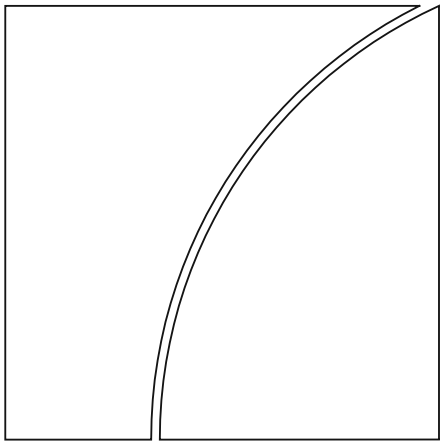
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Sustainability data issues and central banks' experience

September 2026

Contributions in this volume were prepared for the proceedings of the IFC Satellite Seminar on "Sustainability data issues and central banks' experience", co-organised by De Nederlandsche Bank and the Irving Fisher Committee (IFC) in Amsterdam, Netherlands, on 4 October 2025.

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The quest for policy-relevant sustainability data in central banking

Andréa Barnava, Patty Duijm, Jolien Noels, Christian Schmieder, Ünal Seven, Ömer Kayhan Seyhun, Olivier Sirello, Bruno Tissot and Elena Triebskorn[1]

Executive summary

Modern societies face important sustainability issues, spanning economic and financial considerations as well as an increasing range of environmental, social and governance aspects. Sustainability is a broad, evolving and multidimensional concept, which can be typically defined as the capacity to satisfy the needs of current generations without compromising the ability of future generations to meet theirs. Its growing relevance nationally and globally has sharpened the demand for adequate data and measurement frameworks, going beyond traditional economic and financial indicators that are already well established in the current statistical apparatus.

The interest of many central banks for sustainability indicators has expanded over time to support their various responsibilities, from monetary policy and financial stability analysis to statistics, supervision, regulation, reserve management and payment oversight. As data users, they often rely on available information to inform their policies, in particular through environmental, social and governance (ESG) metrics. As data producers, they increasingly compile novel or experimental indicators related to sustainability, often as a complement to other statistical authorities that serve as the primary providers. Central banks' focus has been in particular on sustainable finance – that is, financial activities that improve the condition of the environment or society or governance practices – and green finance – which focuses on environment-related aspects specifically.

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Despite the active policy demand for better and more insights on sustainability, important information gaps persist. First, measuring sustainability is complex because it combines various quantitative and qualitative dimensions and trade-offs that evolve with social expectations, policy priorities and scientific advances. Second, assessing the sustainability of well-being calls for measuring a wide range of resources, ranging from economic to non-economic types of capital, such as human, social and natural. Third, information in this area is often incomplete, heterogeneous, insufficiently granular, difficult to compare, dependent on modelled estimates or costly to access. In practice, this requires increasingly sophisticated techniques to integrate innovative and various data sources and types, including text, imagery and geospatial information.

Addressing these issues requires further active efforts to improve the quality of sustainability statistics, especially in terms of relevance, availability and accessibility, reliability and comparability. First, the data should be relevant and "fit for purpose" to answer defined policy questions as well as other user demands. Second, availability and accessibility are key to supporting analysis in a timely, sufficiently granular and accessible way. Third, compiled indicators must be reliable and adhere to the widely recognised scientific and ethical standards guiding official statistics, not least to ensure their integrity, objectivity and independence. Fourth, while available data are often grounded on local and disparate frameworks, most sustainability issues have a global nature, calling for better cross-border comparability, including through harmonised concepts and indicators. Ultimately, this calls for supporting coordination among the various stakeholders involved as well as adequate governance mechanisms, leveraging the longstanding experience of central banks and official statisticians in adhering to high-quality information standards and providing actionable and evidence-based insights for policy.

Several international statistical initiatives are underway to promote harmonised collection and dissemination of sustainability indicators. Ambitious global work plans have already been designed, including the G20 Data Gaps Initiative (DGI), updates to key international statistical standards and, more broadly, the Sustainable Development Goals (SDGs) of the United Nations (UN). Additionally, progress will require expanding data collections, leveraging innovative data sources, types and techniques, implementing global information standards and, perhaps more significantly, allocating additional resources to support national and global statistical capacity. Central banks, along with other financial authorities and international organisations, will continue to play an important role in this agenda by helping to both produce and use sustainability data, helping to secure the provision of high-quality reference information to better inform policymakers and the public at large.

1. Introduction: the concept and measurement of sustainability

In recent decades, **there has been an increased focus on addressing a wide range of increasingly prominent sustainability issues**. These include poverty and food insecurity, social and health inequalities, climate change and biodiversity loss. While not new, such topics have been receiving pronounced and growing public attention

in the wake of global and diverse crises, including the Great Financial Crisis of 2007–09, the Covid-19 pandemic and recurrent extreme climate-related events (IPCC (2023); Lawrence et al (2024)).

At the conceptual level, **sustainability can be defined as the capacity to satisfy the needs of today's population while ensuring that future generations can also satisfy theirs** (UN (2015); UN et al (2025)).[2] From this perspective, the current level of human well-being is sustainable if it can be maintained, or improved, in the future (Stiglitz et al (2009)). This assessment should be done based on economic, social and environmental considerations, with both a dynamic – from the present situation to the future – and holistic – encompassing both local and global levels as well as individuals and societies – perspective.

In practice, **measuring sustainability can be a complex task**. One approach is to assess the increase or preservation of the different types of resources that support well-being. This can be done, for example, by quantifying the evolution of the available stocks of economic, social (including institutional or governance aspects), human and natural capitals (Graph 1).[3] Such a measurement should be expressed in net terms, that is, accounting for asset depreciation (eg obsolescence effects) and depletion (ie reduced availability or exhaustion of finite resources). Ultimately, measuring sustainability calls for going beyond traditional economic indicators, which are already relatively well captured in the current statistical apparatus, to encompass the broader range of human and natural activities – a task that is arguably still in its infancy.

Below the surface, **measuring the various types of resources supporting well-being entails a number of difficulties**. First, it demands achieving coherence across various statistical frameworks, particularly between environmental, economic and social accounts, which deal with heterogeneous phenomena and are de facto often fragmented (MacFeely (2025)).[4] Second, the measurement of non-economic types of capital is much less developed, not least because of the difficulty of expressing them in monetary terms.[5] This reflects both conceptual – eg how to quantify the quality of institutions – as well as practical – eg what deflator to choose to value natural resources – challenges. Finally, while most produced assets can be renewed relatively rapidly to maintain or improve well-being over time, this can be much more difficult

[2] See the foundational definition of *sustainable development* introduced in the Brundtland Commission report as a process that "meets the needs of the present without compromising the ability of future generations to meet their own needs" (UN WCED (1987)).

[3] This is indeed the approach recommended in the 2025 System of National Accounts (SNA), which applies the integrated framework of national accounts to the measurement of well-being and sustainability (see the newly introduced Chapter 2).

[4] This need for improved coherence, also highlighted by the recent methodological review of the concept of well-being in the 2025 SNA, suggests developing a comprehensive framework encompassing economic, social and environmental accounts. This could be done by integrating the SNA, the SEEA and the proposed system of population and social accounts (SPSA) into a new "system of systems" (Havinga (2022)) or by designing the SNA to become a System of National Economic Accounts (SNEA; Vanoli (2017)).

[5] The scope of the integrated framework of national accounts is delimited by so-called boundaries which may prevent the wider measurement and analysis of sustainability, especially related to non-economic capitals. A typical example is the measurement of some key natural resources – eg the atmosphere, biosphere – which are not subject to ownership or monetary assessment, hence excluded from the SNA (see Chapter 35 (UN et al (2025)).

for other resources – such as biodiversity and institutional factors – that can be irreversibly damaged or not easily regenerated.[6]

The above challenges highlight the need to approach the measurement of sustainability by looking beyond the "traditional" contribution of economic resources to well-being and focussing primarily on a better assessment of the roles played by human, social, institutional and natural capitals. In practice, **the concept of "sustainability-related" data** (or "sustainability data") **is thus commonly understood as a shortcut referring to the broad range of sustainability metrics (especially non-economic ones) captured by the ESG framework** (Box A).[7] Launched under the UN Global Compact in 2004, this framework aims to incorporate ESG factors into investment decisions (UNECE (2013, 2025a)). In turn, it has led to the development of internationally recognised principles and indicators of sustainable finance, defined as the financing of projects or activities that sustain or improve the condition of the environment or society or governance practices (IFC (2021a); UN et al (2025); OECD (2025)).[8] More specifically, following the Paris Agreement adopted at the 2015 UN Climate Change Conference (COP21; UNFCCC (2015)) and reflecting the increasing threat posed by climate change,[9] particular attention has been devoted to the environmental dimension of ESG finance, or "green finance" (OECD (2022); Noss et al (2024); Nefzi et al (2025)).

In practice, **the demand for reliable sustainability data, notably related to non-economic aspects, has been particularly important to support central bank decision-making**. Given both their micro- and macroeconomic impacts, ESG factors can affect the conduct of central banks' various functions, including monetary policy, reserve management, supervision, regulation and payment oversight. In particular, growing evidence on climate-related hazards has underscored the importance of making use of market information on sustainable – and especially green – finance to tackle the risks to the financial system stemming from physical and transition risks (NGFS (2026a)). Central banks have also been increasingly producing novel or experimental sets of ESG indicators, along with other statistical agencies, such as national statistical offices (NSOs) and international organisations.

However, persistent information gaps remain especially as regards non-economic sustainability data. First, there are acute methodological challenges, beginning with the still limited availability of harmonised taxonomies, vocabularies and classifications, which are essential for ensuring cross-border comparability (IFC (2021a)).[10] This makes the actual measurement of ESG factors particularly complex,

6 For example, the development of sound institutions or the strengthening of social setups will typically span several generations (Deaton (2013)), while the exhaustion of natural resources (or the accumulation of CO_2 in the atmosphere) has proved to be quasi-irreversible.

7 See in particular Annex V in the 2025 SNA, § A5.63.

8 The recent evolution of the international statistical manuals is also grounded on previous initiatives, such as the "Who Cares Wins" under the UN Global Compact in 2004 that eventually led to the Principles for Responsible Investment (PRI) in 2006, Principles for Sustainable Insurance (PSI) in 2012 and Principles for Responsible Banking (PRB) in 2019 (UN (2004), IFC WB (2004), UNEP (2025)).

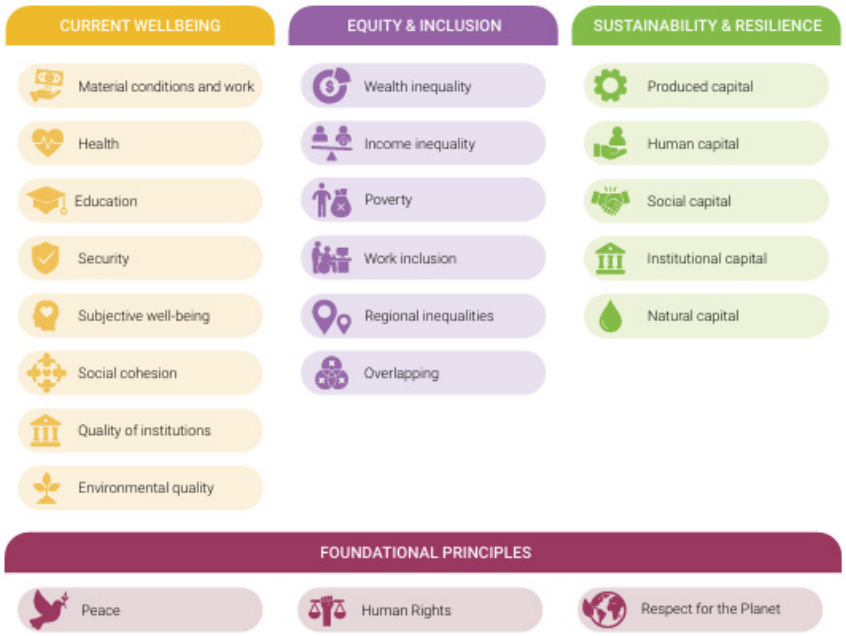
9 The so-called Paris Agreement explicitly called for "making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" (see article 2.c).

10 A recent survey showed that the leading obstacle reported by central banks is methodological – eg the absence of harmonised definitions and taxonomies (IFC (2021a)).

for example to estimate environmental constraints (Jansen et al (2024); Khanh Nam (2026)). Second, ESG data often originate from poorly standardised, unstructured or novel sources, such as entity-level corporate reports, financial market transactions, satellite imagery and geospatial information. Making sense out of this heterogeneous information requires careful assessment to integrate such micro, entity-level and often alternative data into the macro, comparable and (sufficiently) quality-assured statistics that policy requires.

Major statistical initiatives are underway to address these gaps globally. One strand complements traditional, "GDP-type" indicators with broader measures of human development, such as the recommendations by the UN High-Level Expert Group (HLEG) on Beyond GDP covering well-being, equity and inclusion, sustainability and resilience (Graph 1; UN (2026)). A second strand relies on the updated core statistical standards, including the 2025 System of National Accounts (SNA) and the seventh edition of the Integrated Balance of Payments and International Investment Position Manual (BPM7) to promote a more integrated approach across environmental and economic accounts and introduce harmonised classifications for sustainable finance (UNSC (2024); Dilip et al (2026)). A third strand concerns corporate sustainability disclosures, for which the International Sustainability Standards Board (ISSB) standards and the recommendations by the Taskforce on Nature-related Financial Disclosures (TNFD) provide foundational inputs (IFRS Foundation (2026); TNFD (2023)).

The Beyond GDP dashboard — Graph 1

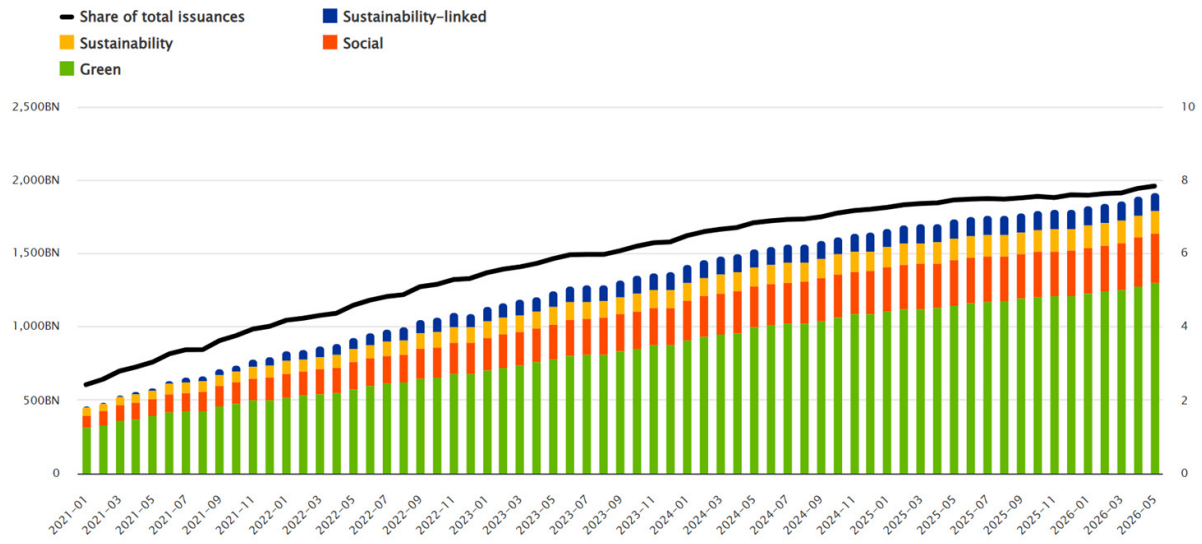


Source: UN (2026).

Another important milestone is the third phase of the G20 DGI (DGI-3), launched in 2022 with a five-year horizon (IMF et al (2023)) and actively supported by the central banking community. Its workplan – centred on people, planet and economy – aims to deliver actionable insights to better inform economic and financial

policies, with 14 recommendations directly or indirectly related to the measurement of sustainability. Specifically, half of them focus on environmental issues spanning greenhouse gas emissions and national carbon footprint measurement; energy accounts; foreign direct investment (FDI) carbon footprints; climate finance [11] forward-looking physical and transition risk indicators; government climate-impacting subsidies; and climate change mitigation and adaptation expenditures. In addition, the DGI-3 also includes a number of socially relevant data gaps related to financial inclusion, income and wealth distribution. Overall, this workplan has supported significant methodological progress and triggered new global collections of sustainability-related data, for instance on the issuance of ESG securities (Graph 2).

Euro area issuances of sustainable debt securities – all levels of assurance — Graph 2



Left-hand scale: EUR, outstanding amounts at face value; right-hand scale: percentages. "Share of total issuances" refers to the amount of all sustainable securities as a share of all debt securities issued in the euro area.

Source: ECB Centralised Securities Database (CSDB).

Against this background, **the Irving Fisher Committee on Central Bank Statistics (IFC) of the Bank for International Settlements (BIS) and De Nederlandsche Bank co-organised "Sustainability data issues and central banks' experience"** as a satellite seminar to the 65th World Statistics Congress (WSC) of the International Statistical Institute (ISI) in 2025. The event reviewed central banks' production and use of sustainability data with a focus on ESG dimensions. It discussed the analytical contribution of sustainability information, the tools needed to unlock its value and the challenges it poses for statistics and policy, paying particular attention to: (i) environmental data; (ii) the relevance of other social and governance considerations for central bank activities; and (iii) the global statistical infrastructure needed to make these data policy-useful. This overview examines why data on sustainability that go beyond economic considerations matter for central banks

[11] The DGI-3 purposedly led to the setup of shared common definitions with the 2025 SNA regarding ESG and green financial instruments.

(Section 2) and sets out a quality framework along four dimensions, namely relevance, availability and accessibility, reliability and international comparability (Section 3).

2. Why broad sustainability dimensions can matter significantly for central banks

An input for central banks' responsibilities and activities

Central banks' interest in sustainability data beyond the "traditional" focus on economic development is both demand- and supply-driven. As users, they look for reliable sustainability-related metrics to support their analyses, with a primary focus on the consequences of climate- and nature-related events on the financial system (Gardes-Landolfini et al (2024)). They have been also looking for sustainability indicators beyond those related to climate and the environment, including to cover topics such as social resilience, governance factors and wealth and income effects in the population (Mehrotra and Yetman (2015); IFC (2021a); FSB (2024)). All these insights have proved relevant for many of their tasks, spanning the areas of monetary policy, financial stability, supervision, research, statistics, payments and portfolio management (Tan (2023); NGFS (2026a, 2026b, 2026c)). In practice, central banks often reuse and link the various types of data sources available, including official statistics produced by NSOs and international organisations, supervisory reports and payment and financial market data.

On the supply side, **central banks have also been increasingly producing novel indicators themselves, especially to assess sustainability-related impacts on financial institutions** (IFC (2021a)). This has typically been done as a complement to the information already available in the sustainability data ecosystem, and often on an exploratory basis[12] – for instance to monitor the development of sustainable finance and assess banks' climate-related risks. They have also actively contributed to the development of new statistical concepts, methods and sources to address previously unmet data needs in the sustainability area (Aurouet et al (2023)). A noteworthy case is the DGI-3 fourth recommendation, co-led by the BIS and European Central Bank (ECB), which is a testimony to the collaboration of central banks, NSOs and international organisations to count and classify sustainable financial instruments including debt securities and listed shares. Central banks have been also capitalising on their close synergies with financial stakeholders beyond the statistical community, including accountants, standard setters, regulators and supervisors, such as in the case of carbon content measurement (Alfieri et al (2024)).

[12] NSOs' primary responsibility for collecting and disseminating sustainability-related indicators, including climate ones, reflects both their well-established role as coordinators of the national statistical system and their long-standing experience in the broad area of social, environmental, demographic and economic statistics (UNECE (2014, 2025b)). This prominence has been further strengthened in the context of the UN SDGs initiative; see the Cape Town Action Plan for Sustainable Development Data and the 2030 Agenda for Sustainable Development (UN (2015, 2017); UNSC (2017)).

Box A

Sustainability and sustainable finance: clarifying the link

Sustainable finance represents the full range of financial activities that aim to improve environmental, social and governance (ESG) factors. Specifically, environmental aspects include climate change mitigation and adaptation as well as broader issues related to the preservation of biodiversity, pollution prevention and reduced resource waste through the circular economy. Turning to social considerations, they refer to issues of inequality, inclusiveness, investment in people, their skills and communities, as well as human and labour rights issues. Furthermore, sustainable finance also encompasses the governance of public and private institutions, ranging from the degree of legal protection to corporate ethics, management and remuneration.①

This definition of sustainable finance has been incorporated in the 2025 SNA, which identifies two primary types ESG and green finance. Specifically, ESG finance comprises all financial "activities or projects that sustain or improve the condition of the environment or society or governance practices". Green finance, on the other hand, is a subset of ESG finance focusing on the "activities or projects that sustain or improve the condition of the environment", including climate-related ones.② Yet, in practice, the scope of sustainable finance taxonomies is often grounded on existing national metrics and may vary significantly across countries, depending on statistical frameworks and policy priorities.

The above considerations highlight that, while sustainable finance and sustainability are closely related concepts, they have a distinctive objective, scope and approach. First, sustainability is a development objective that encompasses a large breadth of considerations, including economic ones. The focus of sustainable or ESG finance is narrower as it deals with steering financial investments towards sustainable objectives. Second, and relatedly, ESG serves as operational enabler (or a *means*) for taking a broad range of well-being considerations when directing financial resources in specific areas ; by contrast, sustainability should be understood as a normative concept intended as an end in itself (or a *goal*), ie the preservation of human well-being. Third, sustainability has a holistic approach, spanning different levels together (local and global; individual and society). Sustainable finance, as captured through the ESG criteria, focuses on individual or units, such as entities or investment projects.

① For example, see the sustainable finance overview by the European Commission and OECD (2025). ② See paragraph 12.151 of the 2025 SNA.

