%, see **Figure 33**), in comparison to 47% at euro area level. Correspondingly, for those countries the expected losses are reduced by around 40% with respect to the benchmark NEAR indicator (see **Figure 42**, panel a). Meanwhile, Portugal and the Netherlands exhibit the highest share of financial collateral (60% and 50% of the loan portfolio respectively) that is not threatened by physical risk. This is reflected in a heavy reduction of potential losses in the loan portfolios in relation to the indicator that does not take collateral into account: at around 90% for Portuguese credit institutions and 80% in the case of the Netherlands.

Comparison of NEAR indicators with PESETA IV estimates

Considering the developmental nature of the expected loss indicators, we compare our findings with damage estimates for natural catastrophes in Europe from existing literature. The JRC PESETA IV project[83] offers annual loss projections under three

[83] The PESETA IV project, an initiative of the Joint Research Centre of the European Commission, aims to assess the impacts of climate change in Europe, focusing on understanding the physical and economic consequences across various sectors.

distinct global warming scenarios: 1.5, 2 and 3 °C warmer than pre-industrial times (Feyen et al., 2020)[84]. These scenarios align closely with RCP 4.5 for the lower warming scenarios and RCP 8.5 for the higher 3°C scenario. There are three key distinctions between our indicators and those from PESETA IV:

- Firstly, in terms of geographical scope, our ESCB statistical indicators are specific to the euro area, whereas PESETA IV encompasses the EU and the United Kingdom.
- Secondly, our focus narrows to the effects of natural disasters on bank loan exposure towards non-financial firms, whereas PESETA IV assesses economic damages more broadly.
- Thirdly, PESETA IV flood projections consider not only an intensification of climate risks, but also future socioeconomic conditions, such as demographic trends, labour market dynamics and GDP growth. Meanwhile, our ESCB indicators operate under the assumption of static bank portfolios, thereby portraying the impact of various climate pathways based on current conditions.

The JRC assesses the baseline annual losses at €7.8 billion for river floods, €1.4 billion for coastal flooding and €4.6 billion for windstorms (Feyen et al., 2020). Our estimates, which also account for existing flood defences, constitute around 4% of JRC figures for river floods, and around 7% for coastal floods and windstorms (in absolute terms: €340 million, €100 million and €350 million respectively; see **Figure 40**, panel b).

Further, for floods where RCP projections are also available, we compare the increase in expected losses with the respective baseline. For river floods, the JRC estimates a fourfold increase while the ESCB indicators predict a threefold increase under the moderate RCP 4.5 scenario. For coastal floods, the gap is much larger, especially under RCP 8.5 with a 2100 time horizon, with the JRC estimating €240 billion in damage if no adaptation measures are taken and economic development continues in the coastal areas. With the investment into adaptation measures, the potential damage drops to €23 billion – still a 16 times increase from the baseline. In contrast, our indicators suggest a fivefold increase by the end of the century, assuming the loan exposures remain constant from the reference period of December 2022.

While benchmarking with the PESETA IV project does raise several caveats due to differences in scope and methodology, this exercise provides valuable validation for our experimental indicators. Although absolute figures diverge, the overall magnitude of climate impact is comparable and aligns with the expected relationship. As anticipated, our estimates are a fraction of the PESETA IV figures, which cover a wider geographical area and a broader range of economic sectors. Further, the gap between the two sets widens for the future projections, owing to PESETA IV's

[84] To learn more about the PESETA IV methodology, please see https://joint-research-centre.ec.europa.eu/peseta-projects/jrc-peseta-iv/methodology_en.

inclusion of wealth growth assumptions, which therefore expands the assets at risk from natural hazards and, consequently, the expected economic damage.

Accounting for insurance

Natural catastrophe insurance provides a critical safety net for businesses and individuals, mitigating the financial burden of natural calamities and fostering post-disaster recovery[85]. We illustrate its effects on the expected loss indicators by applying two insurance penetration factors, one based on historical insured losses and another on the current estimate of insurance penetration, as described in Section 3.3.2. **Figure 43** (panel a) illustrates the gap between the two measures that constitute the upper and lower bound for net-of-insurance losses.

The extent to which insurance reduces financial strain is country- and hazard-specific (see **Figure 43**, panel b). For river floods (**Figure 43**, panel a), NEAR decreases on average by 12% across euro area countries based on historical data, while applying the current insurance penetration halves the losses (52%). Slovenia in particular seems to be at high risk, with relatively high expected losses and low insurance coverage according to both insurance factors. Austria is also characterised by the highest expected losses for river flooding, although insurance factors give different signals – with the current penetration factor being much more optimistic and indicating that over 60% of losses could be covered by insurance. The NEAR indicator for river floods is also relatively high for Germany and the Netherlands, though Germany seems to have higher insurance coverage. It should be noted that both countries have sophisticated flood management systems, given their vulnerability to river flooding, although their financial support mechanisms differ. In particular, insurance coverage might not be comparable as the Netherlands relies less on private insurance and more on state-led flood prevention and disaster response (Jongejan & Barrieu, 2008).

For coastal floods (**Figure 43**, panel d), accounting for current estimated insurance penetration drives losses down by an average of 36% across countries. The figures stemming from the approach relying on insured losses should be interpreted with caution, given the scarcity of input data.

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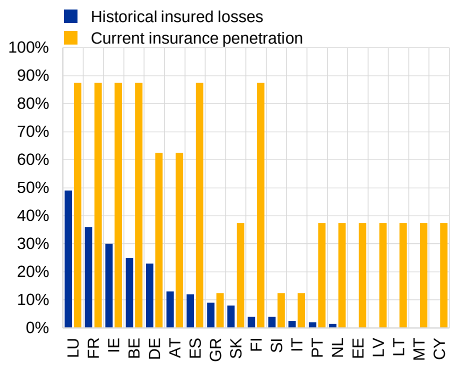
85 It should be noted that our investigation focuses on insurance as a risk mitigant from the perspective of individual debtors. While the intensification of climate risks may have significant impacts on insurers and re-insurers, such considerations fall outside the scope of this analysis. For a consideration of potential amplifications involving the insurance sector, please see (ECB/ESRB Project Team on climate risk, 2023).

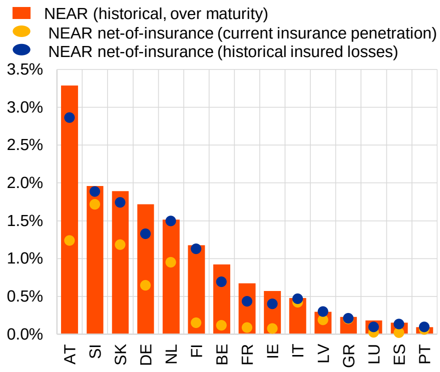
Figure 43

Insurance penetration and net-of-insurance NEAR indicator (historical, over maturity of the loan)

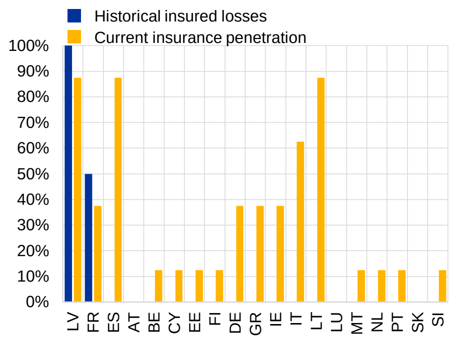
a) Insurance penetration – River and flash floods



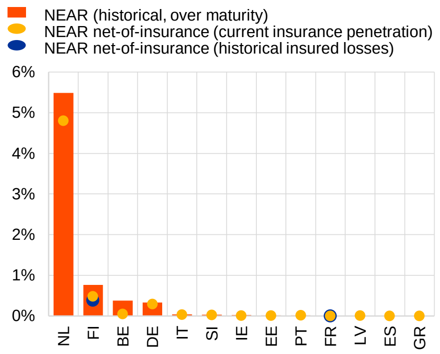
b) Net-of-insurance NEAR – River floods



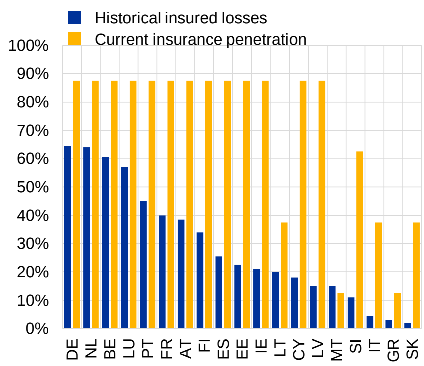
c) Insurance penetration – Coastal floods



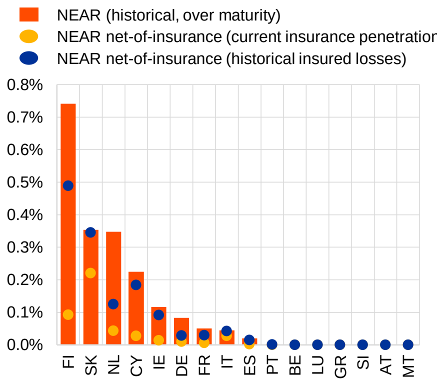
d) Net-of-insurance NEAR – Coastal floods



e) Insurance penetration – Windstorms



f) Net-of-insurance NEAR – Windstorms



Source: EIOPA protection gap dashboard, November 2023 version (including CATDAT, EM-DAT), ESCB own calculations based on AnaCredit and RIAD; calculations based on data from the Delft University of Technology (TUD) for coastal and river flooding and on Copernicus for windstorms.
Notes: Includes data for Deposit-taking corporations except central banks (S122) and Loans. River floods – Panel a): information on historical insured losses is missing for Cyprus (CY). Panel b): data for NEAR are not presented due to low frequencies for: Lithuania (LT), Cyprus (CY), Estonia (EE) and Malta (MT).
Coastal floods – Panel c): information on historical insured losses is missing for all countries except France (FR), Latvia (LV) and Spain (ES). Panel d): data for NEAR are not presented due to low frequencies for: Cyprus (CY), Lithuania (LT) and Malta (MT).
Windstorms – Panel f): data for NEAR are not presented due to low frequencies for: Estonia (EE), Lithuania (LT) and Latvia (LV).
Plotted values do not include flood protection.

Lastly, for windstorms (**Figure 43**, panel f) accounting for current estimated insurance penetration reduces the expected losses across euro area countries by 70% on average, while the impact of applying the historical share of insured losses is more limited (30% reduction on average). Those are the strongest mitigating effects of insurance across the three types of hazards considered for the NEAR indicator. Slovakia is expected to experience high windstorm risk, and at the same time has among the lowest insurance coverage according to the two insurance penetration measures. Conversely, Finland is the country with the highest NEAR indicator for windstorms, though it also has comparatively high insurance penetration. For the other countries with relatively high exposure to windstorms – the Netherlands and Germany – the financial risk seems well mitigated as they have the highest insurance coverage across the euro area.

It should be noted that the analysis is based on a number of assumptions (see Section 3.3.2), and will also be updated with the enhancements to the insurance coverage information.

4 Planned enhancements to the statistical climate-change related indicators

The climate-related indicators presented in this publication are a work in progress and subject to various limitations, as discussed above. It is therefore important that users are well aware of these constraints if they rely on the data to support policymaking and other purposes. However, as Frank Elderson, Member of the Executive Board of the ECB and Vice-Chair of the Supervisory Board of the ECB, already emphasised in 2021: “There are risks to acting on the basis of partial data, but in the case of climate change, the risks of inaction are far greater.”[86]

Much of the progress that can be made down the line in developing these statistics on climate change depends on enhanced non-financial reporting among corporations. This means increasing the availability and quality of the raw climate information reported by corporates, so as to align them with common international disclosure and verification standards, while continuing to push for further ambition in upcoming sustainability reporting standards and requirements, such as the Corporate Sustainability Reporting Directive (CSRD), the Corporate Sustainability Due Diligence Directive (CSDDD) and the Capital Requirements Regulation (CRR), as reviewed in more detail in Box 2. As statisticians, we aim to closely monitor these developments and to incorporate the data as soon as they become available to reduce our reliance on imputations and thereby enhance the quality of the analytical indicators towards statistical standards. We also happen to collaborate closely and actively with various initiatives that seek to enhance the data foundation. These include initiatives focusing on statistical work, such as the G20 Data Gaps Initiative (DGI), Recommendation 5: Forward Looking Physical and Transition Risk Indicators, and the Network for Greening the Financial System (NGFS).

4.1 Sustainable finance indicators

The sustainable finance indicators are released as experimental statistics, as they meet most, though not yet all, statistical quality standards. The key limitations in relation to the sustainable finance market, and subsequently in the underlying indicators/data, stem from a lack of internationally accepted and harmonised definitions of certain key concepts, such as what qualifies as “green”, the still relatively small size of the market. However, as the indicators now fulfil the required ESCB statistics governance and quality standards/principles, they are in the process of being designated as ECB official statistics.

To satisfy users’ needs and at the same time support the increasing demand for greater reliability, transparency and control, also against “green washing”, we also

86 Quote from Frank Elderson’s speech “Patchy data is a good start: from Kuznets and Clark to supervisors and climate” at the ECB-EBRD joint conference on *Emerging climate-related risk supervision and implications for financial institutions*, Frankfurt am Main, 16 July 2021.

publish aggregates considering only sustainable debt securities that have been externally reviewed. These sustainable finance indicators show that the euro area is addressing the growing demand for external review, as almost 85% of the sustainable debt securities issued in the euro area have obtained a pre-issuance second party opinion. In a future release, and with the aim of further harmonising and providing more comparable sustainability information to the public, additional indicators based on alignment with the EU Green Bond Standard (EUGBS) will be made available. It should be noted that as with this enhancement, future aggregates will be added rather than existing series being replaced, as the broad availability of data following different levels of assurance facilitates international comparisons, including with global statistical (e.g. G20) standards. Moreover, future work in the realm of sustainable finance will aim at achieving alignment with decisions taken by the ECB Governing Council in the context of the implementation of the ECB's monetary policy and will take on board EU legislation[87].

Currently, the sustainable finance indicators by sector and country, for both issuances and holdings, cover only green debt securities, which is by far the largest category in the sustainable debt market. As the other types of labelled sustainable debt securities become more sizeable, they will also be made available for all breakdowns.

4.2 Carbon emission indicators

The carbon emissions indicators will be updated in due course in response to methodological enhancements and increased data coverage, and as higher quality input data becomes available.

Regarding the methodological improvements, a key area will be refining existing imputation strategies and incorporating new ones to increase coverage and allow for better cross-country comparison, among other benefits.[88] A key priority will be imputing Scope 2 emissions for bank loans. For single entity-level indicators, Scope 2 emissions might be imputed using Input-Output (I/O) tables to allocate emissions from the energy sector to the debtors in the sample. In addition, a more complex time decomposition might be investigated to merge the decomposition and the exchange and inflation adjustment methods. This would allow us to separate the noise attributed to inflation/exchange rate fluctuations from volatility originating from other factors. Further avenues for investigation may well include forward-looking

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87 The Governing Council of the ECB has decided to adjust corporate bond holdings in the Eurosystem's monetary policy portfolios and its collateral framework, to introduce climate-related disclosure requirements and to enhance its risk management practices. In future updates of the sustainable finance indicators, further breakdowns aligned with the specific measures implemented by the monetary policy operations at that time will be considered.

88 Promising imputation strategies for future work include so called multiple imputation (Rubin D. B., 2018) and incorporating currently unused variables. In addition, constraints could be imposed on imputed variables. Also imputing missing variables not individually – as currently done – but as a system of variables, thus considering existing relations between variables, could be explored in future work. The informative value of the indicators could be enriched by producing upper and lower bounds of indicator values based on the advanced imputation.

carbon indicators[89], reporting on Scope 3 emissions (see Annex 6.3.6.3), increasing the scope of the reported exposures to cover central banks (S121) also, and including sovereign and supranational bonds as well as mortgages as instruments as and when consistent data across the euro area become available.

For the forward-looking indicators, two approaches will be considered. Firstly, using data from commercial data providers[90] and secondly, building forward-looking carbon indicators by developing forecasting methods based on historic microdata. Carbon disclosures among companies should be externally assured[91], since there is a high risk of companies under-reporting their impacts, thus resulting in substantial data quality issues.[92]

Scope 3 emissions are not yet included, as the data currently available are not yet consistent enough and the methodology is not yet aligned. As Scope 3 emissions account for a substantial portion of total emissions in many sectors (see Annex 6.3.6.3), including them in the indicator production would be a relevant topic for future work. For single entity-level indicators, the imputation of Scope 3 upstream emissions is expected to be investigated further through I/O modelling. For group-level indicators, including Scope 3 emissions is dependent on the availability of improved data on such emissions at the company level.

We will continue to evaluate data as it become available, such as from upcoming sustainability reporting standards and requirements (see Box 2) to determine its potential for enhancing the data foundation. This assessment will aim to facilitate adjustments in levels and the removal of breaks in time series, particularly for larger EU companies.

Box 2 - Sustainability reporting standards and requirements

This box gives an overview of currently used reporting standards and of upcoming sustainability reporting standards and requirements that are expected to lead to enhanced reporting among companies.

Carbon emissions data are inferred from AEA[93], EU ETS[94] and ISS. The sources can be distinguished in two dimensions: level and source of disclosure. Carbon emissions data can be provided at either the micro level, i.e. containing emissions of individual companies, or at the macro level, i.e. emissions information is solely available at aggregate country or sector level. Regarding the source of emissions data, there are two primary options. Firstly, data can be voluntarily or mandatorily self-disclosed by an individual company, with mandatory disclosures often entailing subsequent verification by a third party. Alternatively, it can be obtained through estimation by a

89 For further information, please refer to the recent ECB/ESRB report (ECB/ESRB Project Team on climate risk, 2023)

90 For further information on how the estimation of forward-looking transition indicators will be affected by upcoming sustainability reporting standards, please refer to Box 2.

91 As an example, the European Sustainability Reporting Standards (ESRS) mandates companies to disclose whether their declared greenhouse gas emission reduction targets have undergone external assessment.

92 See also the *JRC Working Papers in Economics and Finance*, 2023/09.

93 More information on AEA is available on the Eurostat's website.

94 More information on the EU ETS is available on the European Commission's website.

third party, with commercial data providers often engaging in this type of work. **Figure 44** provides an overview of how existing and upcoming reporting standards can be categorised along these two dimensions.

At the macro level, AEA provide estimated greenhouse gas emissions data by emitting economic activity for EU Member States. On the micro level, the EU ETS is employed for participating companies. The EU ETS relies on the emissions data that companies must disclose, and which undergo subsequent verification. Meanwhile, at the micro level, ISS provides self-reported emissions data.

The Air Emissions Accounts Regulation follows the System of Environmental Economic Accounting (SEEA) concept. EU ETS reporting requirements are specified under the EU Monitoring and Reporting Regulation (MRR) and the Accreditation and Verification Regulation (AVR). ISS relies on companies' self-reported[95] greenhouse gas emissions data from publicly available sources and may therefore rely on various reporting standards.

Several recent or upcoming disclosure requirements are expected to increase the availability and quality of the data available for the estimation of physical and transition risk indicators. The following EU regulatory initiatives are of particular relevance. The Corporate Sustainability Reporting Directive (CSRD)[96] modernises and strengthens the rules concerning the environmental, social and governance information that companies must report and is therefore of particular relevance as a data foundation for the carbon emission indicators. A broader set of corporate groups, including large companies, listed companies and SMEs, will now be required to report on sustainability matters. Disclosures will be made in accordance with the European Sustainability Reporting Standards (ESRS) and will include mandatory, audited disclosures, of both direct and indirect emissions among large and listed companies. In addition, corporations will be required to disclose 1.5-degree compatible transition plans.[97] The (digital) reporting will be gradually phased in, starting with large listed companies from 2025 onwards (for financial year 2024), followed by large non-listed companies, listed SMEs, and non-EU companies if they have securities listed in the EU, have significant activity in the EU, or are parents of in-scope EU subsidiaries.

The Corporate Sustainability Due Diligence Directive (CSDDD) requires companies to identify and mitigate the environmental impact of their own activities as well as those occurring along the value chain, which requires companies to measure and account for their carbon emissions. While it is the CSRD that prescribes the disclosure of transition plans, the obligation to draw up such plans is imposed by the CSDDD. Companies in scope of the CSDDD must adopt a plan to ensure that their business model and strategy are compatible with the transition to a sustainable economy and with the objective of limiting global warming to 1.5 °C in line with the Paris Agreement. Meanwhile, the Capital Requirements Regulation (CRR III) and the Capital Requirements Directive (CRD VI) will require banks to include, as part of their supervisory reporting, a prudential transition plan that includes ESG-related risks and indirect information on the alignment metrics of the financed sectors

[95] Besides self-reported emissions data, ISS also estimates undisclosed emissions or reporting by entities with a low trust metric. However, the emissions modelled by ISS are not considered in the compilation of the indicators.

[96] The legal text can be found here. As a directive, it must be transposed into national legislation to be effective.

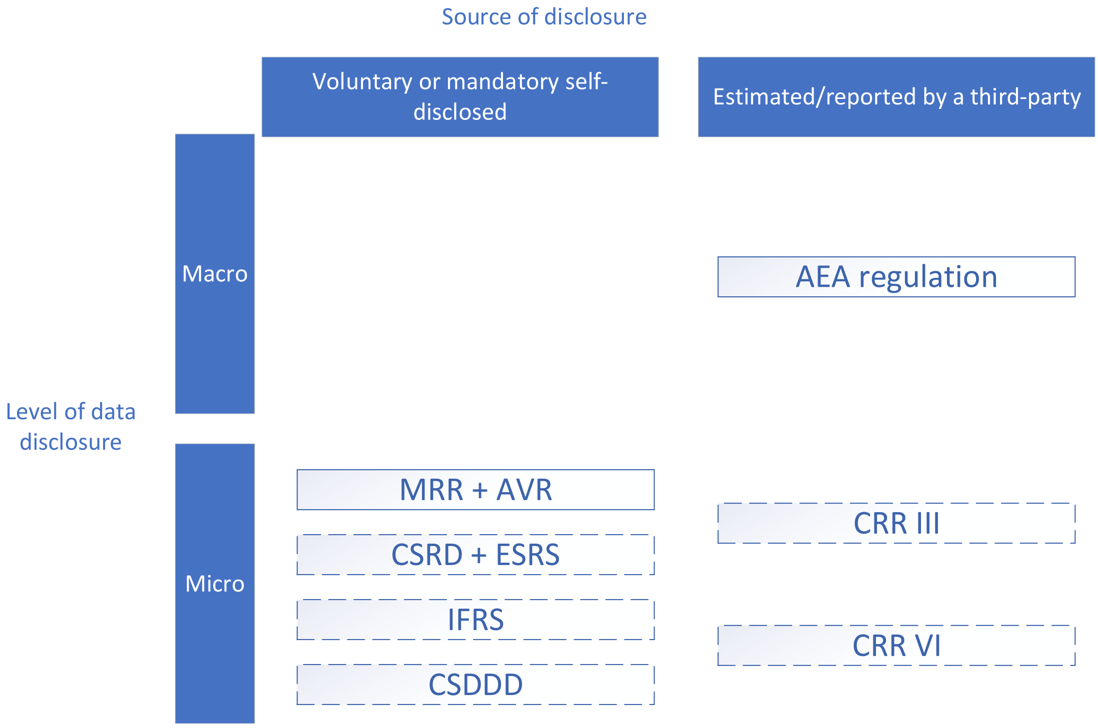
[97] A climate transition plan is a structured timeline detailing how a company will implement credible, short-term actions to realign its strategies and operations with the 1.5°C trajectory advised in the Paris Agreement.

to the net zero emissions target. However, the exact guidance emanating from these legal texts is still being developed.

Under the Capital Requirements Regulation (CRR) (for credit institutions specifically), the European Banking Authority (EBA) has developed Pillar 3 disclosure templates to ensure a uniform set of formats for the information to be disclosed as per CRR Article 449a. They apply to large and listed credit institutions and include qualitative information on ESG topics, as well as quantitative information on climate-related aspects (including, inter alia, the Green Asset Ratio and Taxonomy alignment of exposures towards a broad range of counterparties, net zero alignment, and exposures subject to physical risks). The initiative is applicable semi-annually from 2022, implying first disclosures in 2023 (end-December 2022 reference date) onwards. There will be a later phase-in for some indicators (e.g. financed emissions, Banking Book Taxonomy Alignment Ratio). The EBA is also working to bring ESG data reporting into its regular implementing technical standards for supervisory reporting, thus promising additional data quality assurance. The EU Taxonomy Regulation requires large and listed financial and non-financial undertakings to disclose how and to what extent their activities qualify as environmentally sustainable. Non-financial undertakings within the scope of the Non-Financial Reporting Directive (NFRD) started disclosing Taxonomy alignment data in 2023. Such reporting among financial institutions has been implemented with a lag of one year. Meanwhile, financial market participants managing funds disclosing under Article 8 and Article 9 of the Sustainable Finance Disclosure Regulation (SFDR) started reporting Taxonomy-related information for such funds in 2023.

On the international front, the International Sustainability Standards Board (ISSB) released its global IFRS Sustainability Disclosure Standards in June 2023, which will become effective for reporting in 2024. The non-mandatory IFRS S2 Climate-related Disclosures calls on companies to measure and report their Scopes 1, 2 and 3 GHG emissions in accordance with the Greenhouse Gas Protocol. The reporting standards also call on entities to disclose how they identify, assess, prioritise and monitor the climate-related physical and transition risks to which they are exposed, where such risks are anticipated to affect their cash flow, ability to secure financing, or capital costs over various time horizons. Entities are required to disclose the quantity and proportion of assets or business operations susceptible to physical and transition risk, respectively. For entities operating in asset management, commercial banking and insurance, this includes reporting on financed emissions. Regarding physical risks, the IFRS explicitly mentions storms, floods, drought, heatwaves, sea level rise, reduced water availability, biodiversity loss and changes in soil productivity.

Figure 44
Overview of sustainability reporting standards



Note: The boxes with solid lines refer to the reporting standard currently being used to construct the indicators. The boxes with dashed lines indicate that the reporting standards may become relevant for future indicator construction.

However, it should be noted that most of the aforementioned reporting requirements focus on larger, listed companies, meaning that data coverage for smaller, non-listed companies will likely remain an issue as we move forward.[98] Extensive efforts have been made to ensure the interoperability of reporting under the CSRD with reporting under the ISSB. Notably, an important distinction persists: the EU CSRD employs a dual materiality assessment (considering how the company is affected financially and how the company affects the environment), while the ISSB looks solely at the financial side.

Reporting on emissions reduction targets is part of the CSRD, CSDDD, IFRS S2, ESRS1, ESRS2, CRR, and is further enhanced by a recent initiative of the UNEP-FI Net Zero Banking Alliance.

It is also worth noting that the vast majority of reporting initiatives on the ESG front relate to disclosures rather than reporting requirements vis-à-vis a centralised body such as the ECB or the EBA, considering that reporting requirements have the advantage of providing more stringent quality control, with dialogue between the reporting agent and the data recipient. Going forward, the use of reporting requirements towards centralised bodies should be encouraged where possible, so as to ensure high quality data are made available while also reflecting the statistical burden on enterprises. The European Single Access Point, which is expected to go live in mid-2027, will

98 EFRAG is preparing a EU Voluntary Sustainability Reporting Standard for non-listed SMEs that are outside the scope of the CSRD. The significance of SME reporting is expected to grow in the long term, particularly as inputs from all suppliers will be needed in order for companies (including banks) to report on their upstream Scope 3 emissions.

provide a central access point allowing for automated access to all ESG disclosures in machine-readable format.