Climate-related data as a key focus

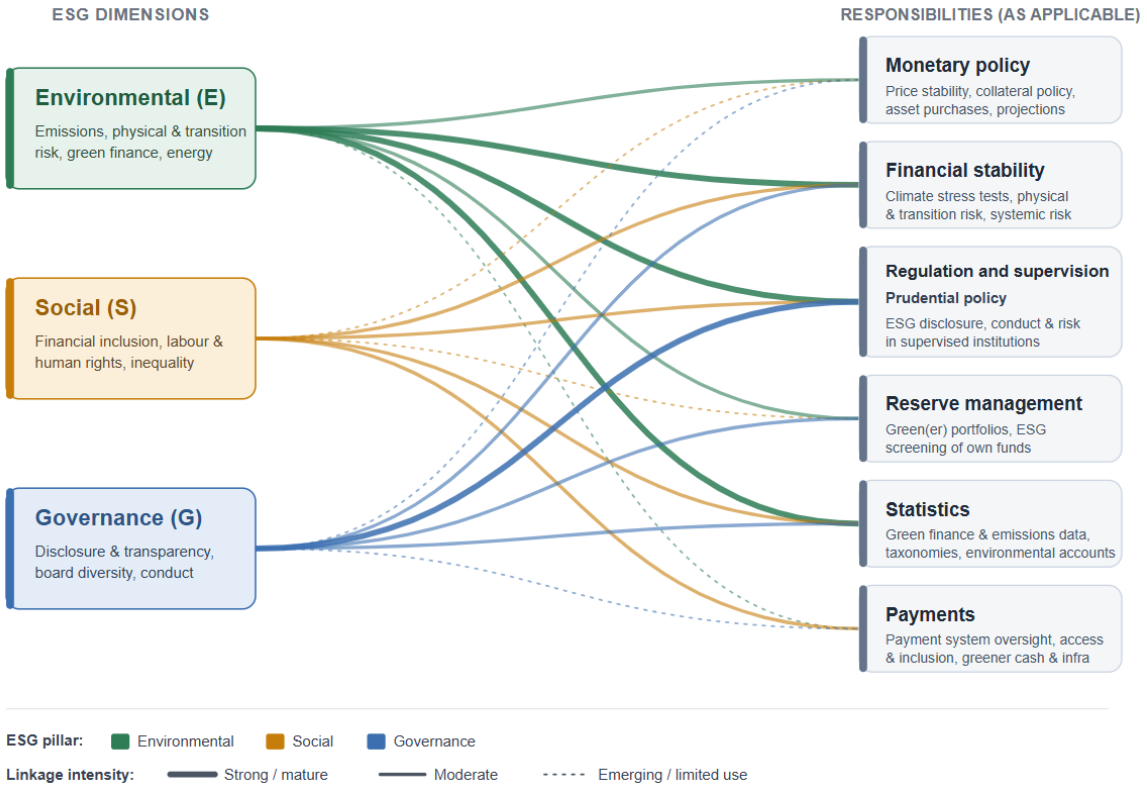
Among the wide range of sustainability issues, central banks have been primarily and closely monitoring the impact of climate change on the financial system in recent years. This impact can be divided into two categories (NGFS (2020)). First, physical-related aspects, such as extreme weather events or shifts in climate patterns, can disrupt macroeconomic variables, including productivity, supply chains, inflation and overall output. Second, transition-related impacts can affect market prices and output due to changes in policy, technological and/or social preferences. Typical effects include asset repricing, capital reallocation and the related distributional consequences across households, firms and sectors (NGFS (2024a)).

A key reason for central banks' attention to climate-related events is that they can affect financial and monetary stability through multiple and interconnected channels. First, they may alter credit quality, collateral values, market liquidity and risk premia, in turn generating broader monetary, financial and economic implications (Sleijpen (2025)). Second, and relatedly, they can pose financial stability risks, at the level both of individual entities, such as banks and insurers

(eg climate stress tests and supervisory exercises; BCBS (2022)), and of the whole financial system (eg propagation of macro shocks and cross-border/sectoral spillovers; Bolton et al (2020)). Third, they are also relevant when making, implementing and assessing monetary policy, for example to adequately incorporate climate-related inflationary impacts, conduct liability-side operations (eg collateral frameworks, asset purchases, reserve management) or evaluate the effectiveness of monetary transmission mechanisms (NGFS (2026a, 2026d)). Fourth, climate- and nature-related data are also increasingly important for assessing central banks' own financial exposures (ECB (2025a)).

Fortunately, the supply of climate data available to central banks has increased steadily in recent years. Advances include publicly disseminated ESG bonds' categories and greater methodological harmonisation, for example in terms of classifications and definitions related to green finance (IFC (2025a)). As a result, environmental data gaps are arguably being closed faster than those related to social and governance indicators. This progress has clearly benefited from enhanced corporate disclosures, more precise emissions inventories and the development of integrated energy and environmental accounts as well as of novel data techniques to harvest non-traditional information sources. It has also been spurred by central banks' increasing demand for those indicators directly relevant for the assessment of the physical and transition risks posed by climate change (Graph 3).

Environmental aspects are particularly important ESG elements for central banks — Graph 3



Source: IFC (2021a).

As regards information sources, climate-related data used by central banks have proved to fall into four broad categories:

1. **Official statistics**, primarily derived from macroeconomic and environmental accounts that measure interactions between the economy and the environment (UN et al (2014)).[13] These are typically produced through structured statistical processes governed by well recognised rules and principles, and involve primarily NSOs, central banks, public environmental agencies and international organisations;

2. **Supranational databases on environmental risk indicators**, compiled by platforms that seek to centralise internationally standardised indicators to quantify climate and environmental risks on a best efforts basis. These data are typically made available on public portals and benefit from significant support by the global statistical community. One example is the EM-DAT international disaster database that contains long historical data on the occurrence and impacts of mass disasters worldwide. Other examples, focused on the European Union, include the Risk Data Hub (RDH) of the Disaster Risk Management Knowledge Centre (DRMKC), with information on environmental disasters' risk, damage and loss, and the AGRI4CAST Resources Portal, which combines meteorological data and crop statistics;

3. **Global public-private platforms providing sustainable finance and ESG information**. For instance, the Sustainable Stock Exchanges Initiative (SSEI) is a UN Partnership Programme that provides a global platform for exploring how exchanges can enhance performance on ESG issues, with access to various databases, for example on trading in carbon markets. Other examples include the various United Nations Environment Programme (UNEP) multi-stakeholder platforms, covering a wide range of issues, eg climate change, biodiversity loss or pollution, as well as those – often fee-paying – databases compiled by private data providers (eg issuance of sustainability bonds);

4. **Forward-looking climate scenarios**. These analytical frameworks explore how economies may evolve under different assumptions about environmental policy objectives and climate impacts, providing structured pathways for assessing physical and transition risk alternative trajectories. Such scenarios, developed by different bodies, including the Network for Greening the Financial System (NGFS; NGFS (2024b)) or the Organisation for Economic Co-operation and Development (OECD; OECD (2021)), are reported to be increasingly integrated into central banks' analytical toolkits.

Within this large universe of available climate-related data, **central banks' attention has focused on a relatively narrow set of indicators**, such as:

- Financial instruments and exposures related to climate finance (eg loans, securities, guarantees, collateral, portfolios);

[13] System of Environmental Economic Accounting (SEEA) accounts are compiled on a regular basis by almost 100 jurisdictions worldwide, yet with still limited coverage in regions such as Africa (UNSC (2026)). These macro statistics are often complemented by global databases, for example, on air emissions (by the OECD) and land use (by the Food and Agriculture Organisation (FAO)).

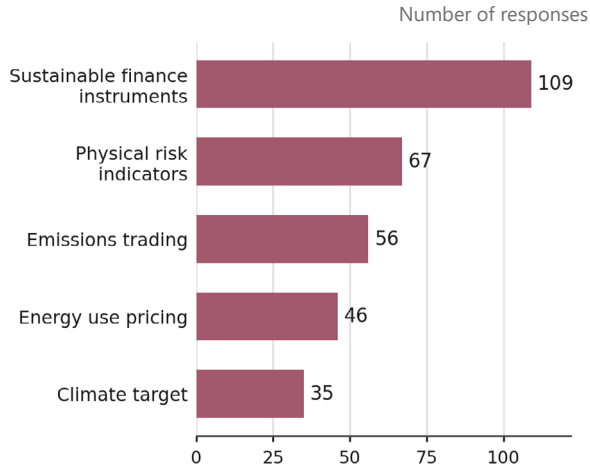
- Characteristics of counterparties and real economy activities (eg sectoral production, balance sheets);
- Wider ESG attributes and factors driving climate- and nature-related risks (eg carbon emissions, physical hazards/vulnerabilities, technology variables);
- Dynamic sustainability pathways (eg forward-looking scenarios, temporal objectives set by transition policies).

More specifically, **data on the issuance and holdings of sustainable financial instruments have been among the most widely used in the recent past**, followed by data on physical risks and emission trading (Graph 4, left-hand panel). In terms of priority, information to monitor the volume of sustainable bond financing and lending have usually ranked high (right-hand panel) among central banks, followed by ESG ratings. Important data gaps nevertheless remain, especially as regards the footprint of privately held firms, cross-border exposures, value-chain linkages and forward-looking measures (NGFS (2022)).

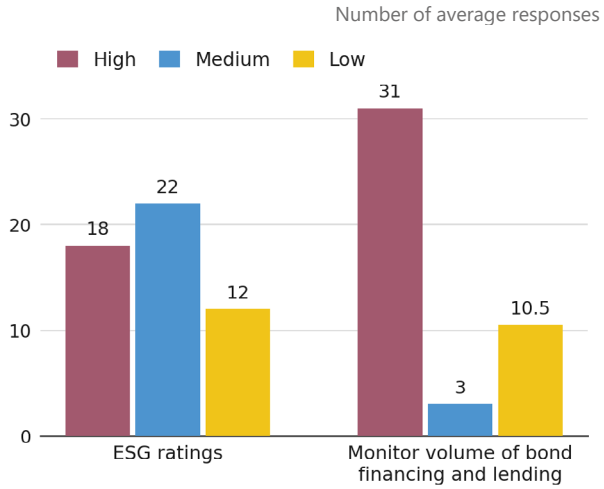
Central banks assign a very high priority to sustainable finance instruments to monitor financing aspects

Graph 4

Among the top environmental indicators, sustainable finance instruments rank highest...



...especially to monitor borrowing and lending activities



Source: IFC (2021a).

Integrating multiple and heterogeneous data

Given the breadth of sustainability data, linking information across sources, types and domains is essential for forming comprehensive, timely and actionable policy insights (Sirello and Tissot (2026)). As regards climate-related data, for instance, such integration often entails combining administrative, statistical and prudential sources to quantify financial institutions' exposures to physical risks (Arslanalp et al (2023)). It also mixes structured and unstructured data, including corporate reports and satellite imagery (Doll et al (2026)). More broadly, it requires embedding new ways of thinking into official statistical frameworks. For instance,

spatial information cuts across domains and purposes in ways that traditional statistical processes may not always capture easily (UNECE (2026a)).

Compiling comprehensive sustainability data also depends on building adequate micro-macro linkages. Granular information collected for individual units, such as entities, persons or instruments, often provides the raw input for computing ESG indicators, drawing on registers, financial statements, instrument-level databases or alternative sources such as utility meter records measuring energy consumption. One challenge is the breadth and variety of the granular data universe that can be considered. For instance, market-based indicators, such as securities spreads, issuance patterns and liquidity conditions, should be monitored alongside real economy metrics to capture transition dynamics and financial amplification mechanisms. Likewise, micro-level financial exposure data must also be aligned with physical indicators, such as geospatial information, not least to assess distributional effects, risk scenarios and policy trade-offs (NGFS (2024a)). A last challenge is to have a sufficient degree of harmonisation, standardisation and comparability so that individual data can be usefully aggregated and combined with macro statistical frameworks that provide the "big picture", for example following well-established environmental-economic accounting standards.

Another issue is combining quantitative and qualitative information, especially for social and governance (SG) topics. As opposed to quantitative measures, often represented numerically, qualitative indicators are arguably harder to standardise as they may leave greater space for both multiple and subjective interpretations. This is especially true for SG indicators, which are more difficult to embed in policy toolkits in a standardised way. Yet, despite the lower attention paid to this information so far, SG considerations can also play a decisive role in shaping the resilience of the productive and financial systems as well as in influencing risk transmission channels. In particular, governance deficiencies can affect risk management, disclosure quality, conduct risk, operational resilience and supervisory assessments. Similarly, social aspects can be important when assessing macroeconomic resilience and the distributional effects of transition processes. In any case, SG indicators have already become relevant in specific central banking areas, including supervision, risk assessment and macro-financial surveillance – although their use in monetary policy operations and reserve management remains more limited than that of environmental data (IFC (2021a)).

Overall, integration requires data pipelines that can combine diverse information sources, types and levels of aggregation. Fortunately, advances in data processing and linkage, especially related to machine learning (ML) and artificial intelligence (AI), can already better support the processing and analysis of granular as well as unstructured information (IFC (2025b)). Integration also requires common data infrastructures that cut across statistical processes, supported by interdisciplinary skillsets and expertise in new domains, such as geosciences. Last but not least, enhancing cooperation between the various data stakeholders – including statistical agencies, international organisations, commercial providers, academia and citizens – appears essential to facilitate data-sharing while preserving confidentiality and data integrity (FSB (2023)).

3. A four-dimensional quality framework for sustainability data

Making further progress in addressing sustainability gaps is key to better inform central bank policies. In practice, improvements can be organised into four quality dimensions: (i) relevance and fitness for purpose; (ii) availability and accessibility, including adequate granularity, timeliness and completeness; (iii) reliability, based on sound concepts, transparent methods and robust production processes; and (iv) comparability, through greater harmonisation and consistency at national and global levels.

Advancing these four dimensions in parallel is essential for three reasons. First, quality shortcomings can limit the usefulness of sustainability information for policy purposes (Table 1). For example, inconsistent estimates of damages, transition costs and risk exposures may undermine forecasting, stress testing and surveillance exercises (Adrian et al (2022)). Second, standardised, open and verifiable data are necessary for securing the objectivity, trustworthiness and credibility of sustainability indicators and the policies they underpin. Third, existing sustainability data gaps are often the result of broader governance challenges, highlighting the need for better coordination frameworks and for making more global progress in terms of data collection, integration and interoperability.

Climate risk data gaps: four main dimensions — Table 1

Data dimension	Objective	Lessons from central banks' experience
Relevance	Ensuring fit for purpose information	✓ Clearly define policy purposes ✓ Identify relevant data for different objectives ✓ Balance benefits/costs in terms of informational value and administrative feasibility
Availability & accessibility	Improving coverage, access, granularity, timeliness	✓ Leverage both micro and macro data and integrate diverse sources ✓ Use innovative analytical tools ✓ Develop data-sharing agreements ✓ Prioritise pilot studies to address blind spots (eg FDI, SMEs), emerging market economies
Reliability	Ensuring the robustness of statistics produced	✓ Establish communication protocols for revisions ✓ Support the public foundation of sustainability datasets ✓ Expand identifiers and data standards (eg Legal Entity Identifier (LEI), the standard for Statistical Data and Metadata (SDMx))
Comparability	Enhancing national and international coordination	✓ Build harmonised global statistical infrastructure ✓ Coordinate internationally to standardise ESG data and methodologies ✓ Strengthen engagement among all stakeholders in the sustainability data ecosystem

Source: Authors' elaboration.

a. First focus point: relevance – making data fit for policy use

A key issue for central banks in addressing sustainability information gaps is to focus on producing the right data rather than merely collecting more. Prioritising quality over quantity fundamentally reflects the importance of relevance and fitness for purpose as essential properties of the data needed. Relevance ensures that information stays meaningful and closely aligned with the needs and contexts it is designed to address. Fitness for purpose, in turn, guarantees that the data are accessed, processed, shared and communicated to support their intended function effectively. Ensuring that these two properties are effectively met is key to keeping pace with constantly evolving scientific advancements, policy priorities and, ultimately, social expectations. Meanwhile, the appropriate use of the data collected requires careful and relentless attention to their design, origin and, perhaps more importantly, statistical quality and ethical standards (Dilip et al (2026)).

In this context, experience shows that **the value of information increases when users clearly specify *which* data are needed and *how* they can support central banks' activities related to sustainability**. These include analytical, statistical, policy and prudential tasks, such as risk monitoring, stress testing, scenario analysis and transition assessment. Operationally, this requires comprehensive, integrated and transparent statistical workflows that document, reconcile and balance trade-offs between input data and policy objectives.

A first starting point is documenting the relationships between sustainability factors and economic and financial outcomes relevant for policy. These can include developments in growth and inflation as well as financial stability conditions. One illustration is the assessment of the impact of heatwaves on economic output, which can vary significantly depending on regional characteristics, income distribution and the importance of the agricultural sector, as shown in a study conducted by the central banks of Germany, Luxembourg, Malta and Spain. Similarly, a recent analysis of bilateral FDI flows in France and Italy underscores how capital allocation can be sensitive not only to the geographic location and sector of the firms involved, but also to the type of climate risks they face. Moreover, as sustainable finance scales up, the links between cross-border positions and physical risk exposures are becoming more salient. This reinforces the need for adequate data to map international investment flows to hazard metrics, including to assess international spillovers and systemic vulnerabilities.

A second step is to adequately reconcile sustainability information across different levels of observation and, in turn, ensure its proper aggregation. For instance, climate-related financial exposures are often recorded at the entity level, whereas physical risks are frequently measured for specific spatial locations and assets. Moreover, the impact of transition risks on both tangible and intangible asset prices typically depends on national factors, such as country-specific technology pathways and policies, further complicating macro-micro linkages. In Belgium, for example, the national implementation of energy performance certificates is estimated to have contributed to a declining trend in house prices for those dwellings constrained by the new policy. At the same time, improvements in the quality of average houses sold, largely driven by greater energy efficiency, have contributed to higher aggregate values. Another example is the Bank of Italy's assessment of firms' nature-related financial risks using micro-level sources (Lavecchia et al (2022)). This

requires combining granular environmental data (eg on households and non-financial corporations' energy consumption and building energy performance) with macro information, such as jurisdiction-level climate transition processes (Box B).

A third consideration is to **balance the value of additional sustainability data collections against associated costs**, including in terms of meaningfulness and reporting burden. There can be value in focusing on a limited yet policy-relevant set of indicators rather than collecting an excessive volume of heterogeneous and noisy data. For example, an increasing number of jurisdictions require more detailed corporate disclosures related to ESG factors, but the usefulness of this information may vary and should be carefully assessed (Elgg et al (2025)). A related illustration, based on large language model techniques, is the finding that the economic impact of sustainability reports by large European issuers can be relatively limited. From this perspective, greater clarity about the policy-relevance of the information collected is essential for prioritising data development efforts and mobilising (limited) resources for statistical compilation, especially in less developed economies. Data reporting frameworks should also be proportionate to firms' capacities, particularly for smaller enterprises, given the potentially broad scope of ESG issues.

Box B

Identifying sustainable data gaps: lessons from Italy

The Bank of Italy has undertaken a comprehensive three-step assessment of climate-related and environmental risk data gaps:

1. **Data requirements**: the study first mapped the information needed on firms' transition plans, net zero commitments, financial analyses and compliance with international, European and national regulations (including supervisory requirements);

2. **Availability mapping**: the exercise then identified which data exist and are accessible – including official statistics (eg Eurostat, European Environment Agency, national agencies, etc), risk indicators (eg European Commission Disaster Risk Management Knowledge Centre (DRMKC)), platforms (eg SSEI) and climate scenarios (eg those available on the NGFS scenarios portal) – versus what exists but remains inaccessible;

3. **Gap identification**: the review pinpointed critical missing data, especially at the micro level.

A key lesson from this assessment is that, while aggregate statistics and risk indicators are generally available, the micro data needed for precise transition risk assessments often remain siloed. In particular, data on household and corporate energy consumption (as available in the Sistema Informativo Integrato) and building energy performance certificates (in the Sistema Informativo sugli Attestati di Prestazione Energetica) exist, but access to them is limited due to privacy and legal constraints. Hence, unlocking these administrative data sets – with due consideration to legal and ethical standards – appears crucial to significantly improve both the macroeconomic monitoring of the climate transition process and micro-level financial risk measurement exercises.

Perhaps more fundamentally, the Bank of Italy experience underscores that addressing environmental data gaps is not only a technical challenge, but also a strategic and governance task requiring coordinated action among the various stakeholders involved, including statistical agencies, regulators, financial institutions and data providers.

b. Second focus point: enhancing data availability and accessibility, including through granularity and timeliness

Availability and accessibility

To be useful, sustainability data have to be made widely available and readily accessible. In practice, however, major gaps remain, especially for environmental data, with heterogeneity in terms of sectors, geographies and reporting institutions (Box C). Limitations include incomplete scope 3 corporate reporting, uneven ESG data for small and unlisted firms, inconsistent assurance of sustainable finance labels and difficulties in linking counterparties across data sets, not least because common identifiers remain incomplete (FSB (2023); IFRS Foundation (2026); TNFD (2023)).

Box C

Main shortcomings in environmental data used by central banks

Environmental data face persistent challenges in terms of relevance, availability, reliability and comparability, reflecting both governance and operational constraints.

For one, **robust data frameworks** require clear processes for governing the availability, accessibility and harmonisation of a wide range of fit-for-purpose indicators – spanning firms' exposures and transition plans, the carbon content of economic activities and climate scenarios underpinning forward-looking risk assessments (IFC (2025a)).

Turning to operational limitations, **important measurement difficulties remain**, for instance in properly assessing value chain exposures, financed emissions and cross-border activities. Furthermore, the information used still relies to a significant extent on assumptions and model estimates because of unobserved data points.