The variety of reporting practices highlights the need for a standardised framework, encompassing reported outcomes as well as methodologies and data input. The exact guidance emanating from these legal texts is still being developed. By harmonising sustainability reporting, we can increase the transparency and comparability of the underlying data regarding physical and transition risks. Several initiatives and alliances are currently developing frameworks and sharing best practices on sustainability reporting, including the G20's new Data Gaps Initiative and the UNEP-FI Net Zero Banking Alliance.

4.3 Physical risk indicators

The physical risk assessment presented in this publication is hindered by several limitations. Some of these issues can be addressed by ESCB statisticians, while others will require gradual enhancements over a long-term horizon, as advancements in climate modelling become available.

Firstly, the risk assessment relies on the RIAD dataset, which collects information at the level of the legal entity. This leads to a misrepresentation of physical risk where companies operate in multiple locations. To improve location information, we envisage exploring national data sources to more reliably identify a company's significant physical assets. Conducting country case studies would help to evaluate the usability of these national datasets and to measure the extent of potential risk mismeasurement. Regarding the location of real estate pledged as collateral, our current risk evaluation is based on regional data at the NUTS3 level. Incorporating finer data, such as postal codes or ultimately addresses, could significantly improve the precision of the damage estimates to physical collateral.

With respect to firm-level data, the total value of fixed assets is used as a benchmark for expected losses. In the case of larger companies, the fixed assets might be distributed across various locations, which might have varying degrees of exposure to physical hazards. Furthermore, data concerning the ratio of tangible fixed assets to total assets are often incomplete and rely heavily on imputed values, leading to potential inaccuracies. More broadly, financial statements at firm level currently suffer from limited coverage in the sources available (notably, smaller companies are often excluded), reporting lag, or missing or inaccurate information.

Furthermore, estimation of damage focuses on the direct destruction of physical assets. This narrow scope overlooks secondary effects such as business interruptions, increased cost of operations, or damage across the supply chain. Other sources of underestimation might include the impact of heat stress on labour productivity, and a broader risk to the economy in which a company generates revenue.

Lastly, when it comes to climate data and modelling, we will look to expand the range of hazards with climate projections (e.g. windstorms). That said, other challenges still remain. More precisely, the models consider hazards independently, thus ignoring compounded impacts. The co-occurrence of events, such as windstorms coupled with coastal flooding, can intensify their effects, leading to greater damage than that implied by summing the individual hazards. To address these complexities, close cooperation between ESCB statisticians and climate experts will be essential.

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6 Annexes

6.1 Common framework for carbon emissions and physical risk indicators

6.1.1 Imputation of financial information of single entity-level indicators

Financial information on single entity-level indicators, i.e. balance sheet total, revenue and number of employees, is imputed using a median approach.

To impute the balance sheet total for a given non-financial corporation, we first determine the total outstanding nominal amount (ONA) of a debtor by summing the nominal amount of loans inferred from AnaCredit and the market value of securities of an issuer from SHSS. Second, the “asset ratio” is determined by dividing the total outstanding amount by the balance sheet total. Third, medians of the asset ratio are calculated with year, country, sector and employee category breakdowns. If the group of firms on which the median is to be calculated contains less than 50 observations, one level of granularity is dropped, meaning year-country-sector breakdowns are considered.[99] Fourth, if there is a positive total amount outstanding, the balance sheet total is calculated as the ratio between the total amount outstanding and the imputed asset ratio. If the total amount outstanding is equal to zero, the balance sheet total is imputed as the median balance sheet total.

Annual revenue is also imputed using an analogous approach, employing “revenue ratio”, defined as the total outstanding amount divided by revenue. The implemented approach increases coverage by construction by ensuring that the imputed balance sheet total is greater than the observed ONA, which is a necessary condition when calculating Financed emissions (FE). Notably, the imputations account for loan-to-asset ratios across creditor relationships, thus taking into consideration that a given debtor may receive funding across various jurisdictions.

Prior to imputing, financial values identified as outliers are manually set to being missing and are thus subsequently imputed as well. Observations are defined as outliers using a threshold-based approach, where thresholds are inferred using various internal data sources.

The employee category distinguishes between microenterprises (1-9 employees), small enterprises (10-49 employees), medium enterprises (50-249 employees), large enterprises (more than 250 employees) and those with missing information. Given the limited number of observations, the country grouping consolidates several countries with lower coverage into two categories: one comprising euro area members (Cyprus, Estonia, Lithuania, Latvia, Malta, Slovenia and Slovakia), and the

[99] For the imputation of the number of employees, this generally means applying a year-sector breakdown. For imputing balance sheet total and revenue, the first fallback option is year-country-sector followed by year-sector.

other encompassing EU countries (Bulgaria, Czech Republic, Denmark, Croatia, Hungary, Poland, Romania and Sweden). The sector category is based on the NACE classification, as described in Annex 6.2.

The imputation approach implicitly assumes that the auxiliary data used for imputation are strongly related to the missing values that are imputed and that the observed data are representative for the missing ones. If these assumptions are not met, or only partially met, the results are prone to bias. In addition, imputed values are inherently uncertain, which may also affect the results of the analysis.

6.2 Debtor/Issuer industrial sector classification

Debtors and issuers are classified into nine categories following NACE level 1 revision 2, as illustrated in the below table. The sector breakdowns are aligned with the physical risk indicators. Alternative sector classifications, e.g. introducing nine NACE sectors (Battiston, Mandel, Monasterolo, Schütze, & Visentin, 2017), were considered since they could deliver insights into drivers of emissions by industry, but were ultimately discarded since more granular levels would likely lead to confidentiality issues.

Table 6 – Industrial sector classification of debtors/issuers

NACE level 1 codes, revision 2	Title	Divisions	Grouping applied
A	Agriculture, forestry and fishing	01 – 03	1 Primary production
B	Mining and quarrying	05 – 09	1 Primary production
C	Manufacturing	10 – 33	2 Manufacturing
D	Electricity, gas, steam and air conditioning supply	35	3 Energy and utilities
E	Water supply; sewerage, waste management and remediation activities	36 – 39	8 Services
F	Construction	41 – 43	4 Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	45 – 47	5 Trade
H	Transportation and storage	49 – 53	6 Transport
I	Accommodation and food service activities	55 – 56	7 Hospitality
J	Information and communication	58 – 63	8 Services
K	Financial and insurance activities	64 – 66	8 Services
L	Real estate activities	68	8 Services
M	Professional, scientific and technical activities	69 – 75	8 Services
N	Administrative and support service activities	77 – 82	8 Services
O	Public administration and defence; compulsory social security	84	8 Services
P	Education	85	8 Services
Q	Human health and social work activities	86 – 88	8 Services
R	Arts, entertainment and recreation	90 – 93	8 Services
S	Other service activities	94 – 96	8 Services
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	97 – 98	8 Services
U	Activities of extraterritorial organisations and bodies	99	8 Services
No NACE code specified			9 Missing

6.3 Carbon emission indicators

6.3.1 Imputation of carbon emissions of single entity-level indicators

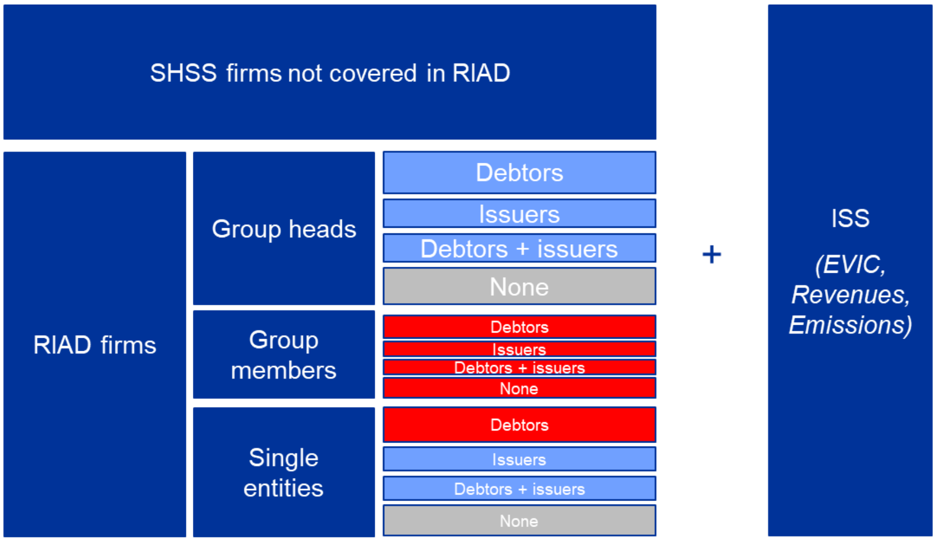
Single entity-level carbon emissions for entities not included in the EU Emissions Trading System (ETS) are imputed using a proportional method. The waterfall imputation methodology uses air emissions accounts (AEA) for Scope 1 emissions whenever there is a lack of EU ETS data. In the absence of EU ETS data, the residual of sector-level AEA Scope 1 emissions is re-allocated to a single entity in proportion to the entity's employment share in the given sector. Therefore, the imputation procedure requires the availability of employment data and a sector classification, meaning that it can be conducted only to the extent that this information is jointly available.

Imputations assume a strong relationship between the auxiliary data used for the imputations and missing values, and their representativeness; failure to fully meet these assumptions introduces bias, compounded by the inherent uncertainty of imputed values.

6.3.2 Group-level imputation of financial and carbon emissions information

The base for the group-level imputation is a restricted sample derived from RIAD, hereinafter referred to as the group frame. The group frame is constructed by first splitting the RIAD sample into group heads, group members, and single entities using a waterfall approach.[100] Second, for each subset, entities are classified as debtors, issuers, both, or neither.[101] Third, SHSS issuers that could not be identified in RIAD are added to the frame. Fourth, the group frame is constructed by keeping all companies except group members and single-entity debtors that are exclusively debtors.[102] In a last step, the constructed group frame is matched with ISS. For an illustration of the procedure, see **Figure 45**. Blue and grey parts are considered in scope for the group indicators, while red parts are excluded.

Figure 45
Construction of the group frame for group-level imputations



Note: The figure is a stylised representation of the group frame used for the imputation of group-level emissions and financial data.

For entities with some self-reported ISS data, imputations are estimated with a fixed effects model using the following equation:

$$\log Y_{i,t} = \alpha_i + \text{Sector}_i \times \text{Year}_i + \varepsilon_{i,t}$$

[100] A firm is defined as a group head if it is the parent (or ultimate parent) of at least one more entity, defined as a group member. Accordingly, single entities are defined as such if they are not integrated into any group structure.

[101] The classification is accomplished by concatenating the RIAD data with the AnaCredit and SHSS datasets used in the indicator compilation respectively.

[102] This is due to the fact that those entities enter the compilation using single entity data.

Where $Y_{i,t}$ denotes the missing record of either Scope 1 or 2 emissions; EVIC or revenue, α_i denotes a firm-specific fixed effect; Sector_i denotes the firm's economic sector; Year_i denotes the respective year; and $\varepsilon_{i,t}$ is a standard idiosyncratic error term. The effect of alternative time trends was tested but discarded since it did not improve the imputations. Incorporating a region-sector-specific time trend could not be estimated due to collinearity. Region-specific time trends have been found to reduce the volatility of the imputed values. However, the volatility of the imputed values using a sector-specific trend better matches the volatility observed in the data and we therefore proceeded with sector-specific trends. In general, region-specific time trends produce very similar values to the sector-specific trends.

For entities with no observed data, missing values were imputed using region-sector-year medians without outliers. Outliers are identified as influential observations with the following model (cf. notation introduced above) using Cook's distance:

$$Y_{i,t} = \alpha + \text{Region}_i + \text{Sector}_i + \text{Year}_t + \varepsilon_{i,t}$$

The Region categories used are Africa, Americas, Asia, Europe, Oceania and Unknown. Both approaches use the NACE classification described in Annex 6.1.

The identified outliers, which account for between 1.6% and 3% of observations, are dropped to produce a truncated median. Removing the outliers also substantially reduced within-measure variability over time.

Besides medians, two additional types of imputations using means were tested. The mean imputations were also calculated on a region-sector-year basis without outliers. To mitigate composition effect and to obtain an approximately representative sample, one mean imputation further restricts the group frame to entities that are also present in SHSS. Since mean imputations are sensitive to outliers, the median imputation was employed.

Similar to the imputations of single entity-level data, the imputation methods assume implicitly that the auxiliary data used for imputation correlate strongly with the missing values and that the observed data are representative of the missing values. If these assumptions are not fully met, the results may be susceptible to bias. Furthermore, imputed values inherently carry uncertainty, thus influencing the analysis results.

6.3.3 Inflation and exchange rate adjustments

Corrections for inflation and exchange rate effects were applied to the WACI indicator.

Inflation and exchange rate data

To correct for exchange rate effects, euro foreign exchange reference rates are used. To correct for inflation effects, we constructed country, time and industry-specific deflators using National Accounts data from Eurostat. The datasets used are National accounts aggregates by industry (up to NACE A*64) (dataset "nama10") for

European countries and Gross value added by A*10 industry- international data cooperation annual data (dataset “naid10”) for the rest of the world. These datasets contain a set of macroeconomic indicators such as GDP, output and gross value added (GVA), specified for each country and time period (yearly) and broken down into industry classifications (more granular for Europe than for the rest of the world). The most intuitive macroeconomic indicator to use as a proxy for revenue is output (Quantity (Q) x Price (P)). However, data coverage for output in the National Accounts is relatively low (with no data being available for half of the euro area countries), such that currently GVA (output less intermediate consumption) is used as a proxy for inflation. The advantage of this construction over the more general approach of using, say, a Producer Price Index, is that GVA data cover all industries (such as manufacturing and services) and combine different deflators based on National Accounts recommendations. A foreseen improvement for future calculations would be to take into account also the effects of intermediate consumption.