Against this background, a key lesson is that addressing environmental data gaps would call first for **improved reporting by firms**. Yet, despite progress in sustainability information corporate disclosures, significant shortcomings persist, including due to complex and/or too detailed reporting requirements, uneven auditing practices, limited comparability and the lack of harmonised international frameworks.

Another issue is the difficulty in **properly apprehending the various and complex interactions between nature-related factors and developments in the economy and the financial system**. One telling example relates to the role of FDI in amplifying or mitigating climate-related risks, which can differ depending on the sectoral composition and location of the investments made.

The importance of current data gaps has been reinforced by the growing demand for sustainability information at both national and global levels. As scientific discoveries advance and policy priorities evolve, data collection exercises need to adapt accordingly. This is particularly true for climate finance, which has been characterised by significant changes in financial instruments and funding structures in recent years. For example, the Central Bank of Malaysia has focused on the growing role of Islamic finance instruments (sukuk securities) in channelling funds for financing sustainable projects. This requires adequate information to assess market depth, measure issuance in a standardised way and evaluate the credibility of instruments labelled as sustainable – including by having reliable and transparent assurance level labels.

One way to address data availability issues is to **promote better sharing and governance**. Options include technical solutions, contractual agreements and legal

frameworks to access and link confidential and/or non-public data sets, including registers (IFC (2025d)). Another avenue would be to improve methodologies for transparently tracing the diverse sources used to produce actionable information, such as textual corporate disclosures, geospatial and administrative records, and financial data. This calls for coordinated action among all relevant stakeholders – ie statistical agencies, regulators, financial institutions and data providers – in order to harmonise standards, improve data-sharing, and support the availability of robust sustainability indicators.

A second, related action point is to **develop comprehensive data inventories and directories**, for instance through collaborative platforms that make it possible to crowdsource, integrate and curate databases provided by various stakeholders. A telling example is the BIS/NGFS project data directory to provide central banks and financial supervisors with an overview of all climate risk-relevant data available globally. Experience shows that such directories can be valuable tools for identifying and addressing data coverage issues. Yet, to be successful, their development should be user-centric and agile, with the provision of advanced search and analytical capabilities.

A third solution is to **conduct targeted pilot studies, especially for data-poor segments such as FDI, small and medium-sized enterprises (SMEs) and emerging market economies** (Borga et al (2023); IFC (2024); Genre et al (2025)). Examples include the Bank of Korea's project to develop exploratory statistics from available micro-level information rather than launching broad new surveys, as well as a recent ECB pilot to measure the exposure of FDI to physical climate risks. Instead of linking aggregate country-level FDI flows to climate indicators, the latter approach decomposes FDI enterprises into elementary units, assesses physical risks at those locations and aggregates risk scores back to the FDI level. Similar initiatives have been used to overcome data gaps on carbon emissions (Box D). One notable lesson of these various examples is that targeted approaches can be particularly valuable because of their proportionality, as they limit reporting burdens while addressing critical blind spots.

A final focus point is to **leverage innovation to improve data accessibility** (IFC (2025c)). Even when sustainability data are potentially available, various technical constraints can make them difficult to access and/or process (Nefzi et al (2025a)). In particular, innovative data science techniques can help integrate novel and heterogeneous information sources – such as supervisory data, payment systems, private sector records and satellite imagery – and extract new signals – eg with the use of generative AI to support text-based analytics (Araujo et al (2026)). Innovation can thus help fill gaps where traditional ESG reporting is incomplete, for example by estimating location-specific physical risks, mapping firms' facilities or inferring exposure networks. Moreover, it can improve the timeliness and granularity of the information available to users, which are important requirements, as analysed below.

Box D

Overcoming data gaps on carbon emissions

Carbon emissions are a useful metric for central banks to inform their policies when dealing with climate-related issues. Yet data gaps in this area are persistent, facing a still limited yet increasing number of corporates disclosing their carbon emissions on a voluntary or, in some cases, regulatory basis (Olesiewicz et al (2021); Elgg et al (2025)).

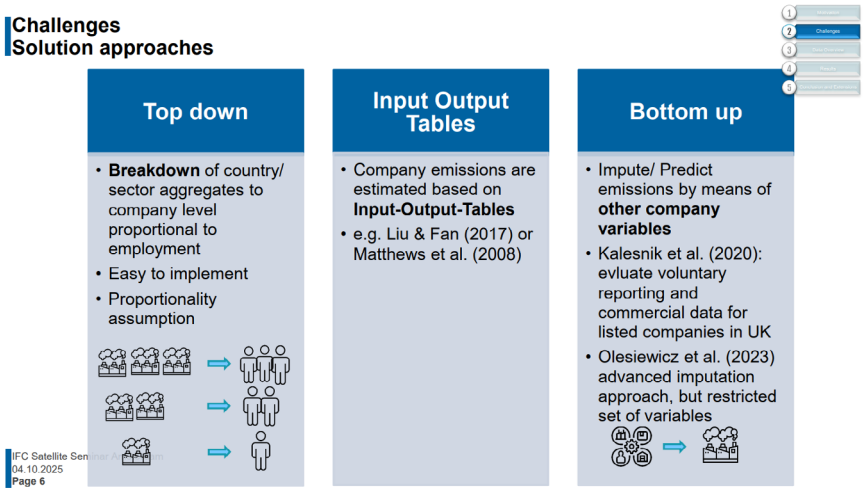
To overcome such gaps, central banks commonly apply three main estimation approaches (Graph D1):

- **Top-down approaches disaggregate aggregate figures to the firm level using proxy variables**. These methods allocate macro-level CO_2 emissions data – such as national or sectoral indicators – to individual firms based on their characteristics, for example in proportion to their labour force. While this approach is relatively straightforward and scalable, it can be imprecise when firms display heterogeneous technologies, energy mixes or value chain structures.
- **Input-output table-based approaches allocate emissions to firms depending on their position in sectoral value chains**. For example, global multi-regional input-output tables and national CO_2 emissions databases can be combined to calculate national and regional emissions as well as those embodied in value chains, using value-added accounts (Liu and Fan (2017)). One benefit of such methods is that they identify upstream and downstream linkages across value chains. But the quality of the results depends critically on the availability and reliability of both input-output tables and the mapping of firms to specific sectors.
- **Bottom-up approaches estimate emissions directly from firm-level information**. One recent example uses firms' balance sheets and income statements to estimate emissions depending on production factors and value added. However, these methods typically require substantial granular data and careful ex post validation.

Regardless of the method being used, the results should be compared and benchmarked against available and well tested statistics. One would also want to provide some breakdowns depending on the type of emissions (eg scope 1, 2 or 3), estimate uncertainty ranges and document the key assumptions being made.

Approaches to estimate missing CO_2 emissions

Graph D1



Source: S Walter (2026): "A comparative analysis of machine learning and classical statistical techniques for the imputation of corporate green house gas emissions", *IFC Bulletin*, no 68.

Granularity

Granular data have become increasingly important for supporting evidence-based policies in the ESG area, as aggregate statistics have often proved insufficient for effective risk monitoring of sustainability issues (IFC (2024)).

Drawing on their longstanding experience in working with micro-level information, **central banks have been actively contributing to the availability of more detailed sustainability indicators in recent years** (IFC (2021b); Brault et al (2024)). For example, the European System of Central Banks has introduced a series of climate-related financial sector statistics[14] comprising detailed information on banks' exposures to carbon-intensive sectors, securities issuance and holdings by green or transition label, borrower-level emission intensities and a detailed distribution of physical and transition risks (Aurouet et al (2023); Kanutin (2024)). This increasingly detailed statistical offering has been accompanied by methodological notes to support consistent compilation and usage.

Yet granular sources also pose operational, statistical and governance challenges. Operationally, they are often voluminous, weakly standardised and poorly interoperable, creating storage, processing and exchange difficulties. Statistically, unit-level observations may not fit directly with macro categories such as institutional sectors and may require dedicated quality management pipelines. Turning to governance aspects, micro data are often sensitive because records can identify individuals, firms or assets. This raises confidentiality risks and requires due diligence to ensure privacy protection and ethical data management.

Addressing these challenges calls in particular for further improvement in the global statistical infrastructure. First, the use of global and unique identifiers can be instrumental to improve standardisation. For example, initiatives such as the LEI can enhance transparency in ownership structures, in turn facilitating the mapping of corporate interlinkages and the quality of ESG group-level indicators (eg carbon emissions). Second, information standards, including the one from SDMx, can be instrumental to facilitate interoperability and integration (IFC (2025c)). Indeed, a key feature of SDMx is its versatility to handle the different data types underlying sustainability information, including geospatial and micro-level information. Lastly, collaboration among stakeholders in the data ecosystem is essential, not least to ensure comprehensive coverage of the information collected. For instance, there is an increasing need to complement bank-based sustainable finance indicators (eg green loans) with granular data on private credit. Collaboration is also key to foster micro data-sharing and interoperability, as experienced in Africa (OECD (2026)).

Timeliness

While users value timely sustainability data, many metrics are reported with significant lags. This problem is particularly acute for two reasons. First, ESG indicators feed into decisions that may require preventive action or fast reaction, including real-time monitoring of systemic risks (UNECE (2020)). Second, many of

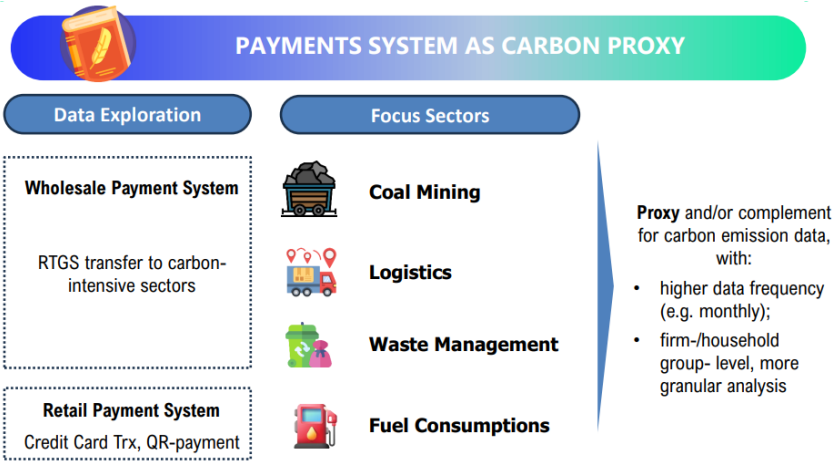
[14] See the climate change-related indicators disseminated by the ECB.

them are new or experimental and therefore more volatile than regular statistics. Climate data, for instance, have faced significant discontinuities caused by changes in reporting concepts, structural breaks or sudden stops in data provision, especially by commercial platforms (Rössler et al (2019)).

Fortunately, innovative data sources and techniques can significantly improve timeliness in the ESG area. They can support more efficient and integrated collection processes, for example when sourcing unstructured information from sustainability reports. Moreover, modern techniques can help link primary and secondary data sources, even when their coverage differs substantially. Additionally, the growing toolbox of data analytics – including nowcasting, text mining and ML – can help provide timelier estimates, though this calls for careful quality checks and transparency on the methods used and the input data. For instance, nowcasting methods can combine historical carbon emissions from macro sources (often available with a significant lag) with higher-frequency proxies inferred from more timely corporate indicators, such as data on energy consumption or payments, as experienced by De Nederlandsche Bank in cooperation with the ECB. A similar approach, developed by Bank Indonesia, leverages high-frequency payment system data to estimate real-time carbon emissions associated with economic activity (Graph 5). In both cases, robust back-testing and transparent revision policies are essential to ensure that early estimates are consistent with the final data produced later.

Estimating emissions through high-frequency payment system data: the Indonesian experience

Graph 5



Source: R A Bimantoro, C Lim, M Khoyrul Hidayat, M Reza Ramadhan and A Ramadhan (2026): "Payment systems as carbon proxies: a novel big data analytics approach to measure the carbon content of economic activities", *IFC Bulletin*, no 68.

c. Third focus point: reliability – building trustworthy sustainability data

Reliability is essential for supporting well informed decision-making in a meaningful and trustworthy way. This quality dimension is particularly essential in

the area of sustainability given the tight interdependencies of scientific, policy and social considerations. To be reliable, the information needs to be accurate, objective and impartial as well as complete, that is, containing all essential elements – including metadata – to enable its accurate interpretation. Experience suggests that the reliability of ESG data depends on three critical factors: integrity, transparency and a robust statistical production pipeline.

Integrity

To pursue integrity, **statistics need to be compiled following open, objective and impartial methodologies** in compliance with well established standards and ethical principles (UN (2014); ISI (2023)).

In practice, this requires **rigorous validation procedures following scientific standards**, for example to ensure that measurements are systematically grounded on solid evidence. It also demands transparent acknowledgement of both data and methodological limitations, accompanied by clear communication to users. A telling example is the quantification of uncertainty, for example of estimates generated by advanced – and often opaque and hard-to-understand – analytical techniques such as ML (UNECE (2026b)). Moreover, high-quality information should aim at the highest degree of objectivity to the extent possible. This is a particularly valid requirement – yet also a challenging one – for sustainability information, which is arguably more prone to subjective considerations compared with more traditional economic indicators (Conigliaro (2021)).

International benchmarking exercises can be another useful solution. One example relates to the finding that, in Korea, national sources suggested limited issuance of green finance instruments by domestic local high-emission industries, such as steel and chemicals, despite the growing need to finance the transition to low-carbon activities there. By comparing these data with the situation observed in Europe, the Bank of Korea was able to document that issuance by Korean firms comprises relatively fewer green bonds and more sustainability-linked bonds. Such benchmarking exercises have also been increasingly developed in the European context (ECB (2025b)).

Transparency

Transparency is instrumental to secure data reliability and trustworthiness. It greatly reduces the likelihood of having indicators based on opaque, unverified or unsubstantiated hypotheses or models as well as of providing a false sense of precision. This, in turn, can mitigate the risks of mis- or even disinformation, which would carry significant social costs (OECD (2024b)).

Enforcing and monitoring transparency is particularly important when dealing with ESG indicators, for at least two reasons. First, they encompass a large variety of data and concepts – from geospatial hazard layers to firm-level emissions inventories, national transition plans and social responsibility – for which applying different definitions or treatments could result in diverging insights (OECD (2025)). Second, ESG indicators have gained prominence in supporting the assessment and rating of corporate performance, which has important financial implications. Hence their compilation calls for responsible business conduct, due diligence, reliable and actionable assurance levels for auditing ESG statements and, broadly, transparency

practices to prevent misleading behaviours such as greenwashing, especially when the data are self-reported (de Freitas Netto et al (2020); OECD (2023, 2024a); Elgg et al (2025)).

Against this setting, a number of actions appear necessary, starting with documenting data provenance. The dissemination of sustainability indicators should in particular be accompanied by systematic and transparent documentation about their origin (Viggo Sæbø et al (2020); Schubert (2025)). This is even more important as most these data make use of non-traditional sources which may be poorly documented yet widely available. This calls also for reinforcing feedback loops between alternative data providers and users of ESG information, both to improve the quality and consistency of new data sets and to adapt statistical compilation to evolving data needs. These challenges have been reinforced in recent years by the increasing use of innovative methods and novel information sources to bridge sustainability data gaps.

A second important focus point relates to documenting revisions, which can be large in a new area such as sustainability statistics, potentially limiting their usability and undermining public trust. Establishing transparent revision policies and clearly defined change protocols for communicating them to the users is therefore crucial. Such protocols should include procedures for notifying stakeholders about the degree of uncertainty involved and expected updates, clarifying the reasons for revision and providing detailed documentation as methods, sources and coverage evolve. Moreover, regular and structured communication channels can help users adapt to revisions while preserving confidence in the accuracy and relevance of the statistics produced. Such trust is a key element to maintain credibility in the statistical production chain, an issue of particular importance in the rapidly evolving, heterogeneous and complex ESG data ecosystem.

Robust statistical production pipelines

Reliable sustainability statistics require resilient data processes, including failure-proof infrastructure and business continuity arrangements. This calls for robust systems for data generation, storage, integration, access, analysis and dissemination. For example, given the multifaceted nature of ESG information, comprehensive, community-driven and multi-purpose open data platforms can be helpful to serve the various user needs effectively. As a case in point, the European Copernicus Climate Data Store provides harmonised data sets through a single interface for research and policy analysis. High-quality metadata are equally important for discoverability, trust and machine/AI readability. These efforts should sit within a comprehensive data governance framework, understood as a system of decision rights and accountabilities for data management (Križman and Tissot (2022); UNECE (2024)).

Well established data standards such as SDMx can facilitate these efforts. Its well structured information model can be a key enabler for metadata-driven processing, standardised statistical pipelines, stronger governance and operational efficiency. SDMx can also assist with innovative techniques, for example by supporting machine-readable formats while improving public access to documented and reliable data sets (IFC (2025c)).

A further priority concerns the statistical infrastructure itself. Better policy use of sustainability information requires improvements in data vocabularies, taxonomies and classifications, common entity identifiers, interoperable global registers, data-sharing arrangements and access to new information sources, including granular, geospatial and privately generated data. Developing more comprehensive and reliable forward-looking indicators is also key to inform scenario analysis, stress testing and transition planning. Lastly, the adequate use of innovation, including AI, can help improve coverage, timeliness and consistency, thereby facilitating central banks' use of ESG analyses across their various mandates.

d. Fourth focus point: comparability and global coordination

Because of their global nature, **sustainability issues need to be addressed comprehensively, requiring more comparable data across regions, sectors and jurisdictions**. Yet sustainability metrics have proved in practice to be highly dependent on local reporting specificities. Moreover, the lack of harmonised definitions across the various accounting and statistical frameworks will typically prevent temporal and/or spatial comparability, thereby further constraining analytical value. For instance, there are important differences in the taxonomies used across the world to define green financial instruments, making it difficult to assess the quality and consistency of the statistics produced (OECD (2020)). This diversity and the absence of commonly accepted global standards, especially as regards definitions of sustainable financial instruments and their assurance levels, may also facilitate a number of misleading practices, thereby further undermining the relevance and usefulness of the indicators being collected (Nefzi et al (2025b)).

Greater coordination among national and international stakeholders, including non-governmental, academic and private actors, can be essential to improve comparability. Enhanced cross-sector and cross-country comparisons would provide various benefits, including better informed policies, accelerated diffusion of good practices and data collection optimisation. It would also facilitate stronger engagement among official statisticians, economists, environmental scientists, technologists and market participants, in turn helping to improve data accuracy and the interpretation of compiled indicators.

Several global statistical initiatives are underway to improve the harmonised collection of sustainable statistics, particularly related to finance. The first stream relates to statistical concepts and definitions, building on the updates of key international statistical standards such as the 2025 SNA, BPM7 and the System of Environmental Economic Accounting Central Framework (SEEA CF). These manuals have, in particular, introduced clear statistical classifications, for example by defining "sustainability" breakdowns of financial instruments. A second avenue concerns the actual collection of sustainable indicators, especially under the third phase of the G20 DGI (IMF et al (2023)). A third focus point relates to the exchange of knowledge and best practices, including for central banks through platforms such as the NGFS or the activities of the IFC (Tissot (2022)). Lastly, the international community is actively supporting capacity-building across jurisdictions, by providing statistical technical assistance and fostering the development of adequate institutional settings.

Looking ahead, the quest for sustainability data could be advanced through a three-step action plan:

- First, **methodological frameworks should be strengthened**, building on global statistical initiatives already underway. The priority remains climate change data, but biodiversity, governance and social indicators should also be developed actively where concepts are sufficiently mature and data are available.
- Second, **the global statistical infrastructure should be upgraded to improve the usability of the wide range of sustainability data.** This calls for a renewed impetus for developing common standards, classifications, identifiers and registers as well as for integrating micro data and facilitating both the access to administrative and private data and their adequate sharing.
- Third, **data collections could be expanded gradually by leveraging those promising initiatives already developed across jurisdictions, including through the use of innovative data techniques and sources**. Success will depend on stronger global commitments and adequate resources, underscoring the importance of continued support from policy authorities.