GVA is expressed in a range of unit measures. “Current prices” (CP) expresses GVA in millions of euro and includes (due to the way National Accounts are constructed) inflation effects. “Previous year’s prices” (PYP) expresses GVA in volume measures and does not include inflation effects, such that the relationship between the two implicitly contains the inflation numbers of interest. CP and PYP are related via index numbers, which are chained over time with respect to a certain base year, resulting in a “chain-linked volumes” index series (e.g. CLV_I15, another unit measure in the dataset). Note that PYP values are mentioned here to illustrate how inflation enters the chain-linked volumes index numbers, although in practice the deflators are calculated using only the unit measures CP and CLV_I. For more information on unit measures, please refer to Eurostat’s metadata documentation (nama10 and naid10).

The steps taken to arrive at the deflator numbers are as follows:

- The chain-linked volumes index numbers CLV_I10 in the dataset (base year = 2010) are converted to base year 2018, the first year in our time series:

$$\mathrm{CLV\_I18}\ (t) = \mathrm{CLV\_I10}\ (t) \,/\, \mathrm{CLV\_I10}\ (t = 2018) * 100$$

- Current prices, from the dataset, in base year 2018 (CP_MEUR (t = 2018)) are multiplied by the new CLV_I18 numbers, to arrive at the value (of the macroeconomic indicator) in year t in a chain-linked volumes estimate of the value (with reference year 2018):

$$\mathrm{CLV18\_MEUR}\ (t) = \mathrm{CP\_MEUR}\ (t = 2018) * \mathrm{CLV\_I18}\ (t)$$

- The deflator in year t is now given by the ratio between the current price and the chain-linked volumes estimate value (both in year t). The deflator is the factor with which to multiply revenue - valued in current year prices – to obtain the value of the revenue in chain-linked volume estimates of its value, with reference year 2018, i.e.:

$$\mathrm{DEFL\_CLV18\_EUR}\ (t) = \mathrm{CLV18\_MEUR}\ (t) \,/\, \mathrm{CP\_MEUR}\ (t)$$

Revenue corrections

In order to correct revenue for exchange rates and inflation, the process is as follows:

If an issuer/debtor is within the euro area, we correct revenue only for inflation (note that the approach employed does not consider that revenue shares may not exclusively be generated in the same country and currency), by multiplying each year's value with the deflator. The new revenue series expresses revenue "as if no inflation has taken place since 2018", allowing us to observe volume trends.

If an issuer is based outside the euro area, we first correct the revenue (expressed in euro) for exchange rates using the yearly average; second, we correct for inflation in the local currency, and lastly we convert the time series back to euro using the yearly average exchange rate in 2018. This constant exchange rate is applied to address inflation and exchange rate effects at once (Janssen, et al., 2021). In the current scope we have no debtors outside the euro area, and so all loans are already adjusted under the previous, euro area case.

Securities holdings / Outstanding Nominal Amount (ONA) corrections

As mentioned in the main text, securities holdings (ONA for loans) are not corrected for inflation since the relationship between holdings and inflation is not straightforward. Holdings (and ONAs) are corrected for exchange rate effects only, by multiplying the time series with the end-of-year exchange rate (where the exchange rate currency is based on the nominal currency value). Without inflation effects, the time series is subsequently multiplied directly with the constant (2018) end-of-year exchange rate to adjust the time series for exchange rate effects and to express it in "2018 EUR" values.

Adjusted WACI

Lastly, WACI is adjusted for inflation and exchange rates by using adjusted revenues, holdings and ONA when compiling the indicator.

6.3.4 Flex balancing method

Variation in sample composition over time induces excess variation of the analytical carbon indicators and can often confound genuine drivers of the indicators with noise. To control for sample composition, practitioners of econometrics or statistics usually resort to the construction of balanced samples, which means that they keep in the sample of interest only those units, here denoted $i = 1, \dots, N$, that provide a non-missing record across all available time periods, here denoted $t = 1, \dots., T$. In contrast to this, the flex balancing method developed here differentiates across the two possible sources of missingness in the indicator construction: first, a lack of financial or emissions data and second, due to investments and divestments occurring between $t = 1$ and $t = T$. Specifically, the algorithm removes those units (i.e. firms) from the compilation sample that have a missing record in any time period due to a lack of emissions or financial data but retains in the sample those firms whose missing data stems solely from investment or divestment movements. This ensures that records that genuinely appear in less than the full panel are maintained, thus allowing for compositional variation over time that reflects the investment decisions made by financial institutions.

A stylised representation of this is provided in **Figure 46**, where Firm 1 will be removed entirely from the sample but Firm 2 is kept following the aforementioned logic.

Figure 46
Graphical illustration of the Flex balancing method

	Firm 1		Firm 2	
	In sample	Full information (emissions + financials)	In sample	Full information (emissions + financials)
t = 1	YES	NO	NO	NO
t = 2	YES	YES	YES	YES
t = 3	YES	YES	YES	YES
Result	• Firm 1 will be **removed entirely** from the sample because it has incomplete information due to missing data in t=1 despite an investment value being observed in that period (i.e. it is technically in sample in t = 1) • The flex balancing method thus removes noise from the data that stems solely from missing data		• Firm 2 will be **kept in the sample for the two periods it appears in the sample** because it has complete information in periods t = 2 and t = 3 • Notably, the lack of info in t=1 stems just from the fact that **no investment into this firm could be observed** across all creditor/debtor or holder/issuer relationships • The algorithm thus accommodates for this unlike a strict balancing exercise, which would require presence in all periods	

Note: The figure describes the flex balancing method to account for sample composition over time. The method keeps firms with complete information in the sample even if actual in-sample presence is below the sum of the time periods and thereby allows for divestment/investment over time.

6.3.5 Time series decomposition

To better understand the dynamics of the indicators over time, we disentangle the effects of investment choices by the creditor/holder from the effect of emissions reductions by the debtor/issuer. Therefore, we apply a time series decomposition method to the FE, WACI and CFP indicators in order to disentangle holder-side effects from issuer-side effects due to the greening of the underlying assets.

The decomposition method for the WACI indicator is as follows:

The WACI indicator can be expressed as

$$\mathrm{WACI_{i,t}} = \sum_{\mathrm{i}} \mathrm{w_{i,t}\,CI_{i,t}} = \sum_{\mathrm{i}} \mathrm{w_{i,t}} \frac{\mathrm{e_{i,t}}}{\mathrm{r_{i,t}}}$$

where $\mathrm{w_{i,t}}$ denotes the portfolio weight of firm i in year t, $\mathrm{CI_{i,t}}$ the carbon intensity, $\mathrm{e_{i,t}}$ the emissions, and $r_{i,t}$ the revenues.

The change in WACI over time is decomposed into three parts, although a decomposition in two parts could also be performed:

$$\Delta_t^{WACI} = \Delta_t^{w} + \Delta_t^{CI} = \Delta_t^{w} + \Delta_t^{E} - \Delta_t^{R}$$

where Δ_t^{WACI} denotes the change in WACI over time; Δ_t^{w} its decomposition into the capital reallocation effect; and Δ_t^{CI} the carbon intensity effect.

Three methods were considered: Marshall-Edgeworth-type decomposition (Marshall, 1887; Edgeworth, 1925), Growth accounting (Berkhout et al., 2023) and Paasche-type decomposition (De Boer & Rodrigues, 2020). Two methods for the decomposition were implemented and tested – a method based on growth accounting, as described in Berkhout et al. (2023), and the so-called Marshall-Edgeworth method.

Table 7 provides a comparison of the three decomposition methods applied to WACI. For the sake of brevity and ease of comprehension, the ensuing comparison focuses on a decomposition in two parts only.

Table 7 – Mathematical comparison of decomposition methods on the WACI indicator

	Growth Accounting	Marshall-Edgeworth	Paasche-type decomposition
Δ_t^{WACI}	$\Delta WACI_t$	$\Delta WACI_t$	$\Delta WACI_t$
Δ_t^{w}	$\sum_i \Delta WACI_{i,t} \frac{\Delta \log w_{i,t}}{\Delta \log WACI_{i,t}}$	$\sum_i \Delta w_{i,t} \left(\frac{CI_{i,t} + CI_{i,t-1}}{2}\right)$	$\sum_i \Delta w_{i,t} CI_{i,t}$
Δ_t^{CI}	$\sum_i \Delta WACI_{i,t} \frac{\Delta \log C I_{i,t}}{\Delta \log WACI_{i,t}}$	$\sum_i \Delta CI_{i,t} \left(\frac{w_{i,t} + w_{i,t-1}}{2}\right)$	$\sum_i \Delta CI_{i,t} w_{i,t-1}$

The Marshall-Edgeworth method was chosen as it satisfies the properties deemed desirable for the decomposition analysis (Huerga & Steklacova, 2008); see Table 8.

Table 8 – Methodological comparison of decomposition methods: axiomatic properties

	Growth Accounting	Marshall-Edgeworth	Paasche-type decomposition
Exhaustiveness	Log-linearisation of multiplicative terms	Deltas multiplied by average value	Counterfactual
Time reversal	Yes	Yes	Yes
Symmetric reference periods	Yes	Yes	No
Scale	Not applicable	Yes	No
Handle 0s	Yes	Yes	Yes
Translation	No	Yes	Yes

Note: The comparison is based on Huerga & Steklacova, 2008.

6.3.6 Alternative approaches to constructing carbon emission indicators

6.3.6.1 Alternative data sources

For the compilation of single entity-level indicators, we use balance sheet information retrieved from RIAD. The decision to use RIAD was based on an assessment of coverage and consistency of the data used for the compilation from RIAD compared to Bureau van Dijk's commercial database Orbis, which was used in the initial estimations published by the ECB. In general, the coverage of balance sheet information, i.e. number of employees, total assets, revenue, and NACE code, is superior in RIAD, though there are notable differences across countries. In addition, for euro area debtors, the group structure available in RIAD should be superior to the one used in Orbis. Consistency between RIAD and Orbis is generally high, reflected in a high correlation between the financial data.

To enrich the observed carbon emissions and financial data used for imputation at group level, such data were explored by combining ISS with Refinitiv, a commercial provider of financial markets data. However, Refinitiv was ultimately discarded since it did not substantially reduce the uncertainty of the imputations at the micro or aggregate level.

6.3.6.2 Alternative imputation strategy of financial and emissions data

For the imputation of missing financial information, i.e. total assets, revenue and number of employees, in RIAD we must calculate loan-based single entity-level indicators: several specifications based on medians, means and random-forest models were tested. However, imputing the balance sheet total directly led to a considerable loss in coverage for all methods tested due to the occurrence of overfitting and data records, thus resulting in invalid observations. Specifically, coverage is lost since the imputed balance sheet total is for some entities higher than the outstanding amount observed, which violates the assumptions required to calculate the carbon indicators. We therefore opted for indirect imputation based on ratios.

Both mean and median imputations were evaluated across different breakdowns, including year, country and sector, as well as when incorporating the number of employees. A notable drawback of mean-based imputation lies in its sensitivity to outliers. A suitable winsorising strategy would have to be highly customised given the partially limited dataset size and the variation in distributions across different breakdowns.

The non-parametric multivariate imputation method by chained random forest identifies non-linear relationships and variable interactions and was performed in R using the missRanger package (Mayer, 2019). MissRanger simultaneously predicts multiple variables by leveraging all available dataset features as predictors, blending random forest imputation with predictive mean matching. In this method, forests, comprising multiple decision trees, are expanded until the out-of-sample estimation error decreases. Various variations of the random forest implementations were tested that differ in whether the full or a restricted RIAD sample is used and in terms of the variables utilised. A subset of variables was used in every specification tested (year, country, sector, revenue, balance sheet total, company birth date, and number of employees). The hyperparameters of the forest imputation were fine-tuned using data where all columns are filled. On this set, existing values were removed, and imputation accuracy was assessed through root mean square error and mean absolute error metrics. The group-based median imputation approach was marginally more accurate than the random forest method, though the random forest approach excels in capturing economic relationships within the data. A drawback of the machine learning approach is its lack of transparency compared to more straightforward methods such as group median imputation, which makes it less interpretable.

As an alternative to the current approach used to impute GHG emissions for single entities, different model-based imputations similar to the ones used for groups were tested. Various regression models and multiple imputations were explored, though the high uncertainty rendered them unsuitable for our intended use. For example, GHG emissions were imputed using the number of employees, the company's revenue, and the total assets/value of the company taken from RIAD. Missing values in one of the three values are imputed using sector-country-year medians. If the number of employees is known, it is included in the group median calculation. The focus was on NACE sectors C, D, E and H, as the majority of companies participating in the ETS come from these sectors, meaning that both RIAD and EU ETS emissions data are available. However, the imputed values showed a high degree of uncertainty, likely due to the high number of missing data and low data quality.

To impute financial and emissions data with uncertainty at the group level, Multivariate Imputation by Chained Equations (MICE) models (Van Buuren & Groothuis-Oudshoorn, 2011) and regression models were tested. When using observed data to impute missing data, it is implicitly assumed that the missing is at random, meaning the observed data are representative for the missing data. The MICE model uses an iterative series of predictive models to compute 50 imputations on each missing value and summarises it in a mean value and a standard deviation using Rubin's formula (Rubin D. B., 2018) . The imputations with MICE were assessed by examining the level of uncertainty in imputations when aggregating at sector or country level. Since the level of uncertainty when imputing with MICE was high, as the correlation between emissions and covariates used for estimation is low and the number of missing data is high, it was decided to employ simpler methods such as the split-level approach, as described in Section 3.2.2. The regression models tested for the imputation of group-level carbon emissions employed different explanatory variables, several types of transformations, controlled for heteroscedasticity, and imputed an interval.

6.3.6.3 Alternative approaches to emission scopes

Scope 3 is defined in the Greenhouse Gas Protocol as all the indirect emissions of an entity and its products, except for those falling under Scope 2, i.e. it includes emissions across the entire value chain (both production and consumption).

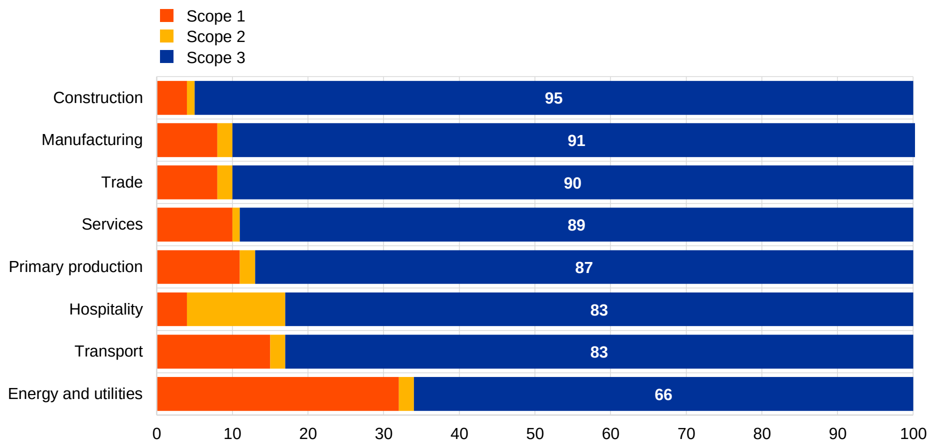
The published statistical indicators do not include Scope 3 emissions information for several reasons:

- Inaccurate and unreliable data: Scope 3 emissions must be collected from all activities along the value chain, which requires emissions data from multiple suppliers, locations, subcontractors, and so forth. In addition, some emissions are not yet reported, especially in the case of SMEs. Thus, companies may rely on secondary data such as industry averages or spend-based emissions factors, which may lead to significant discrepancies when estimating Scope 3 emissions.
- Inconsistency in the number of categories reported: emissions are grouped into categories, depending on where in the value chain they arise. Within the same sectors, companies do not report the same number of categories since the structure of their value chains is different, thus resulting in data discrepancy. Due to this, disaggregation of Scope 3 emissions is not available for all companies.
- Not all companies need to report Scope 3 emissions: if some companies disclose only Scope 1 and Scope 2 emissions, the partial inclusion of Scope 3 emissions would distort the analysis and the indicators.
- Reporting methodologies need to improve: reporting is not yet standardised, and the reporting methodology not clearly defined.
- Gross or net and carbon offsets not clearly disclosed: there is no clear indication as to whether the reported Scope 3 emissions are gross or net (albeit with some exceptions). Along the same lines, there is no clear disclosure of carbon offsets in the reports published.
- Problem with double-counting: considering Scope 3 emissions at portfolio level can give rise to significant double-counting of emissions.

In a bid to further improve the reporting and data quality of Scope 3 emissions at company level, the ECB intends to include these emissions in the calculations at a suitable juncture (preferably once the problem of double-counting can be neutralised). Scope 3 emissions constitute a considerable volume of total emissions in some sectors; see **Figure 47** in particular for sectors such as oil and finance.

Figure 47
Emissions broken down by sector and emission type

percentage



Sources: Emissions data originates from ISS, while data on sectors are taken from CSDB.

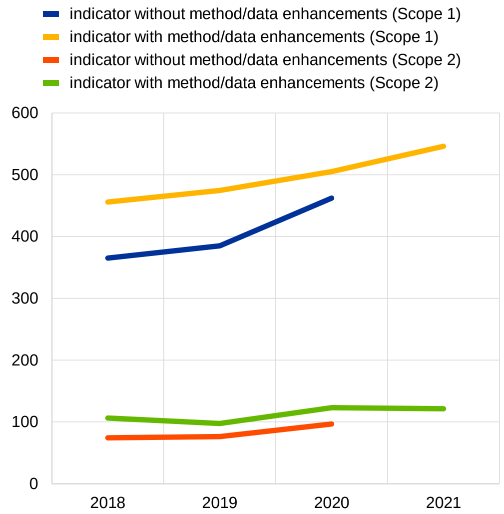
6.3.7 Additional analyses

Figure 48 and **Figure 49** show the development in the carbon indicators on securities held by non-money market fund investment funds and insurance corporations and pension funds respectively. The trends are similar, we see an increase in the financed emission indicator (see subfigure a) and a decrease in the relative indicators (see subfigures b, c, and d) over the time frame studied.

Figure 48
Comparison of carbon indicators with and without methodological and data enhancements: securities held by non-money market fund investment funds, compiled at the group-level

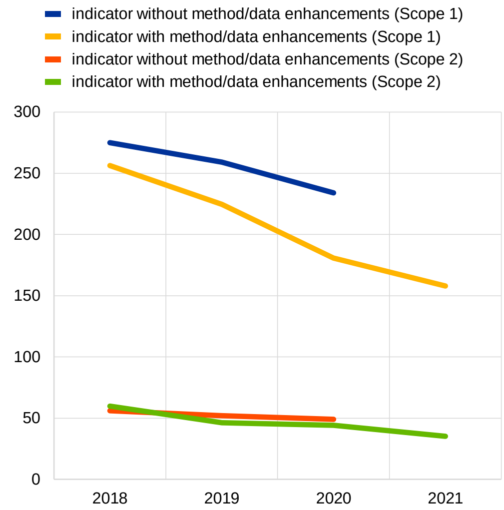
a) Financed emissions (FE), euro area aggregate

million tonnes of CO2



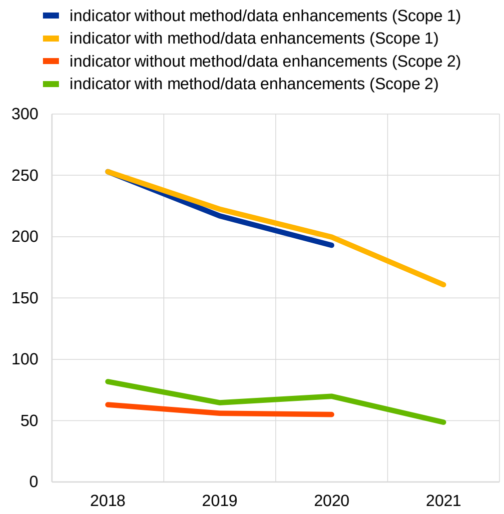
b) Carbon intensity (CI), euro area aggregate

tonnes of CO2 per million euro



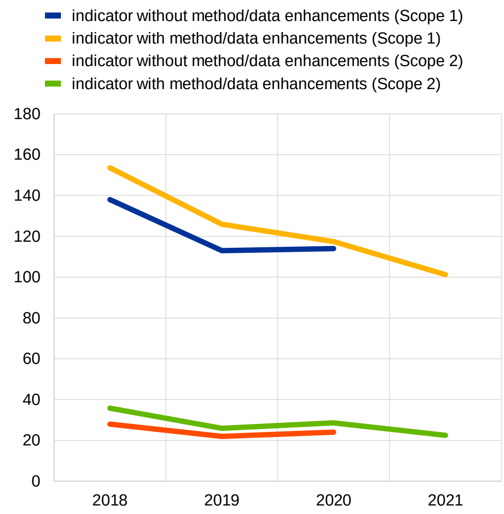
c) Weighted average carbon intensity (WACI), euro area aggregate

tonnes of CO2 per million euro



d) Carbon footprint (CFP), euro area aggregate

tonnes of CO2 per million euro

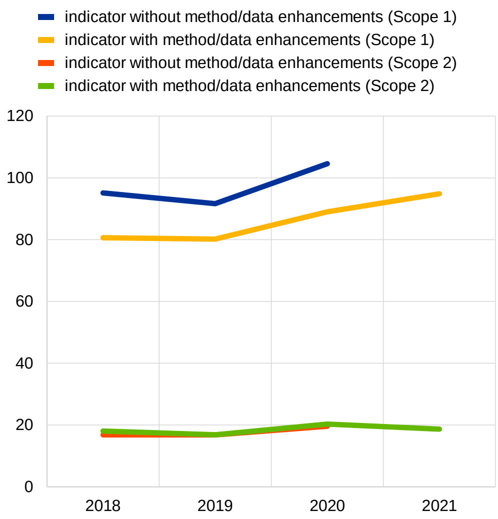


Sources: ESCB calculations based on data from Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), and Institutional Shareholder Services (ISS).
Notes: Securities include listed shares and debt securities of deposit-taking corporations (S122) and are computed at group level. The charts comprise Scope 1 and Scope 2 emissions. WACI is adjusted for inflation and exchange rate effects.

Figure 49
Comparison of carbon indicators with and without methodological and data enhancements: securities held by insurance corporations and pension funds, compiled at the group-level

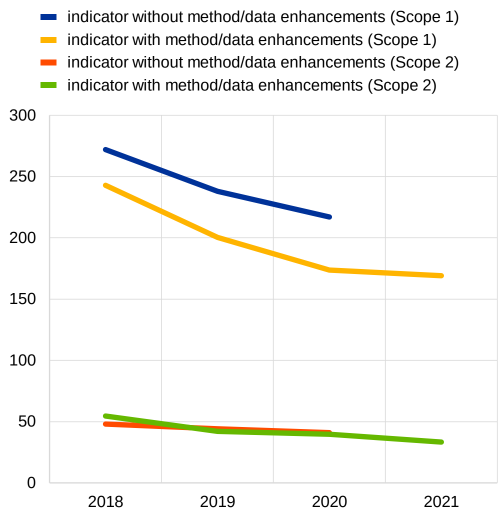
a) Financed emissions (FE), euro area aggregate

million tonnes of CO2



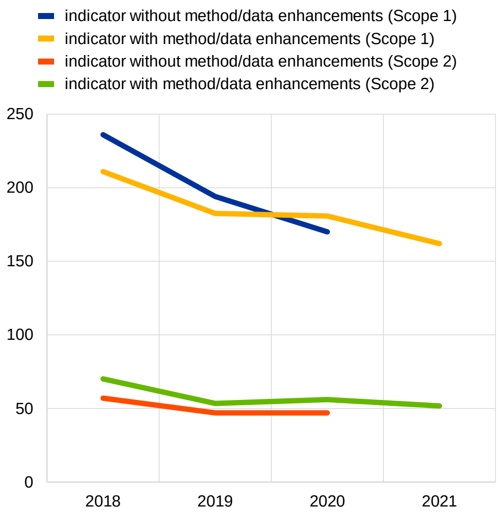
b) Carbon intensity (CI), euro area aggregate

tonnes of CO2 per million euro



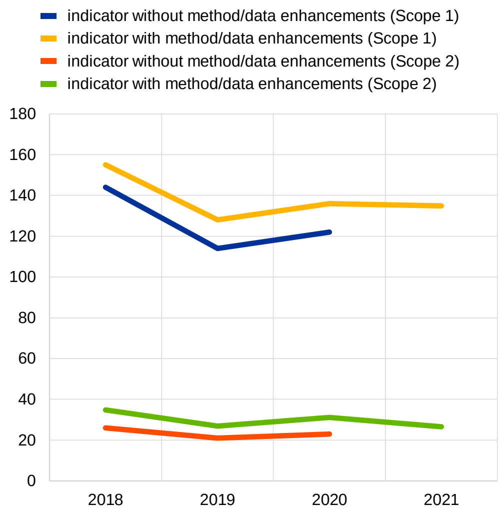
c) Weighted average carbon intensity (WACI), euro area aggregate

tonnes of CO2 per million euro



d) Carbon footprint (CFP), euro area aggregate

tonnes of CO2 per million euro



Sources: ESCB calculations based on data from Register of Institutions and Affiliates Data (RIAD), Centralised Securities Database (CSDB), Securities Holding Statistics (SHSS), and Institutional Shareholder Services (ISS).
Notes: Securities include listed shares and debt securities held by insurance corporations and pension funds (S128 + S129) and are computed at group level. The charts comprise Scope 1 and Scope 2 emissions. The WACI is adjusted for inflation and exchange rate effects.

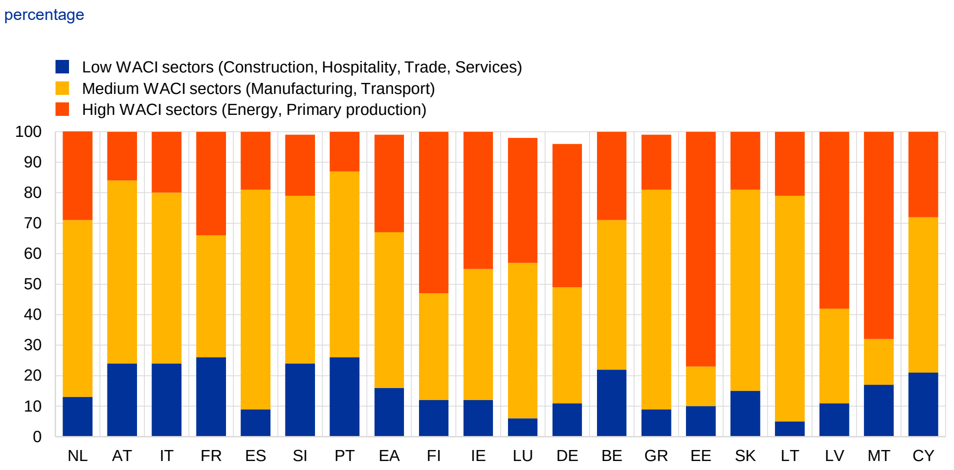
In **Figure 50**, the share of financed emissions by industrial sector, categorised by their carbon intensity using the WACI for 2021, is shown for each euro area country. The countries are arranged based on their WACI values in ascending order. In the period for which data are available the relative size of the carbon intensity has remained relatively stable. Energy and Primary production have recorded the highest

WACI, followed by Manufacturing and Transport, while Trade, Services, Hospitality, and Construction displayed the lowest WACI.