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Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

The effects of annual reports on volatility: a European point of view

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This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

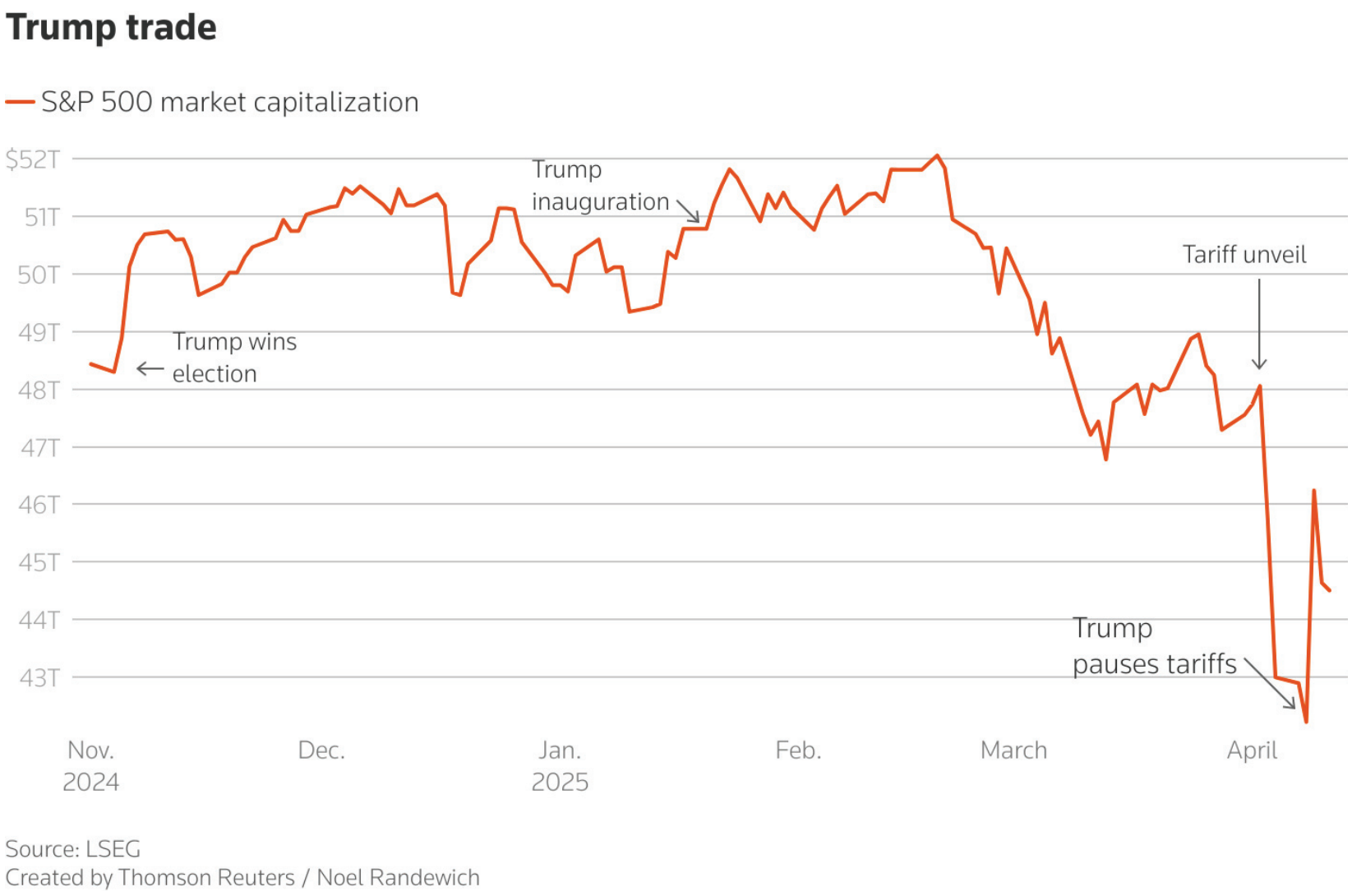
The effects of Annual Reports on Volatility: A European Point of View

Fulvio Raddi

Babeș-Bolyai University,
Raiffeisen Bank International

October 4, 2025

Motivation


Trump trade
S&P 500 market capitalization
$52T
51T
50T
49T
48T
47T
46T
45T
44T
43T
Trump inauguration
Tariff unveil
Trump wins election
Trump pauses tariffs
Nov. 2024
Dec.
Jan. 2025
Feb.
March
April
Source: LSEG
Created by Thomson Reuters / Noel Randewich

Assumptions and Research Question

- Financial Markets react **quickly** to events.
- Volatility cannot be entirely forecasted using historical data

Research Question

How much the emissions of annual reports affect the EURO STOXX 50 constituents?

From Keynes to FinBERT

The General Theory of Employment, Interest and Money, John Maynard Keynes (1936)

Most, probably, of our decisions to do something positive, the full consequences of which will be drawn out over many days to come, can only be taken as a result of **animal spirits** – of a spontaneous urge to action rather than inaction, and not as the outcome of a weighted average of quantitative benefits multiplied by quantitative probabilities."

FinBERT

FinBERT is a pre-trained NLP model to analyze sentiment of financial text. It is fine-tuning it for financial sentiment classification.

Text Data

Algorithm: For each annual report $i \in$ STOXX 50 of 2023 ,divide it in chunks (each one of 500 tokens), use FinBERT to label the chunks as positive, negative, or neutral. Then

$$a_i = \frac{\#neutral\ chunks}{\#total\ chunks},$$

$$b_i = \frac{\#positive\ chunks}{\#total\ chunks},$$

$$c_i = \frac{\#negative\ chunks}{\#total\ chunks}$$

Net Positivity Score

The *Net Positivity Score* x_i of a report i is defined as $x_i := b_i - c_i$.

Positive Tone

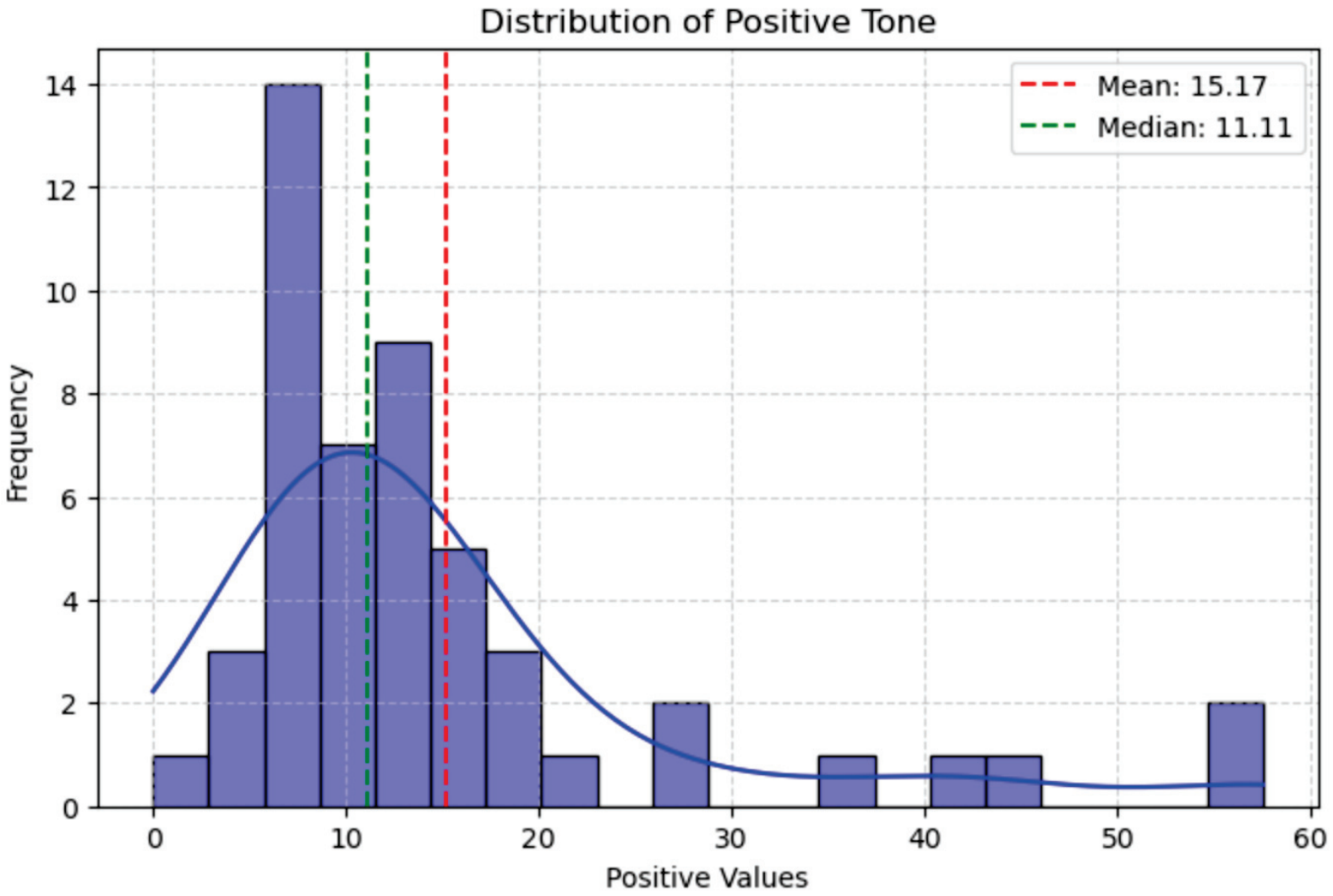


Figure: Histogram of Positive Tone across the reports

Negative Tone

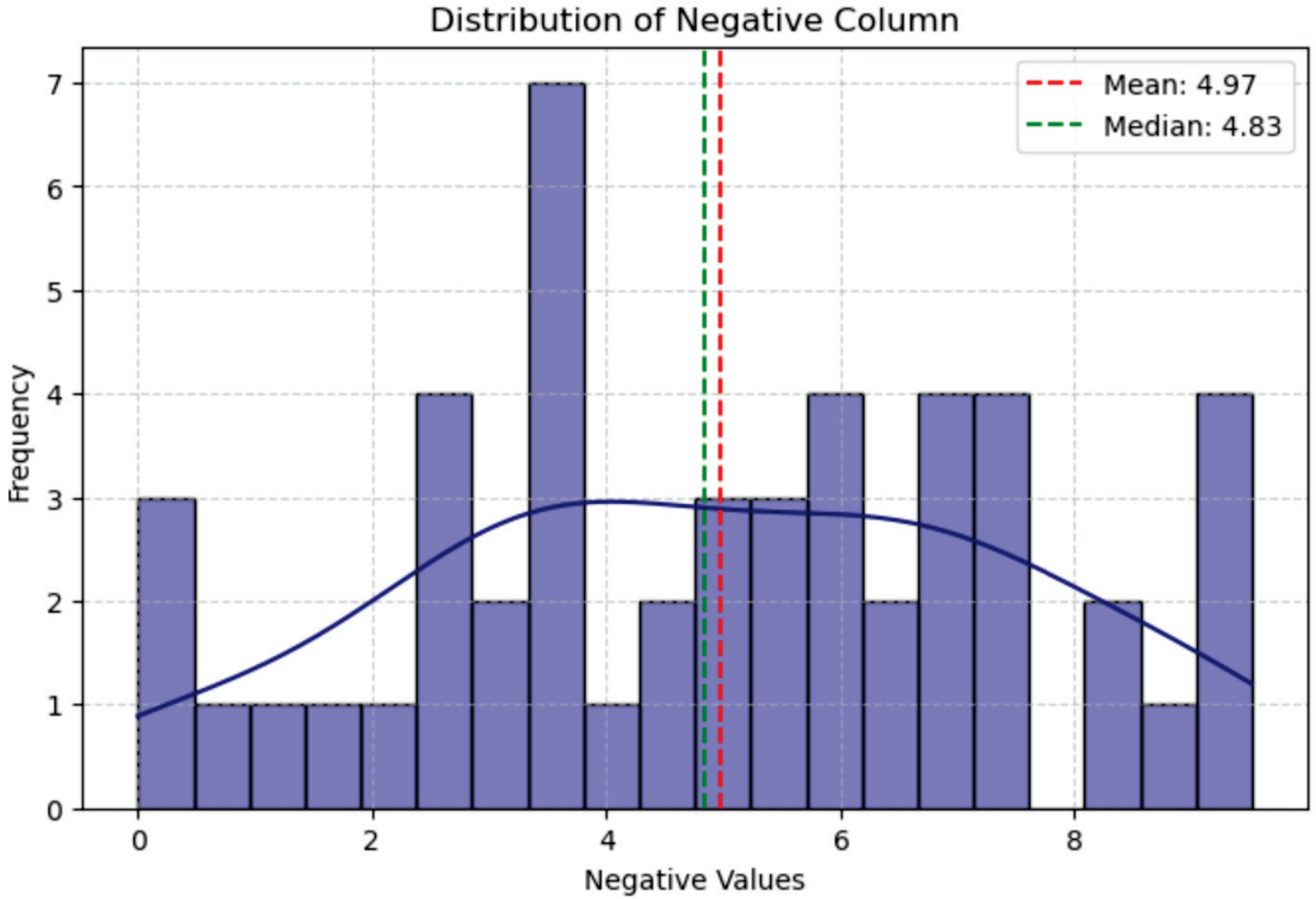


Figure: Histogram of Negative Tone across the reports

Neutral Tone

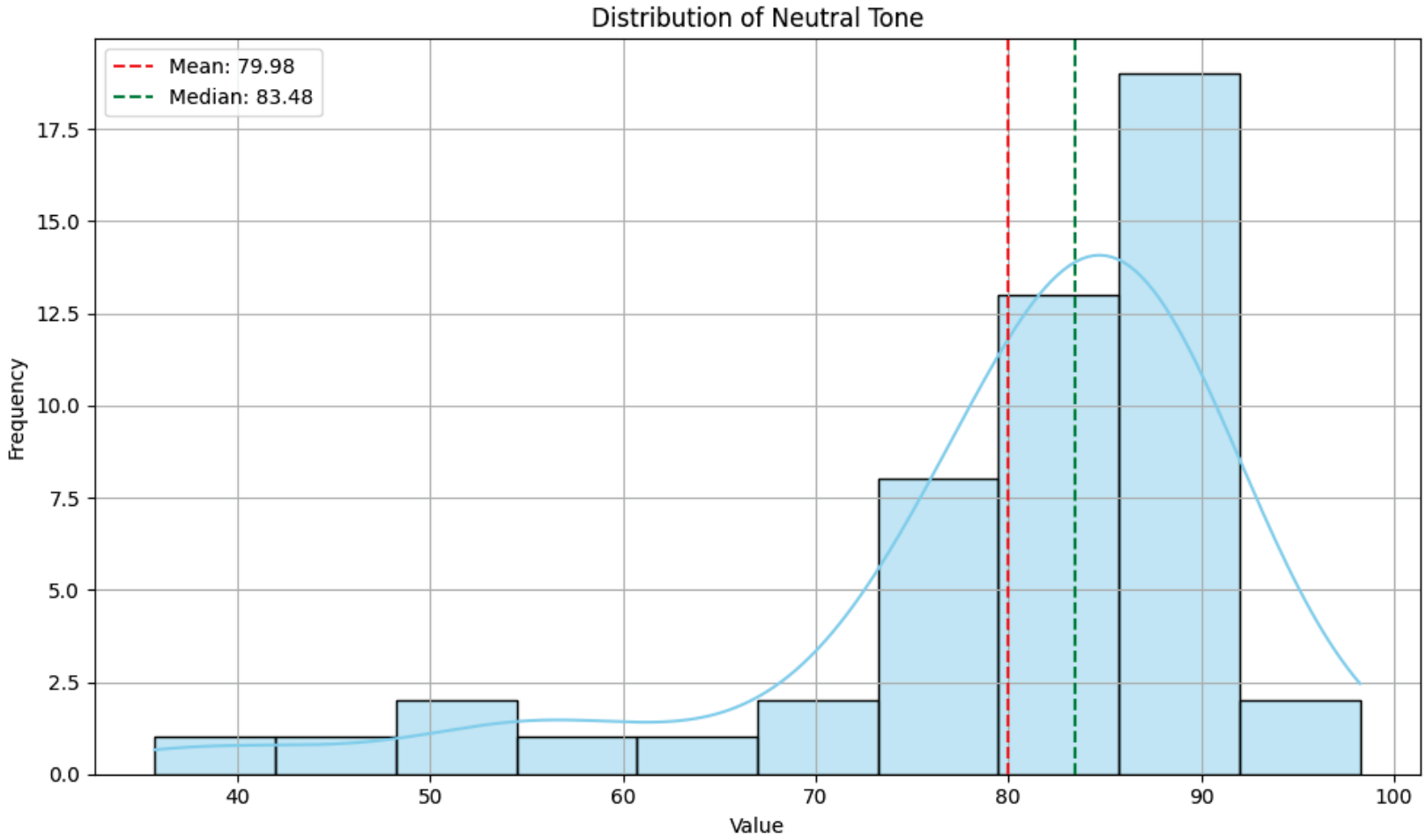


Figure: Histogram of Neutral Tone across the reports

Numerical Data and Model

Data: for each $i \in$ STOXX 50 we collect the daily log return $r_i(t)$ for $t = 1, ..., 7$, where $t = 1$ is the emission day of the annual report.

2-step EGARCH(1,1)

First step:

$$\log(\sigma_{t,i}^2) = \omega_i + \beta_i \log(\sigma_{t-1,i}^2) + \alpha_i \left(\left| \frac{\varepsilon_{t-1,i}}{\sigma_{t-1,i}} \right| - \sqrt{\frac{2}{\pi}} \right) + \gamma_i \cdot \frac{\varepsilon_{t-1,i}}{\sigma_{t-1,i}}$$

Second step:

$$\hat{\sigma} = \beta_0 + \beta_1 x + u_t$$

where x is the net positivity score.

Results

	Const	Net Positivity Tone
coef	-8.3924	0.0151
std err	0.102	0.006
t	-82.462	2.448
P $>$ | **t** |	0.000	0.015
[0.025, 0.975]	$[-8.592, -8.192]$	$[0.003, 0.027]$

Table: Regression Output Summary

R^2	95% Bootstrapped CI
0.015	$[0.0021, 0.0308]$

Table: R^2 and Bootstrapped Confidence Interval on the Tone

Conclusions

1. Derived a variable called *net positivity* score from a collection of annual reports of 2023 regarding the STOXX 50 index.
2. Used it to detect the local volatility after the emission dates.
3. There is a statistical contribution of the tone on explaining the local volatility, but it is not the main driver.

From Annual Report Sentiment to Market Risk

- Subtle deviations from neutral tone in annual reports influence market perception.
- Changes in report sentiment affect equity volatility.
- Increased volatility translates into CSPP/APP portfolio risk.

Policy Implications for CSPP/APP

- CSPP/APP portfolios are sensitive to sentiment-driven risk.
- Integrating sentiment analysis can complement traditional risk measures (ratings, spreads).
- Helps in managing portfolio risk proactively and sustainably.

Sentiment $\rightarrow$ Volatility $\rightarrow$ CSPP $\rightarrow$ Policy

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Q&A

Thanks for your attention!

Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Beat the heat: the role of heat waves and droughts on regional EU economies

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This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, the BIS, or the other central banks and institutions represented at the event.

Beat the Heat

The Role of Heat Waves and Droughts on Regional EU Economies

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Abstract

Heat waves and droughts pose growing risks to regional economic stability in the EU, requiring climate-aware nowcasting tools for climate policy-relevant sectors. Applying machine learning (ML) models (Random Forest and XGBoost) to mixed-frequency climate and economic indicators from 1,117 NUTS-3 regions between 2002 and 2022, this study demonstrates that predictions of real gross value added (GVA) growth is significantly improved with climate-augmented ML models, particularly in agriculture. A complementary simulation exercise quantifies the predictive contributions of concurrent extreme weather events to regional economies, revealing that agriculture could occasionally face yearly GVA growth reductions of up to −10 percentage points in Northern and Central Europe. Conversely, the broader industrial sector shows moderate simulated losses and manufacturing remains largely resilient. These findings underscore asymmetric vulnerabilities between sectors and regions and the value of predictive modelling for climate adaptation policy.

Keywords: regional productivity, weather extremes, heat waves, droughts, machine learning

JEL classification: C6, C8, E37, Q5

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Appendix 15

1. Introduction

Climate change presents asymmetric risks to economic and political stability, exacerbating regional disparities. In the European Union (EU), hot extremes are intensifying, particularly in Mediterranean countries (Seneviratne et al., 2021), underscoring the need for region-specific adaptation policies. Extreme heat already reduced European[1] Gross Domestic Product (GDP) by 0.3-0.5% and could reduce it by 1.5–2.5% till 2060, with respect to historical average GDP levels between 1981 to 2010 (García-León et al., 2021). Under a 3°C warming scenario, drought-related damages are projected to increase fivefold by 2100, relative to the baseline average of drought-related damages during 1981 to 2010, Mediterranean countries remaining the most affected (European Commission et al., 2020). Heat exposure could also reduce working hours by 15–60% in the RCP8.5 scenario[2] (Casanueva et al., 2020).

The literature studies how climate change affects the economy through multiple channels, including productivity losses, capital damage, and increased energy demand. Early research focused on long-term impacts, while recent studies indicate growing short- and medium-term risks from extreme weather. Macroeconomic models show persistent GDP losses, especially in vulnerable regions (Motta et al., 2025; Kahn et al., 2021; Dellink et al., 2019). Much of this work focused on agriculture, where rising temperatures and shifting rainfall have already slowed productivity (Wang et al., 2018; Praveen and Sharma, 2019). However, many studies rely on low-resolution data and linear methods, with machine learning (ML) tools still mostly limited to carbon tracking and pricing contexts (Li et al., 2022).

Few studies use ML to integrate climate and economic data for macroeconomic forecasting. One exception is Rossi et al. (2023), who applied ML to assess drought risks across interconnected EU systems[3], estimating sector- and region-specific losses under current and projected climate conditions. Their approach used Decision Tree Classifiers trained on detrended impact data, aggregated into vulnerability groups, and applied to historical (1979-2021) and future risk scenarios. Building on this, we employ Random Forest and XGBoost, ensemble tree-based methods. Random Forest mitigates overfitting via bootstrapped sampling and random feature selection, while XGBoost sequentially corrects residuals and applies regularisation.

Usman et al. (2024) analysed the impact of heat waves, droughts, and floods on regional production in the EU, following the nomenclature of territorial units for statistics (NUTS), over five years using a local projections difference-in-differences framework. They found that summer heat waves and droughts reduced annual production by 1.4 and 2.4 percentage points, mainly through declines in employment, hours worked, and productivity. Droughts caused persistent losses in agriculture, lower investment, and reduced productivity. Conversely, heat waves boosted capital investment but lowered productivity. The impact of floods varied: high-income regions saw reconstruction-driven growth, while low-income areas struggled to recover. Usman et al. (2025) extended this work, estimating that extreme weather in the summer of 2025 reduced gross value added (GVA) by €43 billion (0.26% of EU output), with cumulative losses projected to reach €126 billion by 2029, suggesting both immediate and lasting regional effects of extreme weather.

Based on Usman et al. (2024, 2025), we adopt a predictive framework using similar climate indicators to model heat waves and droughts. We compare linear regression with two ML models, Random Forest and XGBoost, to predict per capita real GVA growth in all NUTS-3 EU regions, focussing on climate-

[1] Including EU-27 countries, the United Kingdom and EFTA countries.

[2] RCP8.5 is one of the Representative Concentration Pathways (RCPs) used in climate science to model possible future greenhouse gas concentration trajectories and their impacts. It is often recognised as a worst-case scenario.

[3] Including agriculture, water supply, energy, river transport, and terrestrial and freshwater ecosystems.

relevant sectoral NACE aggregations A, B-E, and C.[4] These sectors, identified as possible targets of climate policies (Battiston et al., 2022), provide a rich dataset encompassing cross-country, within-country, and cross-sectoral variation. This heterogeneity enables a rigorous evaluation of how economic activity responds to climate conditions in linear and non-linear predictive frameworks. We also assess the compounded predicted consequences of overlapping climate events and regional spillovers. Model performance is evaluated through a nowcasting exercise that leverages mixed-frequency data and integrates feature importance analysis with climate event simulations.

Our results show that ML models can significantly improve the accuracy of regional economic nowcasts under climate stress, especially in agriculture. We show that ML models significantly outperform traditional linear regressions in nowcasting real growth in per capita GVA, particularly for the agriculture (A) and industrial (B–E) sectors when climate indicators for heat waves and droughts are included. Sectoral analysis highlights agriculture's pronounced sensitivity to climate extremes. In addition, compound and spatially correlated climate shocks amplify predicted economic losses, especially in low-GVA regions, although their associations remain heterogeneous across Europe. These findings support the use of predictive modelling for timely policy responses and stress the importance of sectoral and regional differentiation in climate adaptation strategies.

To complement the nowcasting analysis, we use a predictive model to simulate the potential contributions of compound scenarios that combine extreme heat waves and droughts to the predicted output, using a nowcasting model. Comparing a no-anomaly climate baseline with a compounded scenario, we find that agriculture suffers the largest simulated losses, with occasional reductions in yearly growth of up to ten percentage points in Northern and Central Europe, while Southern Europe exhibits less pronounced negative consequences, which contrasts with the findings of (European Commission et al., 2020). The industrial sector shows moderate reductions, while manufacturing remains largely resilient, highlighting sectoral differences in climate vulnerability and adaptive capacity.

The paper is structured as follows: Section 2 introduces the data; Section 3 develops the construction of compound climate indicators; Section 4 details the nowcasting methodologies and results; Section 5 presents the design of a simulation and its outcomes; and Section 6 concludes.

2. Data Description

This study builds predictive models for sectoral GVA using economic and climate data from 1,117 NUTS-3 regions between 2002 and 2022, including regional GVA by sector and employment-to-population ratios, and country-level GDP from Eurostat.

A key contribution of this paper is the integration of climate indicators from the Copernicus European Drought Observatory. Table 1 summarises the selected variables: Heat and Cold Waves Index (HCWI) for heat waves, Standardised Precipitation Index (SPI) for meteorological droughts (short- (SPI01), medium- (SPI06), and long-term (SPI12)), Low-Flow Index (LFI) for hydrological droughts, and Soil Moisture Anomaly (SMA) and Fraction of absorbed photosynthetically active radiation (fAPAR) for agricultural droughts.[5]

[4] Sector A covers agriculture; B–E includes mining and quarrying (B), manufacturing (C), electricity, gas, steam and air conditioning supply (D), and water supply, sewerage, waste management and remediation activities (E). Sector C is also modelled separately.

[5] The indices' methodologies are available at https://drought.emergency.copernicus.eu/data/factsheets.

Main Climate Variables

Table 1

Variable	Definition	Methodological Reference
HCWI	Heat and Cold Waves Index: Monitors daily minimum and maximum temperatures, identifying events lasting at least three consecutive days based on percentile thresholds from a 30-year climatology.	Lavaysse et al. (2018)
SPI	Standardised Precipitation Index: Detects meteorological droughts and floods by measuring precipitation anomalies over accumulation periods of 1, 6, and 12 months, comparing observed rainfall to long-term averages. Thresholds below −1 indicate drought conditions, while values above +1 signal excess rainfall or potential flooding.	McKee et al. (1993)
LFI	Low Flow Index: Detects periods of unusually low river discharge compared to long- term thresholds, updated every 10 days. Severity is classified from low to very high.	Cammalleri et al. (2017)
SMA	Soil Moisture Anomaly: Measures deviations in soil moisture from long-term averages, using daily data and 10-day updates. Values below −1 indicate drought stress, while values above +1 suggest unusually wet conditions.	de Roo et al. (2000)
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation: Measures deviations in photosynthetic activity from long-term averages, updated every 10 days. Negative anomalies, below −1, indicate drought-related stress, while positive anomalies, above +1 reflect enhanced vegetation growth under wetter or favourable conditions.	Bojinski et al. (2014)

Source: Copernicus European Drought Observatory

The climate variables used in the empirical analysis capture periods of abnormal conditions relative to long-term averages. Heat wave and drought severity are measured using standardised indices (Table 1), which define threshold values for anomalous events. Accordingly, the variables were coded to indicate only the occurrence of heat waves or droughts, while other conditions were set to zero.[6]

Our data show that most European regions have experienced an increase in the average annual heat wave days (Figure A.1). Summer heat waves were already pronounced in the Mediterranean and Nordic regions at the beginning of the century (Russo et al., 2015). Since then, the largest increases occurred in the Spanish Mediterranean, southern Italy, and northern and eastern Europe. Furthermore, comparing the average HCWI scores between the first and last five years (Table A.1) of the sample confirms that all countries now face more frequent and/or intense heat waves.

The average number of dry months per year, defined as SPI01 values below −1, suggests a trend toward increased dryness in Europe over the past two decades (Figure A.2). Southern Spain and parts of eastern Europe were already prone to frequent dry months in 2002–2006, but the rise between 2018–2022 and the earlier period highlights growing dryness in central Europe. Whereas regions in Finland saw early anomalies that later subsided, areas such as Germany experienced a persistent increase. Country-level SPI data across accumulation periods (Table A.1) reinforce this spatial pattern, indicating a shift toward drier conditions consistent with intensifying meteorological drought in central Europe.

An assessment of hydrological and agricultural drought, indicated by mean LFI values greater than 0 and mean SMA figures below −1, reveals patterns similar to meteorological drought (Figures A.3 and A.4). Between 2002 and 2006, Spain, eastern Europe, and Scandinavia on average recorded up to eight hydrological and five agricultural dry months annually. From 2018 to 2022, these regions, along with parts of France and central Europe, experienced further increases, indicating increased intensity and spread of hydrological and agricultural drought conditions.

[6] Heat waves and droughts are characterised by HCWI and LFI > 0 and SPI, SMA, and fAPAR ≤ −1.

3. Calculating Compounding Indicators

We account for the compounding nature of climate events shaped by temporal and geographic factors. Temporal compounding is addressed by incorporating event duration into climate variables, so that longer events yield higher severity indices, while geographic compounding is addressed by incorporating a variable accounting for the climate conditions across neighbouring regions. Lastly, we introduce a feature to account for the coincidence of heat waves and droughts.

Localised climate shocks can trigger spillover price effects, such as the 50% increase in EU olive oil prices after droughts in Spain and Italy (Kotz et al., 2025), while heat-induced productivity losses cascade through supply chains (Sun et al., 2024). To analyse how spatially compounding heat waves and droughts are associated with GVA, we compute regional averages of climate features across neighbouring areas. For each region r, geographical compounding of a climate indicator $GC^X_{t,r}$ is defined as the mean value of that indicator in neighbouring regions N_{r^*}:

$$GC^X_{t,r} = \frac{1}{|N_{r^*}|}\sum_{i \in N_{r^*}} X_{t,i}\,, \text{ where } X_{t,r} \in \{HCWI_{t,r}, SPI01_{t,r}, SPI06_{t,r}, SPI12_{t,r}, LFI_{t,r}\} \quad (1)$$

where variables are indexed by time (t) and region (r), $X_{t,i}$ represents the climate indicator in region i from the subset of neighbouring regions (r^*) of r. We exclude agricultural drought indicators (SMA and fAPAR) from this aggregation since, within the short- to medium-term nowcasting window, they exhibit minimal cross-regional compounding effects (Sepulcre-Canto et al., 2012). Geographic compounding captures shared climate systems and cross-border influences, refining regional exposure measures. Correlation analysis shows weak intercorrelations among individual indicators but strong associations (0.6–0.9) between geographic compounding variables and their respective features (X). Such multicollinearity challenges linear models but is mitigated in ML through regularisation techniques that shrink or penalise correlated coefficients.

Usman et al. (2024) show that concurrent heat waves and droughts significantly reduce medium-term regional output, especially in less wealthy areas. Studying these compound events is essential to understand their predictive contributions. In our models, compounding is captured by variables interacting HCWI and SPI. To ensure comparability, each indicator (V) is scaled using Min-Max normalisation with a zero lower bound as follows:

$$\tilde{V}_{t,r} = \frac{V_{t,r} - \min(V)}{\max(V) - \min(V)}, \quad (2)$$

We model heat wave–drought compounding by interacting the scaled HCWI and SPI across accumulation periods $p \in \{1,6,12\}$. The compounding indicator $EC_{t,r}$ for each p is defined as:

$$EC^p_{t,r} = \begin{cases} \widetilde{HCWI}_{t,r} \times \left|\widetilde{SPI^p_{t,r}}\right|, & \text{if } HCWI_{t,r} > 0 \text{ and } SPI^p_{t,r} \leq -1 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

with the indicators for each p aggregated as:

$$EC_{t,r} = f_{p \in P}\left(EC^p_{t,r}\right) \quad (4)$$

This formulation captures concurrent heat wave–drought events by multiplying heat stress (HCWI) and drought severity (SPI) across accumulation periods p. The indicator activates only when a heat wave occurs ($HCWI > 0$) along with a meteorological drought ($SPI \leq -1$). Multiple SPI periods reflect differing drought-related ecological outcomes. However, due to sparsity, indicators from all periods are combined into a single measure as shown in Equation 4[7]. Coinciding events were most frequent in Mediterranean

[7] The functional form of $f_{p \in P}(\cdot)$ in Equation 4 depends on the mixed-frequency approach in Section 4.1, whereby a singular factor is extracted from the monthly aggregates of the different $EC^p_{t,r}$ for every p.

countries, primarily Italy, Spain, Cyprus and Malta, and parts of Central and Eastern Europe, notably Germany and Hungary, predominantly in later years.

4. Nowcasting Exercise

Predictive Approaches

For sector s, with variables indexed by time t, region r and country c, Equation 5 shows our baseline economic model and Equation 6 presents the climate-augmented version. Model 5 predicts real GVA per capita growth ($Y_{t,r,s}$) using its lag ($Y_{t-1,r,s}$), sectoral employment share ($E_{t,r,s}$), lagged country GDP growth ($G_{t-1,c}$), geographic controls (M_r, R_r, C_r), and a NUTS-3 indicator (N_r). Model 6 extends f_{ECON} with climate variables capturing heat waves, droughts, and their geographical[8] and event compounding. Parameters and hyperparameters are denoted by $\theta_{ECON,s}$ and $\theta_{CLIM,s}$.

$$Y_{t,r,s} = f_{ECON}\left(Y_{t-1,r,s}, E_{t,r,s}, G_{t-1,c}, M_r, R_r, C_r, N_r;\ \theta_{ECON,s}\right) \tag{5}$$

$$Y_{t,r,s} = f_{CLIM}\begin{pmatrix} Y_{t-1,r,s}, E_{t,r,s}, G_{t-1,c}, HCWI_{t,r}, SPI01_{t,r}, SPI06_{t,r}, SPI12_{t,r}, \\ LFI_{t,r}, SMA_{t,r}, fAPAR_{t,r}, GC_{t,r}, EC_{t,r}, M_r, R_r, C_r, N_r;\ \theta_{CLIM,s} \end{pmatrix} \tag{6}$$

Geographic controls identify mountainous (M_r), rural (R_r), and coastal (C_r) regions. Overall, 44.0% of regions are mixed urban–rural, 35.3% predominantly rural, 20.7% urban; 26.7% include mountain areas, and 29.1% are coastal. These fixed factors influence production, connectivity, and regional heterogeneity. To capture additional heterogeneity, we encode NUTS-3 labels (N_r)[9]. This approach avoids transforming the target and offers a low-dimensional alternative to fixed effects, following Yang et al. (2024) on incorporating cross-sectional attributes in ML panel models.

Our approach addresses the frequency mismatch between yearly economic and daily climate data by applying three mixed-frequency methods, grouped into aggregation and feature extraction techniques (Li et al., 2022) as follows:

1. **Yearly Aggregation:** Climate variables are aggregated to yearly medians and standard deviations, capturing levels and volatility. Deviations from historical averages and within-month variability are measured using the median of monthly standard deviations, following Ciccarelli et al. (2023).[10]

2. **Feature Extraction:** Annual climate indicators are derived from monthly medians data using principal component analysis (PCA) and mixed data sampling (MIDAS), which condense high-frequency variables for each indicator into a single interpretable feature.[11]

We employ two complementary feature-extraction methods: an unsupervised approach (PCA) that summarises climate variation independently of the target variable, and a supervised approach (MIDAS) that aggregates high-frequency indicators using beta-distributed lag weights. The beta weighting

[8] Geographical compounders, $GC^X_{t,r}$ for $X_{t,r} \in \{HCWI_{t,r}, SPI01_{t,r}, SPI06_{t,r}, SPI12_{t,r}, LFI_{t,r}\}$, are represented by $GC_{t,r}$.

[9] CatBoost encoding replaces categories with smoothed conditional means of the target, while applying Bayesian smoothing to reduce overfitting and carefully incorporating the global mean to prevent data leakage.

[10] Geographic compounding variables remain separate, while event-compounding indicators across drought durations are averaged via $f_{p\in P}(\cdot)$ in Equation 4 to reduce sparsity.

[11] Geographic compounding variables ($GC^X_{t,r}$) are included with their base indicator X. This setup reduces multicollinearity by extracting a singular feature for each climate indicator. Event compounding indicators ($EC^p_{t,r}$) are combined using PCA or MIDAS, so $f_{p\in P}(\cdot)$ in Equation 4 applies the chosen extraction method, reducing sparsity.

scheme parsimoniously captures the delayed, non-linear influence of past climate conditions, i.e. the gradual build-up, peak, and decline of droughts and heat waves (Duo, 2025).

To estimate and compare nowcasting performance for $Y_{t,r,s}$, we employ a linear regression benchmark (Martín Cervantes et al., 2020; Kahn et al., 2021; Mohaddes et al., 2022) and two tree-based ML models, Random Forest and XGBoost. The models are trained on data up to 2017 and evaluated out-of-sample. These ensemble methods are well suited to capture non-linearities and interactions between climate and economic variables (Rossi et al., 2023).

Random Forest builds an ensemble of decision trees on bootstrapped samples, introducing randomness by selecting predictor subsets at each split. For each input, the prediction is the average across trees, reducing variance and making Random Forests robust to overfitting in the presence of collinear climate indicators, while providing interpretable variable importance (Breiman, 2001; Pedregosa et al., 2011). XGBoost, in contrast, sequentially adds trees to correct residuals, based on the learning rate. It improves gradient boosting with second-order gradients and regularisation, making it effective for modelling non-linear climate–economic dynamics (Chen and Guestrin, 2016).

Model performance, based on Equations 5 and 6, is evaluated through a nowcasting exercise using an expanding rolling window and out-of-sample root mean squared errors (RMSEs). To interpret predictions, we apply SHAP (SHapley Additive exPlanations) values to identify key predictive drivers, particularly climate variables influencing $Y_{t,r,s}$. SHAP values fairly attribute feature contributions across all combinations, offering transparent insights (Shapley, 1953; Lundberg et al., 2018).

Nowcasting Results

Table 2 reports RMSEs from the nowcasting exercise, revealing clear contrasts between linear and ML models across sectors. Predictive ability testing indicates that climate-augmented linear models were unable to significantly outperform f_{ECON} for all sectors, whereas ML models show sector-specific gains. For agriculture, climate-augmented ML models significantly improved accuracy over f_{ECON}, driven by heat wave and drought indicators. In contrast, f_{CLIM} did not surpass f_{ECON} for sectors B–E and C within the same model class and sector. However, ML predictions for B–E significantly outperformed all linear counterparts, while most ML predictions for sector C did not.

Nowcast RMSEs

Table 2

Model	Linear Regression			Random Forest			XGBoost		
	A	B-E	C	A	B-E	C	A	B-E	C
Economic (f_{ECON})	21.64	14.11	77.9	23.05	13.83†	72.81	28.15	13.89†	76.73†
Climate (f_{CLIM})									
Medians & St. Deviations	22.12	14.20	77.95	20.93*†§	14.01†	73.64	20.54*†§	13.95†	77.69
PCA Features	22.23	14.17	77.91	21.05*†	13.94†	74.03	21.52*†	14.03†	77.80
MIDAS Features	22.98	14.36	78.03	21.18*†	14.06†	75.19	21.72*†	13.97†	85.34

Note: RMSEs are calculated over annual nowcasts of $Y_{t,r,s}$ from 2018 to 2022. Sector A covers agriculture; B–E includes mining (B), manufacturing (C), utilities (D), and waste management (E), with C also modelled separately to obtain direct predictions for manufacturing. The symbols to denote statistically significant improvements in predictive performance are: $*\ p < 0.05$ indicates predictive improvements relative to the respective economic counterpart of the same model type; † $p < 0.05$ indicates predictive improvements relative to the respective linear regression counterpart; and § $p < 0.05$ indicates predictive improvements relative to the respective linear economic model for the same sector.

Among the climate-augmented models, the simpler aggregation of climate variables into yearly medians and standard deviations performs at least as well as, and often better than, the more complex PCA and MIDAS feature-extraction techniques. As shown in Table 2, this specification generally yields the most accurate climate-augmented nowcasts of $Y_{t,r,s}$, particularly in agriculture, where it significantly outperforms both the corresponding economic model and the linear regression benchmark.

SHAP values combined with factor loadings reveal key patterns in model predictions (Figures A.5 and A.6). Economic variables remain most predictive, but climate and geographic factors also matter, varying by sector and specification. HCWI is consistently influential in climate-augmented models, while drought indicators show sector-specific relevance. In agriculture, heat wave indicators[12] dominate, alongside short- to medium-term meteorological drought (SPI01, SPI06). In sectors B–E and C, heat waves retain influence, but drought importance shifts to hydrological measures and long-term droughts (LFI, SPI12). These differences highlight sectoral dynamics and ML's ability to adjust weights via regularisation, enhancing climate-augmented models over linear ones. The prominence of heat waves aligns with Usman et al. (2024), showing strong short-term contributions, while droughts indicate medium- to long-term contributions.

Strong regional heterogeneity in how heat waves, droughts, and their interactions affect outcomes is revealed by SHAP values. Heat waves influence both high- and low-GVA regions[13], sometimes benefiting higher-GVA areas, while droughts disproportionately harm lower-GVA regions. Climate-related predictive contributions are more pronounced in below-median GVA regions, underscoring their vulnerability. Consistent with this, Usman et al. (2025) find that droughts cause persistent losses in low-GVA regions, while some high-GVA regions may gain short-term benefits from heat waves, highlighting asymmetric climate vulnerability.

Geographic compounding indicators have a pronounced influence on predicted outcomes, reflecting both competitive and complementary dynamics[14]. Regions often exhibit beneficial associations when neighbours face heat waves, consistent with competitive dynamics, while the contributions of hydrological drought are mixed, suggesting complementarity shaped by geography and trade routes and competitive behaviours being evident when drought conditions force deviations from established routes. Dellink et al. (2019) demonstrate that climate-induced economic effects vary significantly between regions, with some benefiting from neighbouring disruptions due to trade and sectoral shifts, while others suffer compounded losses, underscoring these dynamics and the need to study them within integrated ecological–economic systems.

The interplay between heat waves and droughts can amplify, offset, or mirror their individual contributions, highlighting the complexity of compound climate shocks[14]. Event-based indicators are especially relevant in models using feature extraction, where factor loadings vary non-linearly across drought horizons. Under the Medians & St. Deviations definition of f_{CLIM}, which weights drought horizons equally, SHAP values suggest that the joint contribution is generally smaller than the sum of individual values. In contrast, feature extraction yields more diverse outcomes: agricultural predictions are driven by short-term droughts, while sectors B–E and C respond more to long-term droughts. This reflects sectoral sensitivities, where agriculture reacts to immediate vegetation stress, whereas industry is more affected by hydrological drought. These findings align with Zhu and Li (2024), who show climate risks have non-linear,

[12] Includes yearly median, standard deviation, and geographic compounding for the Medians & St. Deviations version of f_{CLIM}, and extracted features for PCA- and MIDAS-based implementations.

[13] High- and low-GVA regions are defined by a time-invariant distribution of real GVA per capita growth, with low (high) regions below (above) the midpoint.

[14] Supporting data is reported in Figures A.5 and A.6, and Tables A.2, A.3 and A.4.

sector-specific economic effects, and Yin and Slater (2023), who find compound events often diverge from additive impacts, underscoring the need for models that capture sectoral and temporal nuances.

5. Application: A Simulation of Extreme Compounded Events

Simulation Design

To further examine the influence of heat waves and long-term meteorological droughts on GVA growth, we design a comparative analysis of two distinct scenarios: the *non-event* and *event* scenarios. These simulations are estimated using XGBoost with the yearly aggregation approach.[15]

The *non-event scenario* is a counterfactual where sectoral real GVA growth evolves without contributions from heat waves or droughts. All climate variables are set to baseline values, where the heat wave and drought indicators, including their standard deviations, are set to zero, while economic variables remain as observed. In contrast, the *event scenario* keeps economic variables as observed but simulates climate conditions for heat waves and droughts. Specifically, we set HCWI and LFI to their 99th percentile values, whilst all other climate indices were set to their 1st percentile values, of each variable's pooled series across regions and years. This simulation design ensures the reflection of the compounding effect of heat waves and hydrological drought, whilst mitigating the influence of other forms of droughts. Additionally, given that our climate variables are expressed as indices rather than absolute measures of temperature or precipitation, applying the same percentile threshold of heat waves and droughts represents comparable extremity levels across all NUTS-3 regions.