The figure highlights that, while the share of carbon-intensive sectors in a country can partially explain the variation in WACI amongst countries, it does not fully explain it. This conclusion is supported by the small Spearman's rank correlation coefficient of 0.28 found between the WACI and the share of high-WACI sectors both analysed at the country level across the studied years. The figure as well as the correlation analyses were performed on the single-entity loan portfolio.

Figure 50

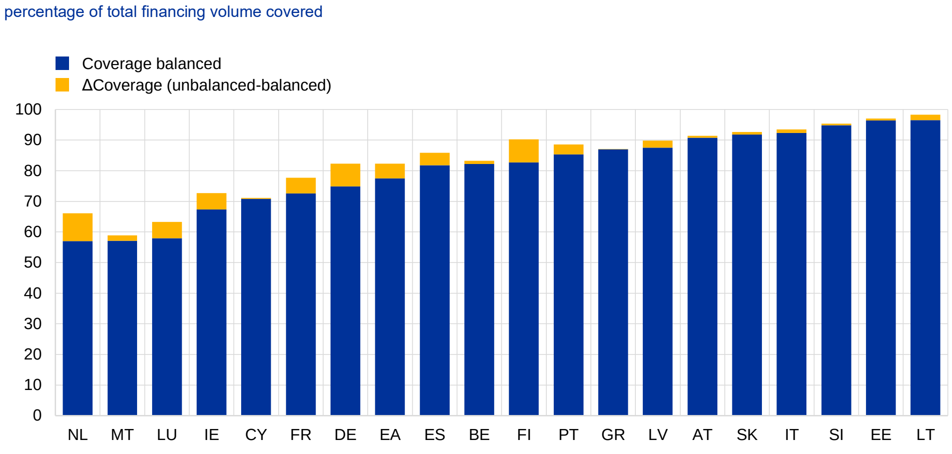
Share of financed emissions by industrial sectors categorization according to the WACI across euro area countries, 2021, single entity-level loan portfolio



Sources: ESCB calculations based on data from AnaCredit, Register of Institutions and Affiliates Data (RIAD), EU Emissions Trading System (EU ETS), and Eurostat Air Emissions Accounts (AEA).
Notes: The charts comprise only loans computed at single entity level for Scope 1 emissions. The WACI is adjusted for inflation and exchange rate effects. The countries on the x-axis are arranged according to their WACI values in ascending order. The sectoral shares do not sum up to 1 for all countries because the "Missing" sector is omitted.

Figure 51 shows that coverage across euro area countries for the loan portfolio studied at group level varies by country. Flex balancing leads only to a small loss in coverage across all countries.

Figure 51
Coverage by country for loans compiled at the group-level

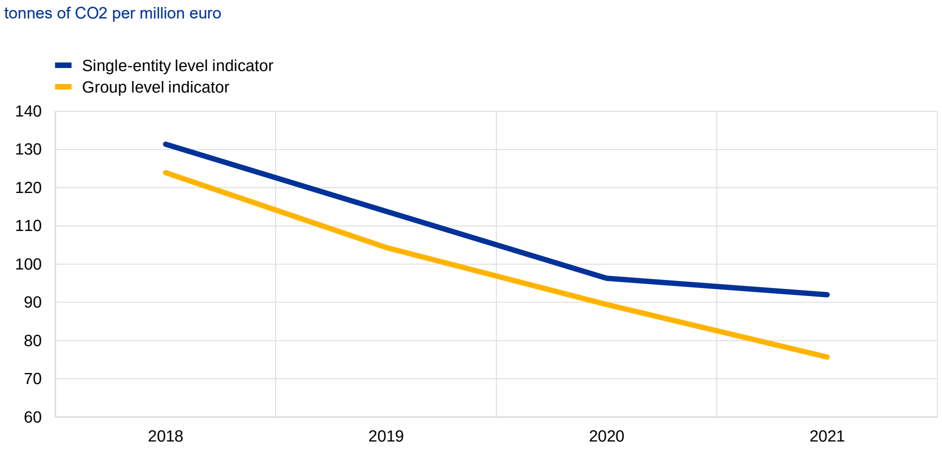


Sources: ESCB calculations based on data from AnaCredit and Institutional Shareholder Services (ISS).
Notes: Loans are computed at corporate group level. The charts comprise only Scope 1 emissions.

Figure 52 compares the loan-based unadjusted WACI single-entity level indicator and its counterpart at the group level.

Figure 52
Comparison of single entity and group-level unadjusted WACI on the loan portfolio

Unadjusted weighted average carbon intensity (unadjusted WACI), euro area aggregate, Scope 1, single entity-level loans



Sources: ESCB calculations based on data from AnaCredit, RIAD, EU Emissions Trading System (EU ETS), Eurostat Air Emissions Accounts (AEA), and Institutional Shareholder Services (ISS).
Notes: Loans are computed at single entity and group level. The charts comprise only Scope 1 emissions.

6.4 Physical risk indicators

6.4.1 Methodology for calculating risk scores and expected loss-based physical risk indicators

In this section we elaborate on the technical aspects of the building blocks used for the physical risk indicators. We start from damage functions as the foundation for estimating expected losses. The methodology behind the risk score indicators is described next, emphasising their reliance on expected loss calculations. Lastly, we examine the specificities of expected loss indicators, namely NEAR (normalised exposure at risk) and CEAR (collateral-adjusted exposure at risk), focusing on how financial attributes are integrated into the compilation of the physical risk indicators, enhancing the framework for the risk assessment.

Damage functions

In this publication, we integrate existing damage functions for floods and windstorms into the process of compiling the physical risk indicators. These functions are crucial tools in assessing the potential impact of natural disasters. They represent the relationship between the intensity of the disaster (such as flood depth or wind speed) and the resulting damage (usually in monetary terms).

Flood damage functions, developed by Huizinga et al., are primarily based on historical flood data (Huizinga, de Moel & Szewczyk, 2017). The extent of the damage sustained is influenced not only by water depth but also by different types of properties and land uses, with distinctions across different sectors (see **Figure 53**, panel a). For instance, in residential areas, factors like building materials, elevation and the presence of a lower ground floor play a significant role in determining flood damage. In the context of commercial and industrial sectors, the presence of inventories and equipment is a significant factor, As these assets often constitute a substantial portion of the property’s total value and are crucial in assessing potential damage.

For the windstorm damage curves, we rely on the work of Koks and Haer, which offers a wind damage model specifically tailored to Europe[103] (Koks & Haer., 2020). It incorporates several elements: storm footprints data from Copernicus[104], fragility curves proposed by Feuerstein et al. (Feuerstein, 2011), estimated reconstruction costs are based on Huizinga et al. developed for floods (Huizinga, de Moel & Szewczyk, 2017) and lastly, information on building type is derived mainly from OpenStreetMap, complemented with other sources. The latter is used to account for regional differences in building practices, materials and designs across countries, which affect vulnerability to windstorms (see **Figure 53**, panel b).

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103 The authors share the model as an open-source tool that can be replicated and adapted: https://wisc.readthedocs.io/en/latest/.

104 See https://climate.copernicus.eu/windstorm-information-service.

Huizinga et al. (2017) indicate that damage functions are not static and may evolve over time due to economic growth, urban development and environmental changes. Moreover, damage estimations are often limited to direct physical damage, overlooking broader economic impacts like business interruption – a drawback that also translates to a narrow focus on direct damage in the case of our indicators.

Figure 53

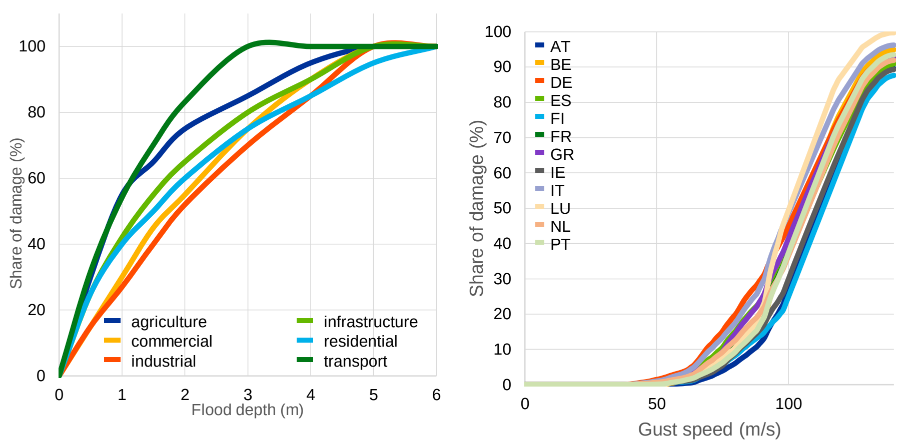
Damage function for floods and windstorms by sector category

a) Damage functions for floods

water depth (m)

b) Damage functions for windstorms

Gust speed (m/s)



Source: Panel a): Huizinga, J., de Moel, H. & Szewczyk, W., 2017, "Global flood depth-damage functions. Methodology and the database with guidelines", EUR 28552 EN: Publications Office of the European Union; DOI: 10.2760/16510. The flood damage functions and related data are available from the JRC Publications Repository at https://publications.jrc.ec.europa.eu/repository/handle/JRC105688. Panel b): ESCB calculations based on Koks and Haer (2020), Copernicus WISC.

Estimation of expected annual loss (EAL)

Expected loss is a key input when compiling risk scores as well NEAR and CEAR indicators for hazards, where hazards intensities and damage function are available, i.e. flooding and windstorms.

To compute the key ingredients, we follow the JRC DRMKH methodology (Antofie et al., 2020). The hazard data are expressed in return periods, which indicate the period of time (typically years) which corresponds to a probability that a given value (e.g. x meters of flood depth) would be exceeded at least once per unit of time.

This probability is called probability of exceedance P_{T_n} and is the inverse of return period $\frac{1}{p}$ where p is the return period. The probability of exceedance relates to the probability of any single event of a certain magnitude occurring, as follows: $P_{T_n} = 1 - \prod_{i=T_1}^{T_n}(1 - p_i)$,

where P_{T_n} is the probability of exceedance for an event with a return period of Tn and p_i the probability of occurrence for a single event.

Subsequently, probability of occurrence can be derived as follows: $p_n = \frac{p_{T_n-1}}{\prod_{i=T_1}^{T_{n-1}}(1-p_i)} + 1,$

where p_n is the probability of occurrence of an event with a return period of T_n.

Overall, average loss expected over all return periods for all events in j-years is: $U_i = \sum_{i=T_1}^{T_n} p_{i,j} L_i$, where L_i is the loss associated with a single event and probabilities over the multiple years are calculated as $p_T(j) = 1 - (1 - p_T)^j$. In Antofie's study (Antofie et al., 2020), estimated area exposed to flooding is used as L_i and varies by return period. Given that an area might be flooded multiple times, the expected area flooded for all return periods might be larger than the total area.

In the case of our statistical indicators, a share of a company's physical assets at risk is used instead. While a company might re-build an asset after a disaster event, we analyse expected loss from the perspective of a creditor where the financial exposure cannot exceed the debtor's assets. Thus, we assume that the maximum loss over all return periods is 100% of physical assets for each entity.

First, the expected annual loss is calculated as a share of the damage caused to the value of the exposed assets:

$$EAL_l = \sum_{i=T_1}^{T_n} p_n \cdot dmf\left(hazard\ intensity_p\right)$$

where dmf is damage function, i.e. the share of damage and depends on a hazard intensity at a specific return period p, identified at specific location l, which could be the location of firm f or the location of physical collateral c.

Second, expected annual loss (expressed as a share of the value of the exposed asset) is compounded over the remaining maturity of an instrument (currently only loans):

$$EL_l(m) = [1 - (1 - EAL_l)^m]$$

where m is the remaining maturity (in years); $EL_l(m)$ is the expected loss over the remaining maturity of an instrument calculated for a specific location l (which could be the location of firm i or the location of physical collateral c).

The risk scores are based on the expected annual loss, while the NEAR and CEAR indicators are available on an annual basis and over the maturity of a portfolio.

Risk scores methodology incorporating expected annual loss (EAL)

The share of expected annual loss is used to build the risk scores for flooding, windstorms and landslides[105]. For each hazard type, data are available in the form of

[105] Landslides are available per return period as scores on a scale of 1 – Low risk to 5 – High risk and the methodology is adopted on the assumption that a score of 5 implies 100% damage to an asset.

a map with a separate file for each return period.[106] All five available return periods are used for flooding, while for landslides and windstorms, four common return periods (10, 50, 100 and 500 years) were selected. Different return periods can hamper comparability, especially shorter return periods, which may have a strong impact on the results, given the high probability of occurrence (Ward et al., 2011). Thus, we selected the 10-year return period as the starting point for all hazards, although the other return periods used are different for floods on the one hand, and windstorms and landslides on the other.