The predicted GVA growth rates under the event and non-event scenarios are denoted by $\hat{y}^{*}_{t,r,s}$ and $\hat{y}_{t,r,s}$, respectively. The simulation of the compounded heat wave and long-term drought event on $Y_{t,r,s}$, $\Delta\hat{y}_{t,r,s}$, is calculated as the difference between these predictions, such that:

$$\Delta\hat{y}_{t,r,s} = \hat{y}^{*}_{t,r,s} - \hat{y}_{t,r,s} \ .$$

Simulated Outcomes

The simulated values of the compounded heat wave and hydrological drought event on $Y_{t,r,s}$, described in Section 5, is averaged over the timespan of 2002 to 2022 at the NUTS-3 level for each sector.

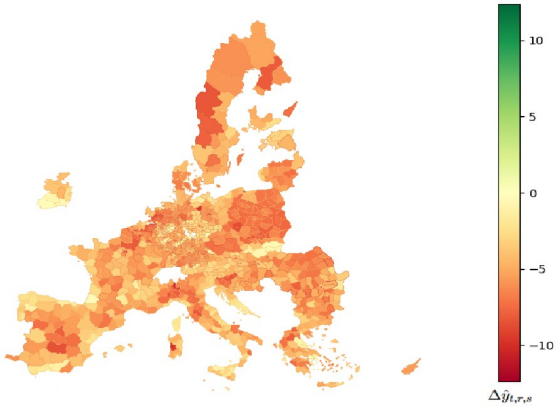
The outcomes of the simulation, depicted in Figure 1, show that EU agriculture would experience widespread negative contributions from compounded heat wave and drought events, with simulated values ranging from approximately -10 to 0 percentage points,[16] indicating substantial regional heterogeneity in the magnitude of $\Delta\hat{y}_{t,r,s}$. Northern Europe, especially Scandinavia and the Baltics, faces the most severe simulated losses (around -8 percentage points), while Central regions, such as Germany, Poland and France, experience moderate to severe simulated consequences (-4 to -8 percentage points). Southern Europe would experience less severe negative outcomes. The spatial distribution suggests that agricultural systems in cooler, traditionally less drought-adapted regions may be disproportionately sensitive to extreme compound climate events, possibly due to lower baseline resilience to simultaneous heat and water stress conditions, as indicated by Lesk et al. (2022) and Tabari and Willems (2023).

[15] This model and approach were chosen since it generally resulted in the lowest RMSEs for the climate-augmented models as described in Section 4.2.

[16] The 5th and 95th percentiles of $\Delta\hat{y}_{t,r,s}$ for agriculture equals -9.78 and 0, respectively.

Simulation of Heat Waves & long-term Drought on Sector A

Figure 1

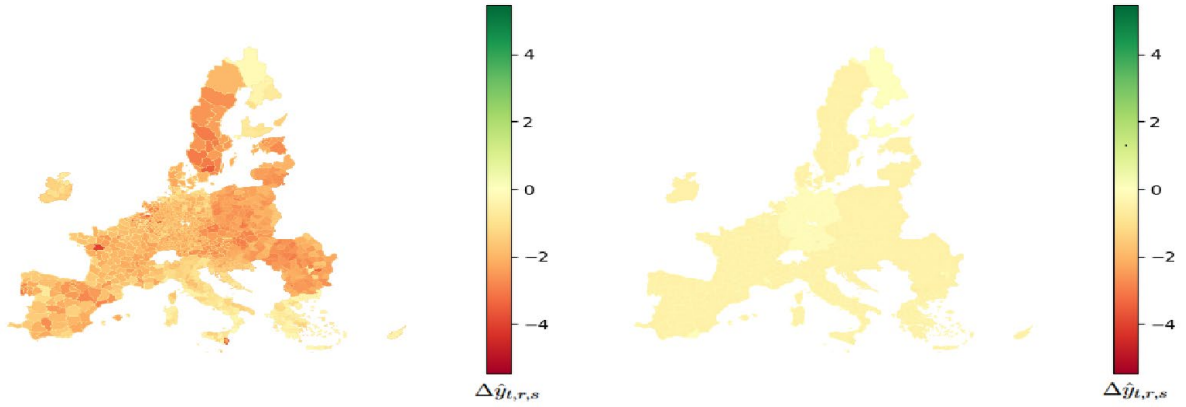


Note: Figure 1 illustrates $\Delta\hat{y}_{t,r,s}$ for agricultural (A) GVA growth from a compounded heat wave and long-term drought across the EU. The figure displays the differences between the non-event and event scenarios defined in section 5, using a green-to-red gradient (positive to negative differences of ten percentage points).

Source: Authors' calculations

Simulation of Heat Waves and long-term Drought on Sectoral Aggregates B-E (left) & C (right)

Figure 2



Note: Figure 2 illustrates $\Delta\hat{y}_{t,r,s}$ on industrial (B-E, left) and manufacturing (C, right) GVA growth from a compounded heat wave and long-term drought across the EU. The figure displays the differences between the non-event and event scenarios defined in section 5, using a green-to-red gradient (positive to negative differences of four percentage points).

Source: Authors' calculations

The simulation results for the broader industrial and energy sector, shown on the left of Figure 2, reveal moderate but spatially heterogeneous negative outcomes across the EU, with most NUTS-3 regions experiencing GVA growth reductions of 0-2 percentage points under our compound heat wave and drought scenario.[17] Northern and Central Europe, especially Germany, northern France, Poland, and Scandinavia, are most affected, reflecting the vulnerability of energy-intensive industries and thermal power generation to heat stress. Southern regions show milder simulated values, likely due to existing adaptation measures and infrastructure suited to higher baseline temperatures.

[17] The 5th and 95th percentiles of $\Delta\hat{y}_{t,r,s}$ for sectors B-E equal -2.3 and 0, respectively.

The right panel of Figure 2 indicates that the manufacturing sector remains largely unaffected by compound heat wave and drought events, with real GVA per capita simulated losses up to 0.5 percentage point across the EU.[18] This resilience from extreme weather events likely stems from controlled indoor environments, lower water dependency, and advanced climate control systems. The uniform pale-yellow shading reflects stable productivity, supported by automation and reduced exposure to ambient conditions, unlike agriculture or energy sectors.

6. Conclusion

This paper examines how extreme heat waves and droughts affect regional economic performance of three NACE sectoral aggregations across EU NUTS-3 regions. Using mixed-frequency data and ML models (Random Forest and XGBoost), we find statistically significant improvements in nowcasting accuracy over linear regression, especially in agriculture. Climate variables, such as heat wave intensity and short- to medium-term drought indicators, play a key role in predicting real GVA per capita growth in this sector, compared to other sectors.

Our nowcasting results suggest that climate-augmented ML models outperform both economic and linear regression benchmarks in out-of-sample RMSEs. In agriculture, using climate indicators within ML models, especially yearly medians and standard deviations, significantly improves accuracy. For industrial sectors (B–E and C), climate data adds less value, though ML models still outperform regressions for sectoral aggregation B-E. Complex feature extraction methods like PCA and MIDAS offer no clear advantage over simpler aggregations, suggesting that interpretability and parsimony are preferable.

The findings reveal substantial heterogeneity in climate vulnerability between sectors and regions. Agriculture is highly sensitive to climate stress, while industrial sectors show more complex responses, particularly to hydrological droughts. Geographic and event-based compounding tend to further amplify negative contributions to predicted economic outcomes, especially in low-GVA regions, underscoring the asymmetric nature of climate contributions across Europe. These results support the use of predictive modelling to guide timely and targeted policy responses and highlight the importance of sectoral and regional differentiation in climate adaptation strategies.

Simulation results confirm sectoral differences in climate vulnerability. Under compound heat wave and hydrological drought scenarios, agriculture faces widespread simulated real GVA growth losses, with Northern and Central Europe seeing reductions up to -10 percentage points. The broader industrial sector (B-E) shows moderately negative $\Delta\hat{y}_{t,r,s}$ values (up to 2 percentage points), especially in energy-intensive regions. In contrast, manufacturing remains resilient, with minimal reductions (up to 0.5 percentage points), reflecting its controlled environments and lower exposure to weather stress.

Nonetheless, several limitations constrain the interpretability and generalisability of our results. First, the use of yearly aggregations and feature extraction techniques may obscure the temporal dynamics and lagged contributions of climate variables. Second, the study employs a limited set of models; as results may vary with alternative ML architectures or more advanced econometric approaches. Third, economic benchmark models rely on a narrow set of variables, and more sophisticated specifications could present more challenging benchmarks for ML models. Finally, the nowcasting results and feature importance values are sensitive to the chosen time periods and may vary across forecast horizons and regional contexts.

[18] The 5th and 95th percentiles of $\Delta\hat{y}_{t,r,s}$ for sector C equal -0.5 and 0, respectively.

Future research could address these limitations by expanding the set of models, both ML and econometric, and refining climate indicators to better reflect sector-specific vulnerabilities. This includes tuning the selection of heat wave and drought indicators to the sector being nowcasted, incorporating additional economic variables, and extending the analysis to additional sectors beyond agriculture and industry. Moreover, shifting the focus to price dynamics and regional migration patterns could offer deeper insights into the socio-economic consequences of weather extremes and their transmission across regions.

This study contributes to the growing literature on climate–economic modelling by demonstrating the value of predictive modelling approaches to better understand and respond to climate-induced economic risks. The integration of climate data into regional economic nowcasting may not only enhance accuracy but also support the development of more resilient, timely and adaptive policy frameworks across the EU.

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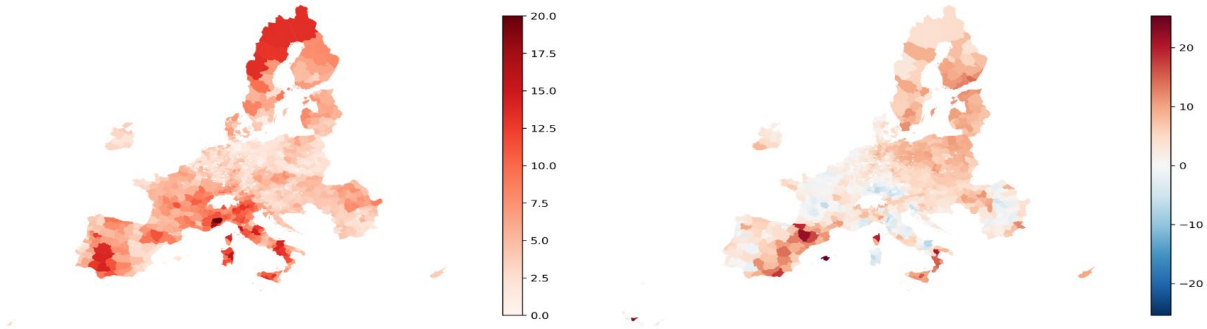
Appendix

Heat Waves over the Hotter Months (May to September)

Figure A.1

(a) Average Heat Wave Days in 2002-2006

(b) Change in Averages between 2018-2022 & 2002-2006



Note: Figure A.1 illustrates heat wave patterns across Europe during the summer months (May to September). Panel (a) presents the average annual number of heat wave days recorded between 2002 and 2006, using a white-to-dark red gradient (0 to 20 average heat wave days). Panel (b) depicts the change in frequency between 2018 and 2022 relative to the earlier period—calculated as the average annual number of heat wave days in 2018–2022 minus that of 2002–2006. The colour gradients convey the intensity of heat wave activity, with red indicating an increase in frequency and blue representing a decline.

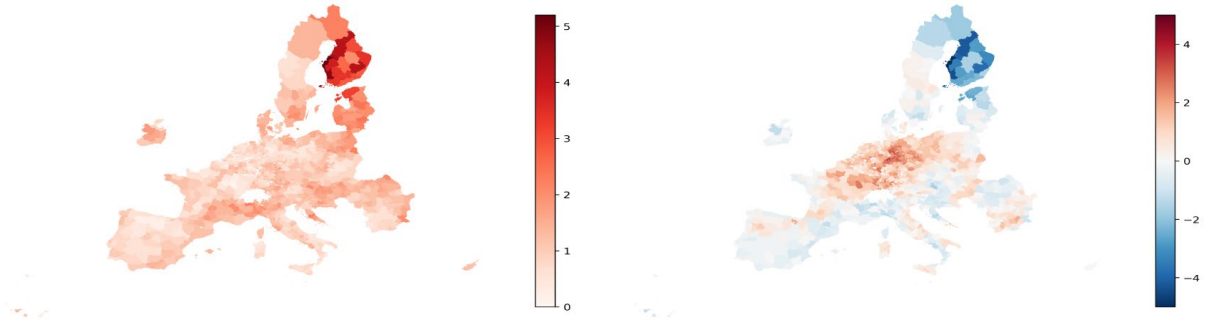
Source: Authors' calculations using HCWI from the Copernicus European Drought Observatory.

Average Number of Meteorological Dry Months (Mean SPI01 < -1) per Year

Figure A.2

(a) Average Number of Dry Months in 2002-2006

(b) Change in Averages between 2018-2022 & 2002-2006



Note: Figure A.2 compares meteorological dry month patterns across Europe. Panel (a) shows the average number of dry months per year from 2002–2006, using a white-to-dark red gradient (0 to 5 months). Panel (b) displays the change in averages between 2018–2022 and 2002–2006, with a blue-to-red gradient indicating decreases and increases, respectively. Dry months are defined as those with mean SPI01 values below −1.

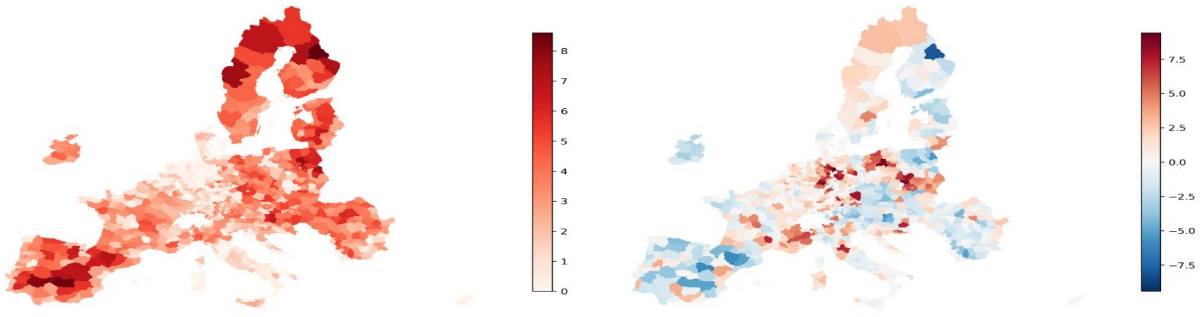
Source: Authors' calculations using SPI01 from the Copernicus European Drought Observatory.

Average Number of Hydrological Dry Months (Mean LFI > 0) per Year

Figure A.3

(a) Average Number of Dry Months in 2002-2006

(b) Change in Averages between 2018-2022 & 2002-2006



Note: Figure A.3 compares hydrological dry month patterns across Europe at the NUTS-3 regional level. Panel (a) shows the average number of dry months per year from 2002–2006, using a white-to-dark red gradient (0 to 8 months). Panel (b) displays the change in averages between 2018–2022 and 2002–2006, with a blue-to-red gradient indicating decreases and increases, respectively. Dry months are defined as those with mean LFI values above 0.

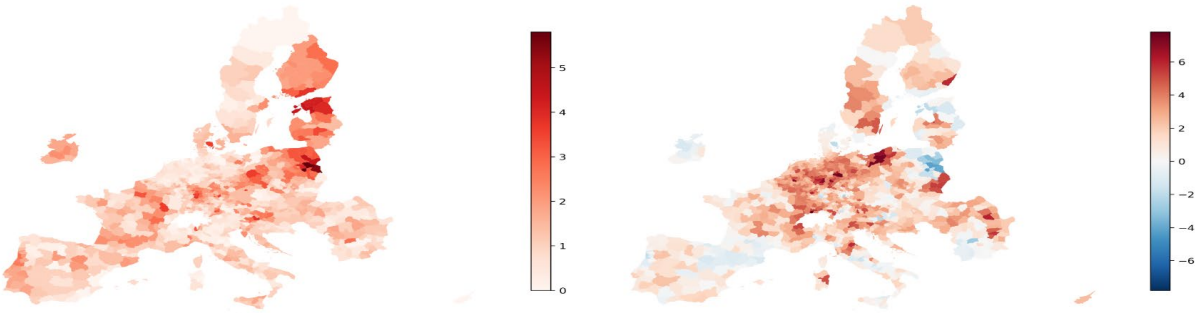
Source: Authors' calculations using LFI from the Copernicus European Drought Observatory.

Average Number of Agricultural Dry Months (Mean SMA < -1) per Year

Figure A.4

(a) Average Number of Dry Months in 2002-2006

(b) Change in Averages between 2018-2022 & 2002-2006



Note: Figure A.4 compares agricultural dry month patterns across Europe at the NUTS-3 regional level. Panel (a) shows the average number of dry months per year from 2002–2006, using a white-to-dark red gradient (0 to 5 months). Panel (b) displays the change in averages between 2018–2022 and 2002–2006, with a blue-to-red gradient indicating decreases and increases, respectively. Dry months are defined as those with mean SMA values below −1.

Source: Authors' calculations using SMA from the Copernicus European Drought Observatory.

Average SPI and HCWI values by country and period

Table A.1

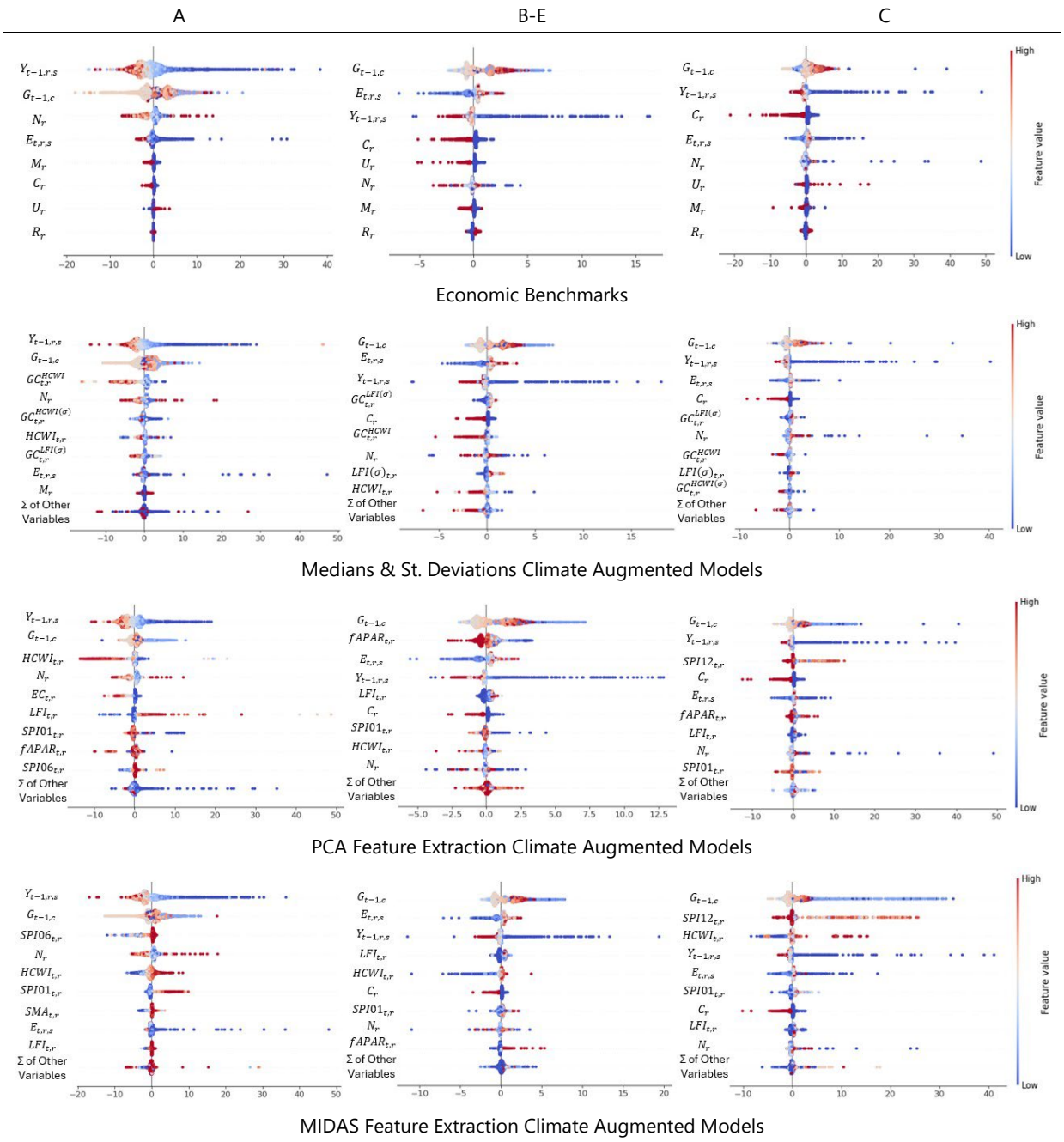
Country	Average Values Over 2002–2006				Average Values Over 2018–2022			
	SPI01	SPI06	SPI12	HCWI	SPI01	SPI06	SPI12	HCWI
Austria	0.0000	-0.0058	-0.0084	0.6131	0.0000	-0.0268	-0.0558	1.2414
Belgium	0.0000	-0.0125	-0.0438	0.7507	-0.0180	-0.2210	-0.2585	0.9366
Bulgaria	0.0000	0.0000	0.0000	0.5963	-0.0146	0.0000	-0.0147	0.8442
Cyprus	0.0000	0.0000	-0.2091	0.6297	0.0000	0.0000	0.0000	1.5645
Czech Republic	0.0000	0.0000	0.0000	0.9195	0.0000	-0.0167	-0.0383	1.5161
Germany	0.0000	-0.0044	-0.0329	0.6947	-0.0136	-0.1796	-0.2810	0.9897
Denmark	0.0000	0.0000	-0.0478	0.7650	0.0000	0.0000	-0.0202	1.2358
Estonia	0.0000	-0.4699	-0.4995	1.0835	0.0000	0.0000	0.0000	1.9151
Greece	0.0000	0.0000	0.0000	0.3528	-0.0069	-0.0418	-0.0488	0.8192
Spain	0.0000	-0.0888	-0.1499	0.6050	0.0000	-0.0045	-0.0153	1.4302
Finland	-0.1511	-0.6627	-0.8369	1.1448	0.0000	0.0000	-0.0119	1.7958
France	0.0000	-0.0257	-0.0638	0.8064	-0.0199	-0.0300	-0.0342	1.3075
Croatia	0.0000	0.0000	0.0000	0.5485	0.0000	0.0000	0.0000	0.8604
Hungary	0.0000	-0.0224	-0.0749	0.6807	0.0000	-0.0552	-0.0913	1.1856
Ireland	0.0000	0.0000	0.0000	0.4099	0.0000	0.0000	0.0000	0.6715
Italy	0.0000	-0.0079	-0.0823	1.0521	-0.0205	-0.0783	-0.0795	1.4173
Lithuania	0.0000	-0.1965	-0.2204	0.8041	-0.0430	0.0000	-0.1123	1.6761
Luxembourg	0.0000	0.0000	-0.4149	0.9569	0.0000	0.0000	0.0000	1.4145
Latvia	0.0000	-0.2935	-0.2907	1.0554	0.0000	-0.0471	-0.2489	1.9054
Malta	0.0000	-0.2156	-0.3345	0.4721	0.0000	0.0000	0.0000	0.8198
Netherlands	0.0000	0.0000	0.0000	0.6678	-0.0069	-0.0326	-0.1974	0.7780
Poland	0.0000	0.0000	-0.0091	0.7130	-0.0948	-0.0103	-0.0170	1.3940
Portugal	0.0000	-0.1631	-0.2619	0.5536	-0.0449	-0.0376	-0.1162	0.7040
Romania	0.0000	0.0000	0.0000	0.6957	-0.0055	0.0000	0.0000	1.3178
Sweden	0.0000	-0.0100	-0.0228	1.0263	-0.0417	0.0000	0.0000	1.6997
Slovenia	0.0000	0.0000	0.0000	0.5543	0.0000	0.0000	0.0000	0.8222
Slovakia	0.0000	0.0000	0.0000	0.7944	0.0000	0.0000	0.0000	1.4916

Note: Table A.1 displays the average values of SPI across the accumulation periods of 1, 6 and 12 months, and HCWI during the five-year periods of 2002 to 2006 and 2018 to 2022. Dryer (Hotter) conditions over time are suggested by smaller (larger) values in the 2018-2022 period, relative to that of 2002-2006.

Source: Authors' calculations using SPI and HCWI from the Copernicus European Drought Observatory.

SHAP Values of Random Forest Models

Figure A.5

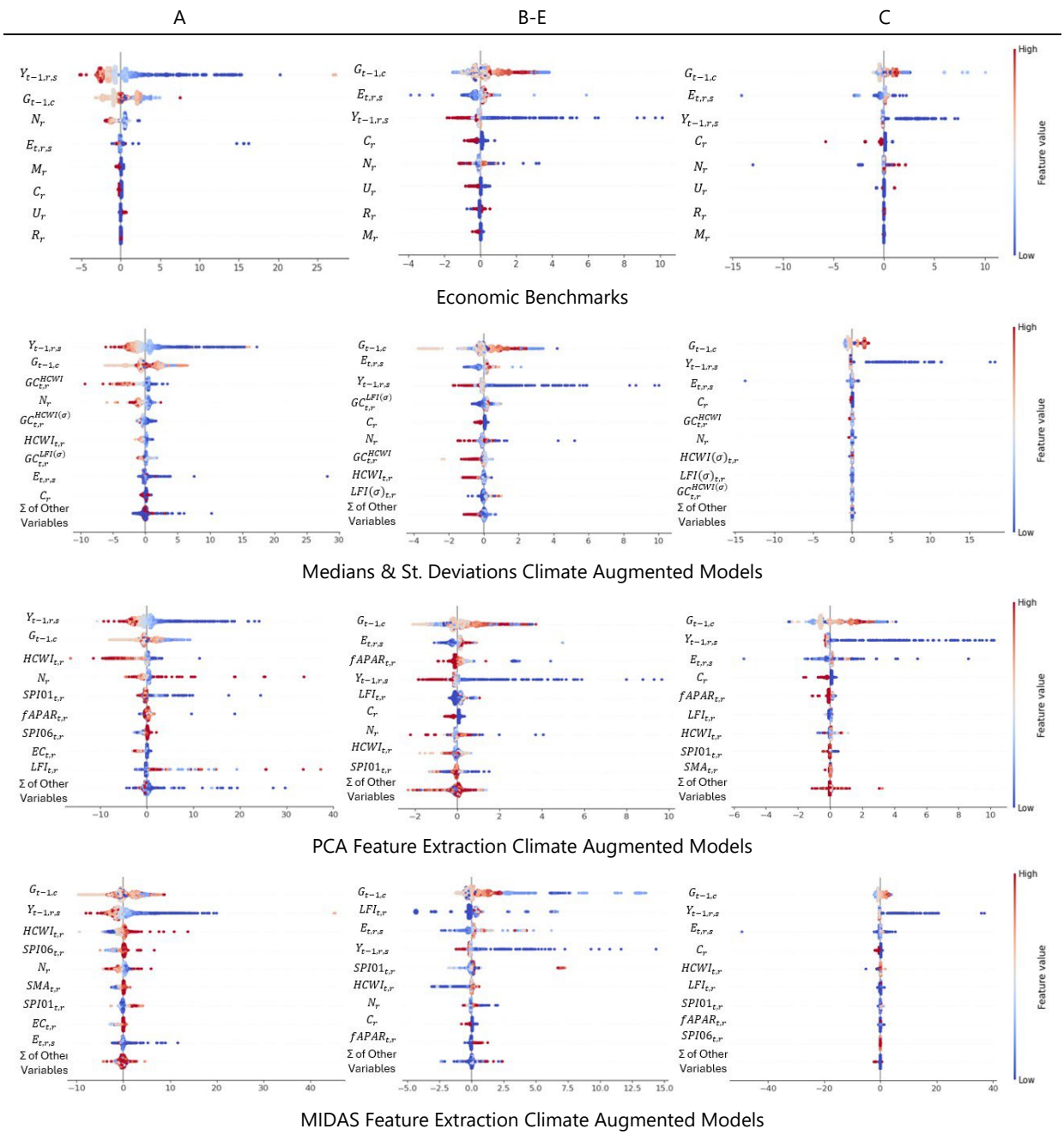


Note: The figure displays the SHAP beeswarm plots of all the estimated Random Forest models. The sub-figures visualise the marginal contribution of a feature to individual predictions.

Source: Authors' calculations.

SHAP Values of XGBoost Models

Figure A.6



Note: The figure displays the SHAP beeswarm plots of all the estimated XGBoost models. The sub-figures visualise the marginal contribution of a feature to individual predictions.

Source: Authors' calculations.

Average Predictive Contributions within the Medians & St. Deviations Models

Table A.2

	Sector A			Sector B-E			Sector C		
	Linear Reg.	Random Forest	XGBoost	Linear Reg.	Random Forest	XGBoost	Linear Reg.	Random Forest	XGBoost
N_r	0.3762	-0.2410	-0.2014	0.1309	-0.0815	-0.0296	0.8213	-0.1562	-0.0076
$E_{t,r,S}$	0.4090	-0.0067	-0.0132	0.5282	0.0084	0.0069	0.0625	0.0293	0.0015
$Y_{t-1,r,S}$	-3.2126	-0.0185	-0.0508	-0.7985	-0.0037	-0.0026	-1.7310	-0.0390	-0.0137
$G_{t-1,c}$	-0.2522	0.0013	-0.0019	0.3931	-0.0358	-0.0194	0.1740	-0.0003	-0.0141
M_r	-0.8854	-0.0272	-0.0117	-0.4552	0.0008	0.0000	-0.6775	0.0016	0.0000
U_r	1.1929	0.0065	0.0003	-1.2317	0.0009	-0.0002	0.0689	0.0014	0.0000
R_r	-0.2779	0.0002	-0.0002	0.2580	-0.0001	0.0005	0.0533	0.0013	0.0000
C_r	-1.4417	-0.0065	0.0004	-0.8270	-0.0071	0.0002	-2.0727	-0.0283	-0.0003
$HCWI_{t,r}$	-4.8562	-0.0958	-0.0065	-1.9701	0.0053	0.0016	0.4587	0.0090	0.0005
$Own\ Region$	1.6550	-0.0063	0.0046	0.2470	0.0018	0.0017	-0.1015	0.0047	0.0001
$GC_{t,r}^{HCWI}$	-6.5112	-0.0895	-0.0111	-2.2171	0.0036	-0.0001	0.5602	0.0043	0.0004
$SPI01_{t,r}$	-1.0812	0.0000	0.0000	2.8646	-0.0002	0.0000	2.3341	-0.0001	0.0000
$Own\ Region$	1.8573	0.0000	0.0000	-4.2821	-0.0002	0.0000	-4.4634	-0.0002	0.0000
$GC_{t,r}^{SPI01}$	-2.9385	0.0000	0.0000	7.1468	0.0000	0.0000	6.7976	0.0001	0.0000
$SPI06_{t,r}$	7.5284	0.0254	0.0000	0.4315	0.0000	0.0001	0.1621	0.0006	0.0000
$Own\ Region$	3.2179	0.0251	0.0010	0.5592	0.0003	0.0000	0.0181	0.0008	0.0000
$GC_{t,r}^{SPI06}$	4.3105	0.0004	-0.0010	-0.1277	-0.0003	0.0001	0.1440	-0.0003	0.0000
$SPI12_{t,r}$	-2.2817	-0.0006	0.0068	0.3016	-0.0007	-0.0001	0.5485	-0.0027	0.0000
$Own\ Region$	-0.9168	0.0013	0.0071	0.2562	-0.0004	0.0002	0.2799	-0.0021	0.0000
$GC_{t,r}^{SPI12}$	-1.3649	-0.0019	-0.0002	0.0455	-0.0003	-0.0004	0.2686	-0.0007	0.0000
$LFI_{t,r}$	-18.3530	0.1007	0.0392	16.2342	0.0169	0.0023	15.1460	0.0194	0.0000
$Own\ Region$	-6.7037	0.0433	0.0111	4.7357	0.0059	0.0014	6.7405	0.0116	0.0001
$GC_{t,r}^{LFI}$	-11.6493	0.0573	0.0281	11.4985	0.0109	0.0010	8.4055	0.0079	0.0000
$SMA_{t,r}$	3.0591	0.0074	0.0061	0.5488	-0.0005	0.0002	0.8182	-0.0007	0.0000
$fAPAR_{t,r}$	-12.1011	-0.0075	-0.0083	0.5397	0.0004	0.0001	1.0788	-0.0002	0.0000
$EC_{t,r}$	-11.7883	0.0000	0.0000	-137.8228	0.0000	0.0001	-114.0757	0.0000	0.0000
$EC_{t,r}^{01}$	-3.9294	0.0000	0.0000	-45.9409	0.0000	0.0000	-38.0252	0.0000	0.0000
$EC_{t,r}^{06}$	-3.9294	0.0000	0.0000	-45.9409	0.0000	0.0000	-38.0252	0.0000	0.0000
$EC_{t,r}^{12}$	-3.9294	0.0000	0.0000	-45.9409	0.0000	0.0000	-38.0252	0.0000	0.0000

Note: The table presents the average contributions to predicted outcomes across all models utilising yearly medians and standard deviations. For linear models, regression coefficients are reported, while for ML models, the average SHAP values are used to quantify feature importance. Heat wave and drought values are represented by the sum of the coefficients, or SHAP values, oof median and standard deviation variables. Climate-related features are decomposed into own region, geographic compounding, and event compounding types (highlighted in grey).

Source: Authors' calculations.

Average Predictive Contributions within PCA-based Features Extraction Models

Table A.3

	Sector A			Sector B-E			Sector C		
	Linear Reg.	Random Forest	XGBoost	Linear Reg.	Random Forest	XGBoost	Linear Reg.	Random Forest	XGBoost
N_r	-4.0549	-0.2976	-0.1316	-0.8570	-0.0653	-0.0269	-1.7629	-0.1504	-0.0141
$E_{t,r,S}$	0.5007	0.0383	0.0024	0.5082	-0.0036	0.0044	0.0446	0.0253	0.0113
$Y_{t-1,r,S}$	-0.8888	0.0491	-0.0010	0.3444	-0.0026	0.0000	0.1142	-0.0398	-0.0115
$G_{t-1,c}$	0.7968	-0.0842	-0.1136	0.1441	-0.0347	0.0088	0.8340	0.0374	-0.0197
M_r	-1.4326	0.0028	-0.0024	-0.6199	0.0005	0.0002	-0.8922	0.0023	0.0000
U_r	1.1591	0.0019	0.0013	-1.1642	0.0008	0.0006	0.1257	0.0053	0.0000
R_r	-0.2013	0.0007	-0.0003	0.2456	-0.0004	0.0003	0.0246	0.0016	0.0001
C_r	-1.7584	-0.0010	0.0039	-0.8752	-0.0035	0.0002	-2.1044	-0.0283	-0.0018
$HCWI_{t,r}$	-0.7032	-0.0584	-0.0074	0.0148	-0.0031	-0.0064	0.0821	-0.0014	-0.0014
$Own\ Region$	-0.3692	-0.0307	-0.0039	0.0078	-0.0016	-0.0034	0.0430	-0.0007	-0.0008
$GC_{t,r}^{HCWI}$	-0.3340	-0.0278	-0.0035	0.0070	-0.0015	-0.0031	0.0392	-0.0007	-0.0007
$SPI01_{t,r}$	2.8046	0.0187	0.0249	0.6473	-0.0174	-0.0101	0.8969	-0.0174	-0.0025
$Own\ Region$	1.3798	0.0092	0.0122	0.3185	-0.0085	-0.0050	0.4413	-0.0085	-0.0012
$GC_{t,r}^{SPI01}$	1.4248	0.0095	0.0126	0.3288	-0.0088	-0.0051	0.4556	-0.0089	-0.0013
$SPI06_{t,r}$	-1.9742	0.0264	0.0055	-0.7002	0.0022	-0.0054	-0.9495	0.0218	0.0039
$Own\ Region$	-1.0172	0.0136	0.0028	-0.3615	0.0011	-0.0028	-0.4857	0.0111	0.0020
$GC_{t,r}^{SPI06}$	-0.9570	0.0129	0.0026	-0.3386	0.0011	-0.0026	-0.4638	0.0106	0.0019
$SPI12_{t,r}$	0.9908	-0.0217	-0.0296	0.2678	0.0171	0.0029	0.4289	-0.0456	0.0098
$Own\ Region$	0.5307	-0.0116	-0.0159	0.1444	0.0092	0.0016	0.2299	-0.0244	0.0053
$GC_{t,r}^{SPI12}$	0.4601	-0.0101	-0.0138	0.1233	0.0080	0.0013	0.1990	-0.0211	0.0045
$LFI_{t,r}$	9.1629	-0.0085	0.0174	1.6230	0.0081	0.0056	1.4679	0.0193	0.0023
$Own\ Region$	5.0917	-0.0047	0.0097	0.9098	0.0045	0.0031	0.8130	0.0107	0.0013
$GC_{t,r}^{LFI}$	4.0712	-0.0038	0.0077	0.7133	0.0036	0.0025	0.6549	0.0086	0.0010
$SMA_{t,r}$	-0.2708	0.0239	0.0287	0.0422	0.0030	-0.0022	-0.0149	0.0069	0.0013
$fAPAR_{t,r}$	-0.9959	0.0864	0.0658	0.3970	0.0352	0.0122	0.1610	0.0445	0.0086
$EC_{t,r}$	-18.9298	-0.0021	0.0012	1.0696	0.0049	0.0027	2.2196	0.0070	0.0005
$EC_{t,r}^{01}$	-9.1976	-0.0010	0.0006	0.5171	0.0024	0.0013	1.0817	0.0034	0.0002
$EC_{t,r}^{06}$	-7.1517	-0.0008	0.0005	0.4060	0.0018	0.0010	0.8375	0.0026	0.0002
$EC_{t,r}^{12}$	-2.5805	-0.0003	0.0002	0.1465	0.0007	0.0004	0.3004	0.0009	0.0001

Note: The table presents the average contributions to predicted outcomes across all models utilising PCA-based feature extraction. For linear models, regression coefficients are reported, while for ML models, the average SHAP values are used to quantify feature importance. Climate-related features are decomposed into own region, geographic compounding, and event compounding types (highlighted in grey), based on factor loadings derived from the PCA kernel.

Source: Authors' calculations.

Average Predictive Contributions within MIDAS-based Features Extraction Models

Table A.4

	Sector A			Sector B-E			Sector C		
	Linear Reg.	Random Forest	XGBoost	Linear Reg.	Random Forest	XGBoost	Linear Reg.	Random Forest	XGBoost
N_r	-3.5201	-0.2815	-0.2119	-0.8314	-0.0726	-0.0270	-1.7328	-0.1662	0.0040
$E_{t,r,S}$	0.2516	0.0480	0.0063	0.5049	0.0038	0.0085	0.0215	0.0284	0.0097
$Y_{t-1,r,S}$	-0.5562	-0.0203	-0.0291	0.3968	-0.0032	-0.0068	0.2238	-0.0350	-0.0181
$G_{t-1,c}$	0.4901	-0.0569	-0.1521	0.1510	-0.0324	0.0025	0.8092	0.0384	-0.0089
M_r	-0.7923	-0.0054	0.0012	-0.2416	0.0011	-0.0001	-0.4998	0.0033	0.0000
U_r	1.1793	0.0030	0.0024	-1.2466	0.0015	0.0008	0.0199	0.0013	-0.0001
R_r	-0.0926	0.0013	0.0012	0.2726	0.0006	0.0000	0.0238	0.0017	0.0000
C_r	-1.8548	-0.0040	0.0038	-0.8945	-0.0051	-0.0008	-2.0580	-0.0256	-0.0227
$HCWI_{t,r}$	0.7173	-0.0470	0.0085	1.1375	0.0064	-0.0006	1.0037	0.0309	0.0074
$Own\ Region$	0.6388	-0.0419	0.0069	0.2571	0.0020	-0.0001	0.1099	0.0155	0.0049
$GC_{t,r}^{HCWI}$	0.0785	-0.0051	0.0016	0.8803	0.0044	-0.0006	0.8939	0.0155	0.0025
$SPI01_{t,r}$	3.1600	-0.0647	-0.0311	0.7348	-0.0015	-0.0053	0.8004	-0.0015	-0.0036
$Own\ Region$	2.8142	-0.0576	-0.0252	0.6543	-0.0013	-0.0043	0.7128	-0.0014	-0.0029
$GC_{t,r}^{SPI01}$	0.3459	-0.0071	-0.0058	0.0804	-0.0002	-0.0010	0.0876	-0.0002	-0.0007
$SPI06_{t,r}$	1.2569	-0.0129	0.0297	-5.7149	0.0037	-0.0015	5.7065	-0.0040	-0.0053
$Own\ Region$	1.1193	-0.0115	0.0241	-1.2918	0.0012	-0.0002	0.6246	-0.0020	-0.0035
$GC_{t,r}^{SPI06}$	0.1376	-0.0014	0.0056	-4.4231	0.0026	-0.0013	5.0819	-0.0020	-0.0018
$SPI12_{t,r}$	-0.3859	0.0043	0.0036	1.2962	0.0003	0.0007	20.8891	-0.0364	-0.0005
$Own\ Region$	-0.3437	0.0038	0.0029	0.2930	0.0001	0.0001	2.2863	-0.0182	-0.0004
$GC_{t,r}^{SPI12}$	-0.0422	0.0005	0.0007	1.0032	0.0002	0.0006	18.6029	-0.0182	-0.0002
$LFI_{t,r}$	0.2515	0.0074	-0.0100	0.8496	0.0136	-0.0033	1.0232	0.0290	0.0104
$Own\ Region$	0.2240	0.0066	-0.0081	0.1921	0.0043	-0.0004	0.1120	0.0145	0.0068
$GC_{t,r}^{LFI}$	0.0275	0.0008	-0.0019	0.6576	0.0093	-0.0029	0.9112	0.0145	0.0036
$SMA_{t,r}$	0.7121	0.0316	0.0250	0.6634	-0.0001	-0.0010	1.3874	-0.0090	0.0000
$fAPAR_{t,r}$	1.9427	0.0126	0.0339	0.7422	0.0066	0.0070	0.6416	0.0020	0.0011
$EC_{t,r}$	0.2448	0.0032	0.0095	12.1794	0.0037	0.0031	-4.7344	0.0039	-0.0001
$EC_{t,r}^{01}$	0.1564	0.0020	0.0050	0.5165	0.0004	0.0001	-0.0788	0.0010	0.0000
$EC_{t,r}^{06}$	0.0843	0.0011	0.0041	6.5674	0.0018	0.0011	-1.6312	0.0019	-0.0001
$EC_{t,r}^{12}$	0.0041	0.0001	0.0004	5.0955	0.0015	0.0020	-3.0245	0.0010	0.0000

Note: The table presents the average contributions to predicted outcomes across all models utilising MIDAS-based feature extraction. For linear models, regression coefficients are reported, while for ML models, the average SHAP values are used to quantify feature importance. Climate-related features are decomposed into own region, geographic compounding, and event compounding types (highlighted in grey), based on factor loadings derived from the beta polynomial function.

Source: Authors' calculations.

Beat the Heat
The Impact of Heat Waves and Droughts on Regional EU Economies

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IFC Satellite Seminar, October 4th, 2025

Presentation Overview[1]

1. **Introduction**
2. **Heat Waves & Droughts**
3. **Nowcasting Exercise**
4. **Assessment of Models**

[1] Disclaimer: This paper should not be reported as representing the views of the authors' national banks, ECB or the Eurosystem.