To obtain a risk score at a specific location, first, maximum annual expected loss is calculated under an assumption of 100% damage to an asset in selected return periods, as follows:

$$EAL_l = \sum_{i=T_1}^{T_n} p_n \cdot dmf\left(hazard\ intensity_p\right) = \sum_{i=T_1}^{T_n} p_n \cdot 100\%$$

For example, for return periods of 10, 50, 100 and 500 years, the maximum annual expected loss corresponds to around 10% damage to a physical asset. The maximum expected loss is then divided into five equal intervals and converted into a score from 1 to 5. Given the low frequencies observed for some categories, those scores were merged into three risk categories: low risk (score 1), medium risk (scores 2 and 3) and high risk (scores 4 and 5).

The methodology based on share of damage to a company's assets makes it easier to compare the risk level categories across the various hazards. Data sources that focus on a single type of hazard or commercial data provider may choose the risk levels based on the distribution of hazard intensity within a geographical area (e.g. Europe) or risk exposure within a selected population (e.g. inhabitants or businesses), potentially leading to different results if the underlying sample changes. From the perspective of the statistical climate indicator, comparability across different types of hazards, time horizons, and climate scenarios is highly desirable. Score formulation relying on monetary damage possesses this property, although at the expense of granularity for certain hazards due to relative differences in damage. This can be observed for windstorms, where most of the exposures are classified as low-risk, partially explained by relatively robust building design in Europe – as opposed to flooding, which may cause relatively higher damage.

The scores methodology also enables flexible modifications to account for adaptation measures, such as flood defences, and metrics under different climate scenarios. Flood protection standards are expressed in return periods up to which a defence structure should prevent the destruction. For example, a protection value of 100 years indicates that a flood with a 100-year return period intensity will be contained, though not a flood with a 300-year return period. Consequently, when calculating expected damage, values referring to return periods shorter or equal to flood protection values (in years) were set to zero. For the climate scenarios,

[106] The availability of return periods is not harmonised across hazards: five return periods are available for river and coastal flood (10, 30, 100, 300 and 1,000); seven for landslides (2, 5, 10, 20, 50, 100 and 500) and five for windstorms (5, 10, 50, 100 and 500).

following RAIN project methodology (Groenemeijer et al., 2016), we assume that the current flood defences will withstand the same water levels in the future. It should be noted that if flood severity intensifies without investment in current flood defence structures, the indicators will lead to an underestimation of the future risk.

Similarly, for the hazards expressed in return periods, the climate projections are expressed either in terms of changes in probability (shorter return period for the same level of intensity) or changes in hazard intensity keeping event frequency constant. The latter was used for our statistical indicators for floods.

Compilation methodology for expected loss-based indicators (NEAR, CEAR)

The NEAR (normalised exposure at risk) and CEAR (collateral-adjusted exposure at risk) indicators provide estimates on expected losses in the portfolios of financial institutions stemming from physical risk. They are calculated only for those hazards for which damage functions are currently available, i.e. floods and windstorms.

NEAR – Normalised exposure at risk

Physical assets at risk are estimated using the ratio of the tangible fixed assets of company i, based on Orbis or a national business register, to total assets (please see Annex 6.4.2 for more information on the estimation process):

$$TFA_i = \frac{Tangible\ fixed\ assets\ _{Orbis,\,i}}{Total\ assets_{Orbis,\,i}}$$

We compute the financial risk ratio, which is a proportion of expected physical losses to total assets at entity level:

$$FINANCIAL\ RISK\ RATIO_{i,Total\ assets} = \frac{Tangible\ fixed\ assets\ _{Orbis,\,i}}{Total\ assets_{Orbis,\,i}} \cdot EL_i(m)$$

It is assumed that the outstanding debt of an entity will be impaired in the same proportion as the financial risk ratio:

$$LOSS\_EXPOSURE_i = EXPOSURE_i \cdot \frac{Tangible\ fixed\ assets\ _{Orbis,\,i}}{Total\ assets_{Orbis,\,i}} \cdot EL_i(m)$$

where $EL_l(m)$ is expected loss (expressed as a share in the value of the exposed asset) over the remaining maturity of an instrument, $EXPOSURE_i$ is the outstanding debt and $LOSS\_EXPOSURE_i$ is the expected loss of outstanding debt calculated at the granular level for each creditor-debtor-instrument combination. We calculate loss of outstanding debt on an annual basis for m=*1 year*, so that $EL_l(1) = EAL_l$ (see section on “Estimation of expected annual loss (EAL)”).

Lastly, expected loss at entity level is aggregated at the level of creditor country, creditor institutional sector and debtor’s economic activity and divided by the value of the total portfolio in a given breakdown:

$$NEAR = \frac{\sum_{i=1}^{N}(FINANCIAL\ RISK\ RATIO_i \cdot EXPOSURE_i)}{\sum_{i=1}^{N_C}(EXPOSURE_i)}$$

The indicator is presented as absolute expected losses (numerator) and as a percentage of the portfolio.

CEAR – Collateral-adjusted exposure at risk

The NEAR indicator is a foundation for CEAR indicator that accounts for the collateral pledged. It requires computations at collateral level (more precisely for each combination of creditor-debtor-instrument-collateral) given many-to-many relationships, i.e. one instrument can be collateralised by several forms of protection and one protection can be pledged for several instruments.

Collateral value is available at the most granular creditor-debtor-instrument-protection level and aggregated to creditor-debtor-instrument level, taking into account the potential loss to the physical collateral, while the full amount is taken for financial collateral:

$$CV_{crdtr\_dbrt\_instr} = \sum\nolimits_{crdtr\_dbrt\_instr} CV\_FIN_{instr\_prtn} + \sum\nolimits_{crdtr\_dbrt\_instr} [1 - EL_c(m)] \cdot CV\_PHY_{instr\_prtn}],$$

where $CV_{crdtr\_dbrt\_instr}$ is collateral value after accounting for potential losses to the physical portion of the collateral at creditor-debtor-instrument level (which is the standard granularity level for all other indicators and otherwise can be denoted as CV_i); $CV\_FIN_{instr\_prtn}$ is the value of the financial collateral allocated to the instrument; the term $[1 - EL_c(m)] \cdot CV\_PHY_{instr\_prtn}]$ is the value of the physical collateral accounting for potential damage identified for the specific hazard existing at the collateral location.

Expected losses to collateral $EL_c(m)$ are calculated over the maturity of the instrument, similarly to the risk estimated at company level. However, it should be noted that real estate collateral is currently reported predominantly at regional NUTS3 level, while debtor location is identified at address level. Thus, debtor risk is extracted at a specific point from a hazard map, and for estimations of real estate damage a median of the hazard's intensity within the NUTS3 region is used. If NUTS3 information is missing, aggregating at larger NUTS2 region or country level of the collateral is applied.

Lastly, the CEAR indicator decreases the expected losses by the value of the financial and physical collateral. To account for overcollateralisation, the losses are limited to 0.

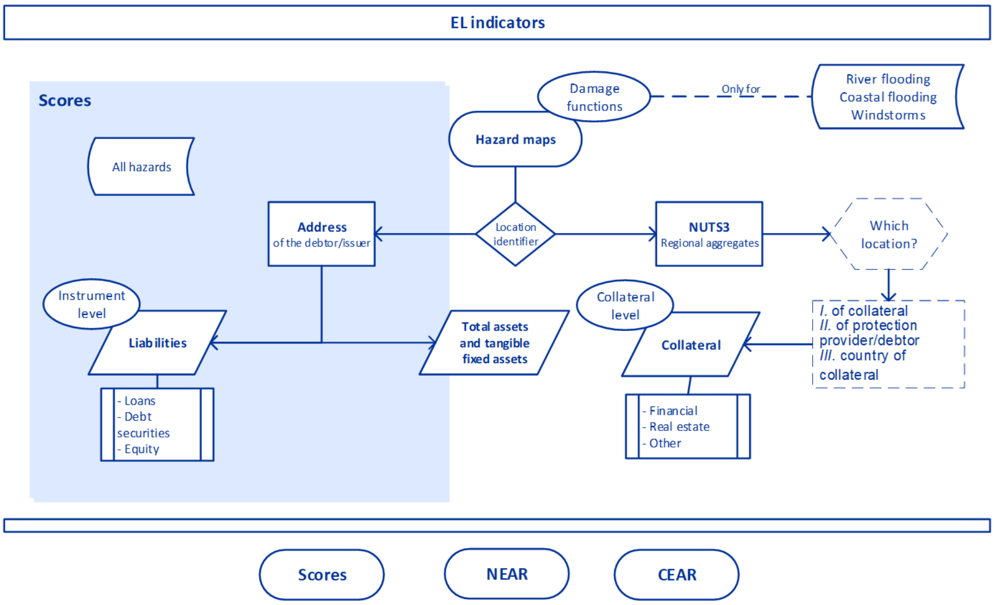
$$CEAR = \frac{\sum_{i=1}^{N} \max\,[0, LOSS\_EXPOSURE_i - CV_i]}{\sum_{i=1}^{N}(EXPOSURE_i)}$$

The indicator is aggregated for the same breakdowns as NEAR and can be expressed in euro values or as a percentage of the portfolio.

Figure 54 provides an overview of the inputs needed to compile each type of indicator.

Figure 54

Overview of the compilation framework for the physical risk indicators



6.4.2 Imputation of the tangible fixed assets ratio

Tangible fixed assets at firm level are used as a proxy for physical assets at risk. Currently, only key accounting variables are available in RIAD (total assets, revenues), so to obtain the amount of tangible fixed assets, data from Bureau van Dijk's database Orbis was used, or otherwise national business register data, if available. When the entity concerned had recorded values for past years but not for the reference year (2022), the last available record was considered. In this way, we were able to retrieve data on fixed tangible assets for around 40% of the sample of debtors.

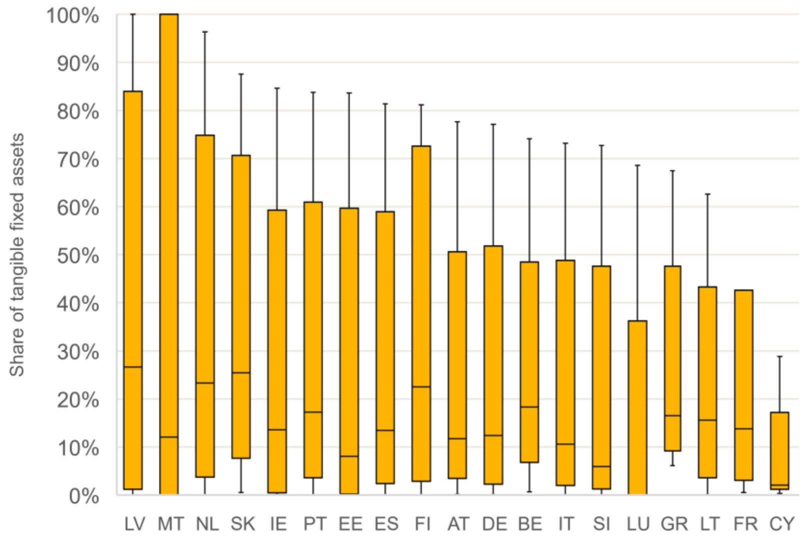
When available[107], estimates based on national business registers were applied instead. For the remaining part, a ratio of tangible fixed assets to total assets was imputed based on country, sector and firm size median. Where information on size or sector was missing, higher aggregates were used:

- if size was missing (59% of the values to be imputed), the median was based on country and sector breakdown;
- if sector was missing (9% of cases), the country and size breakdown was used;
- if both sector and size were missing (9% of cases), the country median was applied.

[107] In the current publication, national data were provided for France and Spain.

Excluding cases where data were available in national registers, data were imputed for 58% of entities. The resulting tangible fixed assets to total assets ratios at country level are presented in **Figure 55**.

Figure 55
Distribution of tangible fixed assets to total assets ratios across countries



Sources: Orbis, national business registers when available (ES, FR), ESCB own calculations.
Notes: The boxplot displays (from bottom to top for each country): 5th (the lower adjacent value), 25th, 50th (median), 75th and 95th percentiles (the upper adjacent value).

6.4.3 Comparison between current and previously released indicators

In this section we present a comparison of the indicators as currently formulated with how they were initially formulated, as published in January 2023 (ECB, 2023). There are several factors affecting the results: group consolidation of exposures at debtor level, sources used for hazard data, assignment to hazard risk categories, and estimates of fixed tangible assets to total assets. The divergence in risk score indicators is due to the first three factors, while for the expected loss indicators, the last factor also plays a role. Note that the reference periods also happen to be different – current figures refer to financial exposures in December 2022, which reported around a 5% increase in comparison to the December 2020 data used previously.

Consolidation explains most of the differences between the PEAR indicators when comparing the two publications (see **Figure 56**, panel a). This is an artifact of the calculation of the risk at group level – which takes the simple average of the entity-level risk scores. Hence, whenever one entity (even a small subsidiary) within a group is exposed to a certain hazard, the entire group is assigned a positive risk score. This could lead to potential overestimation of the risk, as measured by the PEAR indicator. For the NEAR indicator, the overall impact of consolidation can vary in both directions, given that expected losses depend on individual exposures, acting as weights (see **Figure 56**, panel b).

Ultimately, the legal entity level was selected as the foundation for the compilation of the indicators. The legal entity is the basis for the statistical reporting of loans and counterparty data, both creditors and debtors, as it provides a more straightforward interpretation of results. This approach is advantageous in mitigating quality concerns associated with group structure complexities (as highlighted in Section 2). Future releases, which will see further improvements in data and methodology, may introduce indicators based on consolidated debtors, contingent upon users' priorities.

In the current publication, the source used for flood data has been changed: from the JRC estimates to data from the Delft University of Technology (see Section 3.3.1.1 for details). While the change of source does result in a slight increase in risk exposure for river floods, the overall impact is rather limited (see **Figure 56**, panel a).

Altering the thresholds for the assignment to risk categories has a larger impact. This is the case for subsidence, water stress, windstorms and partially also wildfires[108]. For those hazards, the lower risk category was reclassified to no risk, which might a better job in reflecting the actual risk.[109] The risk thresholds serve only as an indicative marker and are not clear cut. This underscores the importance of providing precise information on the score allocation, as this can greatly influence risk levels (see Table 4).

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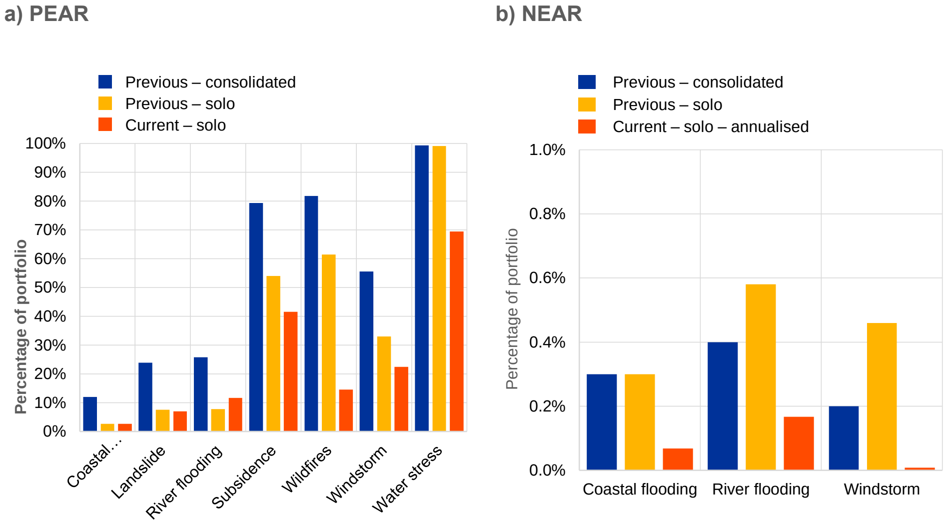
[108] In the case of wildfires, the underlying model and methodology have also been changed (see Section 3.3.1.5 and Annex 6.4.4 for more details).

[109] For instance, in case of subsidence original score 1 refers to "coarse soil texture with clay share below 18%", while according to the original source only soils with clay content greater than 35% are prone to subsidence (see Table 4 for details).

Lastly, improvements in the estimation of tangible fixed assets has a relatively large impact on the NEAR indicator, leading to lower estimates of expected losses (see **Figure 56**, panel b). This is a result of ensuring consistency between tangible fixed assets and total assets, as well as the incorporation of higher quality data from national sources, when available (see Annex 6.4.2).

Figure 56

Comparison with previous indicators across hazards



Source: ESCB own calculations, ESCB Analytical indicators on physical risks, (ECB, 2023)
Notes: Panel a): aggregate scores for all EA countries, for Deposit-taking corporations except central banks (S122), Non-money market fund investment funds (S124), Insurance corporations and Pension funds (S128, S129) and all instruments (Debt securities, Equities, Loans). Panel b): values include Deposit-taking corporations except central banks (S122) and Loans.

6.4.4 Wildfires – methodology for estimation of fire probability

This segment provides technical details on the model and the data underlying the estimation of the fire risk probabilities outlined in Section 3.3.1.5.

Input data for wildfire modelling

The data used as an input for our wildfire model are consolidated into a 2.5 x 2.5 km grid structure, for which we calculate the land cover shares, the burned area in km2, the measured and predicted Fire Weather Index (FWI) in the area and other geographical variables that are seen to be relevant for the onset of wildfire.

The variable of interest is whether there are one or more fire outbreaks within a grid cell. Burned area data are obtained from the MODIS data collection kept by NASA, which provides geospatial files documenting daily fire events on a 500 m resolution. This information was converted to a binary fire flag indicator for each 2.5 x 2.5 km grid cell and year.

The FWI is computed by Copernicus/EFCS[110] and comprises historical simulations from 1970 to the present day as well as projections until 2098 under three different RCPs (2.6, 4.5 and 8.5). It is based on the Canadian Fire Weather Index System Ranking, which is a meteorologically based index that accounts for the effect of fuel moisture and weather conditions on fire behaviour. Daily noon values of air temperature, relative humidity, wind speed and 24-hour accumulated precipitation are required for the calculation of the index. The data are available per grid cell and include such metrics as the total number of days exhibiting a certain fire risk value per year, as well as the daily and the seasonal indicator on the level of fire risk during the fire season in a year. For the computation of the wildfire scores, the historical seasonal (2001-2022) average and maximum FWI values are used for a machine learning-based model development, and the projected seasonal average and maximum FWIs are used to predict fire risk for the period 2025-2050.

To combine the atmospheric conditions for wildfires with their physical and geographical conditions, we use annual (2001-2021) land cover data accessed and extracted via the Google Earth Engine platform (Modis GEE). The data are classified into 17 land cover types based on the International Geosphere-Biosphere Programme (IGBP) classification. The land cover maps thus obtained were transformed into a tabular format that matches the above-described grid cell structure, whereby the area share of all 17 land cover types for each grid cell and year were calculated. This ensures that land cover changes over time – and thus the amount and nature of fire fuel – were adequately represented in the data.

Lastly, a number of time-constant geographical variables, such as distance to closest city, road or railway, were included, since proximity to human settlement as

110 See https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-tourism-fire-danger-indicators?tab=overview.

well as sparks from moving trains have been defined as potential drivers of wildfire (Chen 2022, Sun et al. 2021).

Modelling methodology

The probability of wildfire occurrence is estimated with the help of a binary decision tree-based extreme gradient boosting algorithm (xgboost), which can incorporate nonlinearities and reflect country-level characteristics and other variable interactions (Chen & Guestrin, 2016). The final estimator function explains probability using land cover variables (expressed as the share of a particular land cover type in a given grid cell), distance to the closest road, railway and city, a flag if there was a fire in the given cell during the previous year and country codes.

With this machine learning method, we were able to combine flexibility with intuitive expectations, such as that the higher the FWI, the higher the fire risk; and the greater the distance to the closest road, railway line or city, the lower the fire risk. Although enforcing these monotonic constraints[111] reduces model accuracy in terms of precision and recall[112] compared to an unconstrained model, the constrained model is still materially more accurate[113] than a binary logistic regression.

The most important explanatory features of the model were the average and maximum seasonal FWI values, the distance to the closest railway line, the share of cultivated cropland and the occurrence of fire in the preceding year. While the two latter variables may both sound like natural drivers of fire risk, their importance may also stem from the (gradually diminishing) yearly practice of stubble burning of agricultural residues after harvest.[114] Although stubble fire does not strictly qualify as wildfire, it can get out of control and result in devastating fires.

To predict the occurrence of wildfire under different climate scenarios for the 2025-2050 time horizon, FWI predictions from Copernicus[115] were used, along with the latest values of the explanatory variables, which were kept constant, including land cover[116]. The only exception was the fire event flag variable from the preceding years: for each grid cell and year t, the fire flag t-1 was estimated using a random Bernoulli variable with the predicted fire probability for t-1. Since this means that future predictions depend on the presence or absence of fire in the preceding years, we simulated ten different future pathways, and averaged the final fire probabilities.

111 Monotonic constraints were enforced for the five most important variables (by the gain feature importance metric).

112 Precision and recall are model accuracy metrics for binary classification tasks, such as the fire/no fire case. Precision stands for the share of true fire events among all predicted fire events; recall corresponds to the number of true fire events over the number of true fire events plus the number of false no-fire events.

113 For a given precision value, the recall values are between 10 and 25 percentage points higher with the xgboost model than with the binary logistic model.

114 Despite the gradual reduction in stubble fires, cropland share remains a strong explanatory variable throughout all years when using a 6-year sliding window on the data.

115 Retrieved from https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-tourism-fire-danger-indicators?tab=form.

116 Assuming constant land cover is a strong assumption and should be improved upon during a future model update.

In a final step, future fire occurrence probabilities were converted to a fire risk score based on the following pre-defined cut-off values (see Table 4).

By estimating fire occurrence risk instead of expected burned area (methodology applied in the January 2023 publication), this wildfire risk estimation builds on a more robust methodology. Predicting burned area is subject to many uncertainties, such as differences in fire spread speeds and containment efforts, leading to inaccurate estimates. In addition, the incorporation of land cover and thus burnable fuel in the analysis alters the level and distribution of fire risk markedly. Relying solely on FWI – an indicator that condenses temperature, humidity, wind and rain data – would imply significantly higher and more widespread fire risk, which may not necessarily lead to fire in regions where no burnable fuel is present.

Abbreviations

Countries

BE	Belgium	**HR**	Croatia	**PL**	Poland
BG	Bulgaria	**IT**	Italy	**PT**	Portugal
CZ	Czech Republic	**CY**	Cyprus	**RO**	Romania
DK	Denmark	**LV**	Latvia	**SI**	Slovenia
DE	Germany	**LT**	Lithuania	**SK**	Slovakia
EE	Estonia	**LU**	Luxembourg	**FI**	Finland
IE	Ireland	**HU**	Hungary	**SE**	Sweden
GR	Greece	**MT**	Malta	**UK**	United Kingdom
ES	Spain	**NL**	Netherlands	**US**	United States
FR	France	**AT**	Austria		

In accordance with EU practice, the EU Member States are listed in this report using the alphabetical order of the country names in the national languages.

Others

AEA	Air Emission Accounts
AnaCredit	Analytical Credit Datasets
AVR	Accreditation and Verification Regulation
CDD	Consecutive Dry Days
CEAR	Collateral-adjusted exposure at risk
CFP	Carbon footprint
CI	Carbon intensity
CMIP6	Coupled Model Intercomparison Project Phase 6
CP	Current prices
CRD	Capital Requirements Directive
CRR	Capital Requirements Regulation
CSDB	Centralised Securities Database
CSDDD	Corporate Sustainability Due Diligence Directive
CSEC	CSDB Securities Issues Statistics
CSRD	Corporate Sustainability Reporting Directive
C3S	Copernicus Climate Change Service
DGI	Data Gap Initiative
DRMKC	Disaster Risk Management Knowledge Centre
EAL	Expected annual loss
ECB	European Central Bank
EFAS	European Flood Awareness System
EL	Expected loss
ESA	European System of Accounts
ESCB	European System of Central Banks
ESG	Environmental, Social, and Governance
ESRB	European Systemic Risk Board
ESRS	European Sustainability Reporting Standards
ETS	Emissions Trading System
EU	European Union
EUGBS	EU Green Bond Standard
EUR	Euro
EURO-CORDEX	European continent - European Coordinated Regional Downscaling Experiment
FE	Financed emissions
FWI	Fire Weather Index
GDP	Gross domestic product
GHG	Greenhouse gas
GloFAS	Global Flood Awareness System
GVA	Gross value added
G20	Group of 20
HI	Heat Index
I/O	Input/Output
IFRS	International Financial Reporting Standards
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
ISSB	International Sustainability Standards Board
JRC	Joint Research Centre
LCU	Local currency unit
MFI	Monetary financial institution
MICE	Multivariate imputation by chained equations
MODIS	Moderate Resolution Imaging Spectroradiometer
MRR	Monitoring and Reporting Regulation
NACE	Nomenclature of Economic Activities
NCB	National central bank
NEAR	Normalised exposure at risk
NFRD	Non-Financial Reporting Directive
NGFS	Network for Greening the Financial System
NOAA	National Oceanic and Atmospheric Administration
NUTS	Nomenclature of territorial units for statistics
OECD	Organisation for Economic Co-operation and Development
ONA	Outstanding Nominal Amount
PEAR	Potential exposure at risk
PYP	Previous year’s prices
RCP	Representative Concentration Pathway
RDH	Risk Data Hub
RIAD	Register of Institutions and Affiliates Data
SEEA	System of Environmental-Economic Accounting
SHS	Securities Holdings Statistics
SHSS	Securities Holdings Statistics by Sector
SPI	Standardized Precipitation Index
SSP	Shared Socioeconomic Pathway
WACI	Weighted average carbon intensity
WBGT	Wet Bulb Globe Temperature
WBT	Wet Bulb Temperature
WISE	Water Information System for Europe
WMO	World Meteorological Organization
WRI	World Resources Institute

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The Statistics Committee Expert Group on Climate Change and Statistics
The work of the Expert Group on Climate Change and Statistics is to produce and enhance – within the limitations of data availability – indicators on the exposure of financial institutions to (1) climate-related physical risks, and (2) carbon footprints of their portfolios that are comparable across countries and over time. In addition, the Expert Group seeks to enhance data availability, leveraging existing data collections where possible, taking on board new data sources as they become available, and advocating for new collections where these fall outside of the ESCB statistical responsibility boundaries.

The Working Group on Securities Statistics
The Working Group on Securities Statistics (WG SEC) has under its aegis the operation and further development of two securities databases referring to issues and holdings, respectively: i) the Centralised Securities Database (CSDB) aiming at providing unified, high-quality reference, price and ratings data for securities (issuance side), and; ii) the Securities Holding Statistics Database (SHSDB) that provides granular data on holdings of securities. These granular data on securities issues and holdings are combined to produce integrated micro and macro securities' products and analysis. In the context of the fully-fledged "micro-to-macro" (i.e., compilation of several sets of macro level statistics from the same micro level information), the group supports the production of aggregated securities statistics, those being the official CSDB-based securities issues statistics (CSEC) and the Securities Holdings Statistics (SHS) by sector. With respect to climate, the WG SEC contributes to the fulfilment of the ECB's action plan on climate and the G-20 Data Gaps Initiative. In this context, the group is working on the development and enhancement of the granular sustainable finance data and on the development and dissemination of statistical indicators. Last, but not least, the WG SEC also monitors the standardisation of concepts and processes in the field of granular data for securities and aims at steering the development of a methodologically sound framework for securities statistics.

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