Motivation: Role of Heat Waves & Droughts in Production

- Climate change exacerbates **regional disparities**, threatening economic stability (Seneviratne et al., 2021)
- **Severe heat** caused 0.3–0.5% losses in EU GDP and could reduce it fivefold by 2060 (García-León et al., 2021)
- By 2100, **drought** damages may increase fivefold with 3°C warming (European Commission et al., 2020)
- **AIM:** Nowcast RGVA per capita for sectoral aggregations A, B-E & C at NUTS-3 level, using economic and climate data



Literature Gaps and Contributions

Gaps in the Literature:

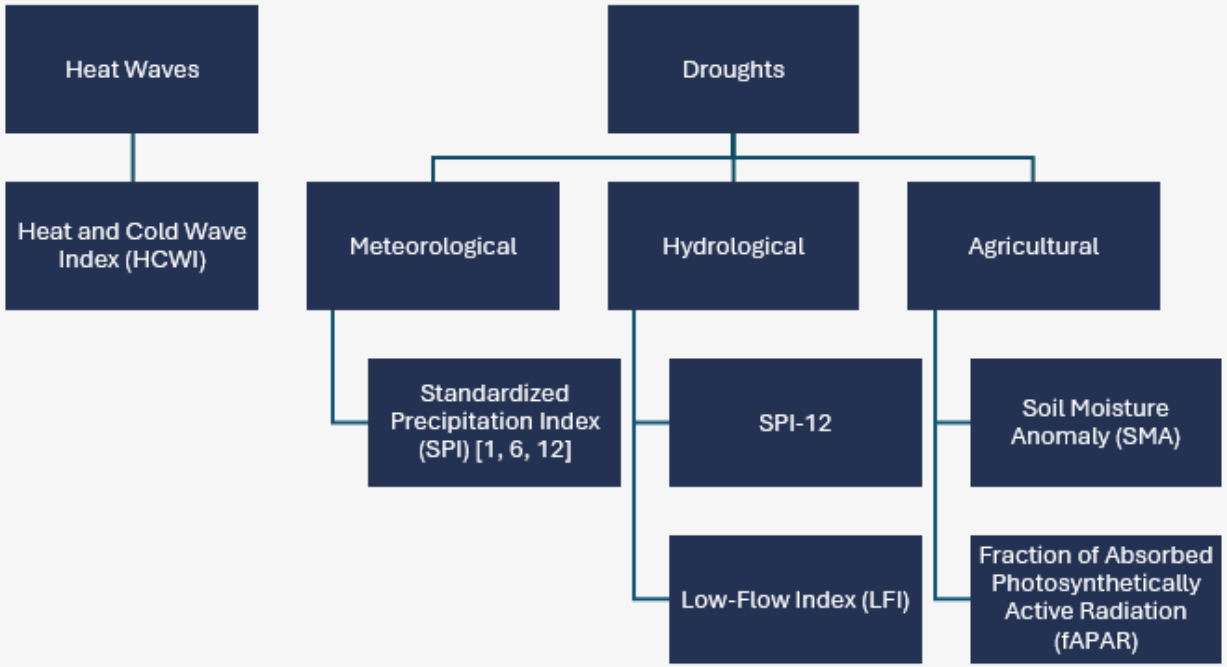
- Earlier work has focused on **long-term impacts** of temperature and precipitation on GDP (Motta et al., 2025; Khan, 2021; Dellink et al., 2019)
- Research is often **sector-specific** (mainly agriculture) (Wang et al., 2018; Praveen & Sharm, 2019) and at **low spatial and temporal resolution**
- Methods remain largely **linear** (Usman et al., 2024)
- Few studies integrate **economic and climate data** for macroeconomic forecasting (Rossi et al., 2023), but compounding events remain understudied

Our Contributions:

- Apply **ML methods** (Random Forest, XGBoost)
- Targeting **climate extremes** (heat waves & droughts)
- Capture **compounding effects** across time, events, & neighbouring regions
- Contrast **linear regression** with non-linear ML approaches

Capturing Heat Waves & Droughts

We incorporate a set of temperature- and precipitation-based climate features, restricted to reflect only heat waves and droughts.



- Variable standardisation allows numerical thresholds to directly map to climate conditions
- HCWI & LFI: values > 0 indicate heat waves and hydrological drought, respectively
- SPI, SMA, & fAPAR: values $\leqslant -1$ denote drier-than-normal conditions

Compounding Climate Effects

- **Temporal:** Event duration is included in climate variable calculations, with longer events implying greater severity

- **Geographic:** For region r with a set of neighbours r^*, the geographic compounding of indicator X, where X excludes agricultural droughts, is:

$$\mathrm{GC}^{X}_{t,r} = \frac{1}{|N_{r*}|} \sum_{i \in N_{r*}} X_{t,i}$$

- **Event-based:** Concurrent heat waves and droughts are captured via an interaction of scaled HCWI and SPI:

$$\mathrm{EC}^{f}_{t,r} = \begin{cases} \tilde{HCWI}_{t,r} \times |\tilde{SPI}^{f}_{t,r}|, & HCWI_{t,r} > 0,\ SPI^{f}_{t,r} \leqslant -1 \\ 0, & \text{otherwise} \end{cases}$$

where SPI periods (f) capture impacts at different temporal scales

Nowcasting Production with Heat Waves & Droughts

- The general structure of our models express the growth rate of RGVA per capita ($Y_{t,r,s}$) using the functional forms: Variable Map

$$Y_{t,r,s} = f_{ECON}(Y_{t-1,r,s}, E_{t,r,s}, G_{t-1,c}, M_r, R_r, C_r, N_r; \theta_{ECON,s})$$

$$Y_{t,r,s} = f_{CLIM}(Y_{t-1,r,s}, E_{t,r,s}, G_{t-1,c}, \mathbf{HCWI_{t,r}}, \mathbf{SPI01_{t,r}}, \mathbf{SPI06_{t,r}}, \mathbf{SPI12_{t,r}}, \mathbf{LFI_{t,r}}, \mathbf{SMA_{t,r}}, \mathbf{fAPAR_{t,r}}, \mathbf{GC_{t,r}}, \mathbf{EC_{t,r}}, M_r, R_r, C_r, N_r; \theta_{CLIM,s})$$

- **Models:** Linear Regression, Random Forest & XGBoost
- **Data Setup:** Mixed-Frequencies with Train-Test Split of 2002-17 & 2018-22
- **Model Structures:** Yearly Medians & St. Deviations, and Feature Extraction Techniques for Climate Variables (PCA, MIDAS) Further Details

Nowcasting Results

We find no evidence that our climate features improve the nowcasting performance of linear regressions, but they can **improve nowcasting in non-linear models, particularly in agriculture**.

Model	Linear Regression			Random Forest			XGBoost		
	A	B–E	C	A	B–E	C	A	B–E	C
Economic (f_{ECON})	21.64	14.11	77.90	23.05	$13.83^{\dagger}$	72.81	28.15	$13.89^{\dagger}$	$76.73^{\dagger}$
Climate (f_{CLIM})									
- Medians & St. Deviations	22.12	14.20	77.95	$20.93^{*\dagger\S}$	$14.01^{\dagger}$	73.64	$20.54^{*\dagger\S}$	$13.95^{\dagger}$	77.69
- PCA Features	22.23	14.17	77.91	$21.05^{*\dagger}$	$13.94^{\dagger}$	74.03	$21.52^{*\dagger}$	$14.03^{\dagger}$	77.80
- MIDAS Features	22.98	14.36	78.03	$21.18^{*\dagger}$	$14.06^{\dagger}$	75.19	$21.72^{*\dagger}$	$13.97^{\dagger}$	85.34

Note: RMSEs are calculated over annual nowcasts of real GVA per capita growth from 2018 to 2022. Sector A covers agriculture; B–E includes mining (B), manufacturing (C), utilities (D), and waste management (E), with C also modelled separately to obtain direct predictions for manufacturing. The symbols to denote statistically significant improvements in predictive performance are:

* $p < 0.05$ indicates predictive improvements relative to the respective economic counterpart of the same model type;

† $p < 0.05$ indicates predictive improvements relative to the respective linear regression counterpart; and

$\S$ $p < 0.05$ indicates predictive improvements relative to the respective linear economic model for the same sector.

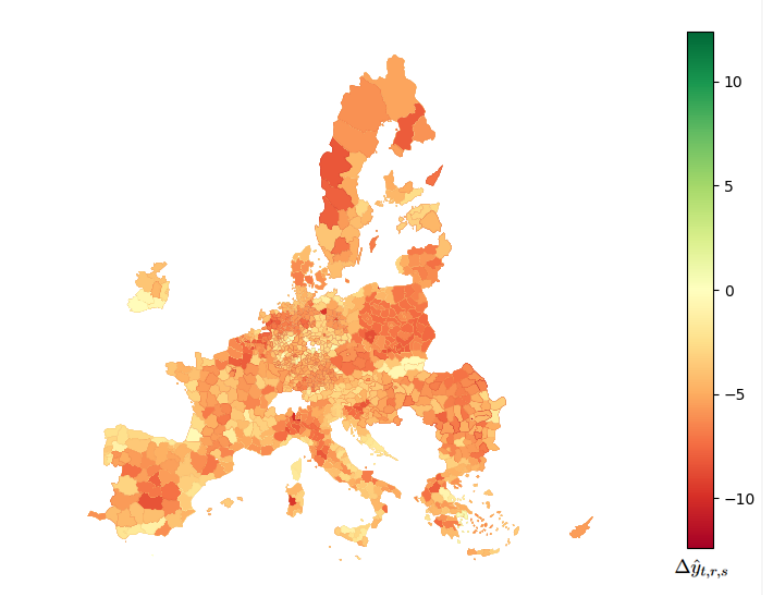
Importance of Climate Features

- SHAP values measure how much each feature contributes to shifting a model's prediction away from the average prediction, providing a clear, additive decomposition of model outputs.
- SHAP values and factor loadings suggest that:
  - **HCWI** consistently ranked among the most **important** features, while **drought** indicators showed **sector-specific relevance**.
  - **Geographic compounding** indicators contributed strongly, reflecting both competitive and complementary regional effects.
  - **Event-based compounding** gained importance in models using feature extraction, with factor loadings non-linearly distributed over short-, medium-, and long-term droughts.
  - **Climate variables** had the largest impact in regions with **below-median RGVA per capita**.

Applying Models for Simulations

- **Climate Scenario:** Heat Wave (HCWI) and Hydrological Drought (LFI) with the intensity of the 99^{th} percentile
- **Simulation Process**:
  1. Select the model with the optimal nowcasts
  2. Generate predictions for 2 scenarios:
     - no heat waves and droughts baseline, &
     - a tailored climate scenario
  3. Subtract values of the desired climate scenario from baseline
  4. Aggregate regional differences across years

Figure 1. Heat Waves Simulation for Agriculture



Thank You

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Variables Map

Nowcasting Approach

Notation	Description
t	Time
r	Region
s	Sector
c	Country
Y	RGVA per capita
E	$\frac{Employed_{t,r,s}}{Population_{t,r}}$
G	RGDP per capita
M	Mountainous Terrain (0,1)
R	Rural Terrain (0,1)
C	Coastal Terrain (0,1)
N	Encoded Region Indicator
$HCWI$	Heat & Cold Waves Index
SPI	Standardised Precipitation Index
LFI	Low Flow Index
SMA	Soil Moisture Anomaly
$fAPAR$	Fraction of Absorbed Photosynthetically Active Radiation
θ	Model Hyperparameters

Feature Extraction

Nowcasting Approach

- Feature extraction techniques are used to map monthly climate data with yearly economic variables
- Extracting 1 feature from the set of high-frequency data of each climate feature maintains a degree of interpretability
- **Principal Component Analysis (PCA):** Transforms correlated features into one component capturing the maximum variance in the data
- **Mixed Data Sampling (MIDAS):** MIDAS uses β distributed lag weights to summarise climate data, with the prediction used as the extracted feature

for X in [HCWI, SPI-01, ...]:

Year	NUTS 3	X [1]	X [2]	...	X [12]

Component Extraction for X:

Opt. 1 → PCA

Opt. 2 → MIDAS

Y =

Year	NUTS 3	$\widehat{X}$

Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Impact on house prices of an energy renovation obligation for homebuyers

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This contribution was prepared for the seminar. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the other central banks and institutions represented at the event.

Impact on house prices of an energy renovation obligation for homebuyers[†]

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Abstract

This article analyses the impact of the Flemish energy renovation obligation on house prices. This policy, introduced in January 2023, obliges buyers of the most energy-inefficient homes to renovate within five years from purchasing the property in order to obtain at least a class D energy performance certificate (EPC). Applying a difference-in-differences technique and leveraging a unique dataset that merges sales data for all Belgian dwelling transactions with datasets on energy performance certificates, asbestos certificates and online real estate listings, we find that energy-inefficient houses in the Flemish Region became about 2% cheaper. This result holds true across multiple control groups: similar houses in the Walloon Region, houses with a class D energy certificate in Flanders, and a triple difference estimation comparing the price differential between EPC classes across both regions. The reasons for this relatively limited effect of the energy renovation obligation are, first, that a majority of buyers of energy-inefficient houses were already renovating their properties to at least a class D EPC prior to its introduction and, second, that the renovation cost was already largely factored into house prices beforehand. The slight increase in the price discount for energy-inefficient homes as a result of the renovation obligation creates some financial leeway for buyers to carry out an energy renovation. However, for those who were not planning to renovate, the renovation obligation results in a large compulsory investment, which could hamper the accessibility of homeownership for potential buyers without sufficient repayment capacity. As Flanders is the only region in the world to have introduced an energy renovation obligation for homebuyers, our findings may be of interest to the many other countries that are considering a similar policy.

Keywords: Climate policy, Energy efficiency, Energy performance certificates, Energy policy, House prices, Minimum energy performance standards

JEL classification: Q48, Q58, R31, R32, R38.

† This bulletin contribution is based on a longer article published in Energy Economics: Reusens, P., van Kempen, T., Vandenbergh, J., Vastmans, F. & Damen, S. (2026). Impact on house prices of an energy renovation obligation for homebuyers. Energy Economics, 158, 109317. https://doi.org/10.1016/j.eneco.2026.109317

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Introduction

Enhancing the energy efficiency of homes is crucial to meet energy efficiency and climate neutrality objectives. In this article, we analyse the impact of the Flemish energy renovation obligation on house prices. Introduced in January 2023, the policy obliges buyers of the most energy-inefficient homes, i.e. those with a class E or F energy performance certificate (EPC), to renovate within five years from purchasing the property in order to obtain at least a class D level. This measure aligns with the European Union's Energy Performance of Buildings Directive (EPBD), which sets energy efficiency targets for the residential building stock of EU member states to be achieved by 2030 and 2035, prioritising renovation of the worst-performing dwellings and establishing minimum energy performance standards as a key potential lever (EC, 2024). The Flemish renovation obligation for homebuyers is an example of such minimum energy performance standards and is the first of its kind worldwide (OECD, 2024), making this study the first empirical evaluation of the impact of this type of measure.

We constructed a unique dataset by merging sales data for all Belgian residential real estate transactions with datasets on energy performance certificates (EPC), asbestos certificates and online real estate listings. This allows us to compare price developments between houses sold in the Flemish and Walloon Regions, the two main regions of Belgium. In addition, our dataset allows us to account for an extensive set of dwelling characteristics, including the energy score, the main heating source, the age of the property, the type of dwelling, the reported building condition, the size of the dwelling, the location and several other characteristics.

We use a difference-in-differences approach to estimate the impact of the Flemish renovation obligation on house prices. This method compares price developments for Flemish houses with a class E or F EPC (the treatment group) to those for similar houses sold in a comparable economic environment but not subject to the requirement (the control group), thereby allowing us to isolate the effect of the policy from other price determinants. We implement three specifications, each with a different control group. First, we use Flemish houses with a class D EPC – just above the renovation obligation threshold – as a control group. Second, we compare Flemish houses with a class E or F EPC to houses with a class E or F EPC in the Walloon Region, where the economic context is comparable but where there is no renovation obligation. Third, we estimate a triple difference (DDD) model to compare the change in the price difference between houses with a class E or F EPC and those with a class C or D EPC in both regions, thereby strengthening identification by controlling for common trends in the EPC-related price differential in both regions and for region-specific house price developments.

We find that the introduction of the Flemish renovation obligation led to a modest decline in the prices of houses with a class E or F EPC. Specifically, energy-inefficient properties became approximately 2% less expensive as a result of the policy change. This effect is consistently observed across all three difference-in-difference specifications and confirmed by multiple robustness checks. For an average house with a class E or F EPC in the year prior to the policy change, the estimated price effect corresponds to approximately €5,800. The price effect did not manifest itself immediately but rather accumulated gradually throughout 2023 and remained broadly stable over the first three quarters of 2024. It should be noted that this price effect comes on top of an already substantial pre-existing price discount for energy-inefficient homes compared to more efficient ones. Finally, our comparison with the Walloon Region suggests that the Flemish energy renovation obligation has not pushed up the prices of houses with better energy scores, as similar price increases were observed in both regions.

We uncovered two reasons for the limited effect of the Flemish energy renovation obligation on the prices of houses with a class E or F EPC. First, an analysis of houses sold twice reveals that a majority of buyers of houses with a class E or F EPC were already renovating their properties to at least a class D EPC prior to the introduction of the renovation obligation. As the overall quality of these houses is often

poor, renovation works – including energy efficiency improvements – are typically carried out. The renovation obligation therefore does not have much impact on these buyers. Second, the price discount for these houses was already substantial prior to introduction of the energy renovation obligation, with the cost of an energy renovation largely factored into the price. Estimating quality-adjusted house prices for each EPC class and region, we find that the energy score has been an important determinant of house prices for many years and that, prior to the policy's introduction, the price discount between the least energy-efficient houses and those with a class D EPC reflected already, to a large extent, the average cost of an energy renovation to a class D EPC.

This article is structured as follows. Section 1 discusses the Flemish renovation obligation as well as broader energy efficiency objectives in the two main regions of Belgium as well as in the EU. Section 2 presents the data. Section 3 examines the effect of the Flemish energy renovation obligation on house prices, while Section 4 explores the underlying factors driving this effect. Finally, Section 5 discusses the policy implications and Section 6 lays out our conclusion.

1. Flemish energy renovation obligation: context and policy framework

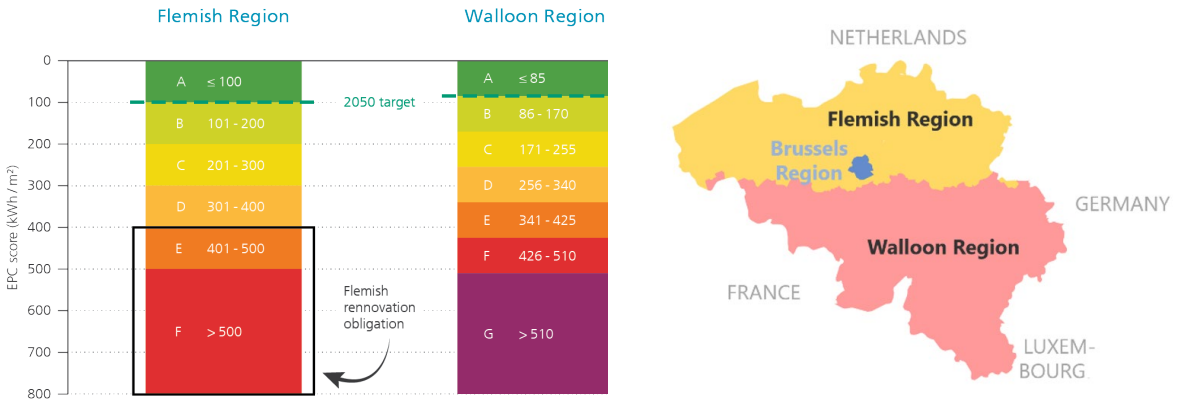
Heating accounts for a substantial portion of household energy consumption and greenhouse gas emissions in Belgium and the EU. In 2022, residential buildings represented 19.7% of total energy consumption in Belgium, with 71.3% of this amount attributable to heating and 14.2% to hot water (FPS Economy, 2024). The share of Belgian emissions from residential heating is 12.6% (Klimaat.be, 2024), which is higher than in the EU, partly due to the fact that Belgian homes are, on average, larger and older compared to the EU average (Eurostat, 2019, 2025).

Making homes energy-efficient and decarbonised is therefore an important part of the Belgian and EU 2050 energy efficiency and climate neutrality objectives. The Flemish and Walloon Regions have set the objective of achieving an energy-efficient housing stock by 2050, with an average energy score of 100 kWh/m^2 for Flanders and 85 kWh/m^2 for Wallonia. The recently revised Energy Performance of Buildings Directive (EPBD) requires EU member states to submit their draft National Building Renovation Plan by the end of 2025 and their final plan by 31 December 2026, outlining a trajectory to ensure that their residential and non-residential building stock becomes highly energy-efficient and decarbonised by 2050 (EC, 2024). In the medium term, the trajectory should substantially reduce the average primary energy demand of homes (i.e. by 16% by 2030 and by 20–22% by 2035), with at least 55% of this decrease derived from renovation of the worst-performing dwellings. Member states have the flexibility to decide which tools they wish to use to achieve these renovation targets, with minimum energy performance standards for existing dwellings – such as the Flemish energy renovation obligation – potentially serving as a key policy lever.

The energy efficiency of homes in the EU is documented by their energy performance certificate (EPC). This document is required when selling or renting a home and is prepared by a certified energy expert based on documentary evidence and visual inspection. The score indicates the theoretical amount of primary energy used by the building for heating and hot water over a year, expressed in kWh/m^2, and depends on the insulation of walls, the roof, floors, windows and doors, as well as on the heating installation, the existence of solar panels and characteristics such as the type of building (detached, semi-detached, terraced or apartment). While the energy score (in kWh/m^2) is calculated using very similar methodologies in the Flemish and Walloon Regions, the grouping of scores for energy class purposes varies greatly from region to region and results in different scales (see Figure 1). For the sake of comparability, we apply the Flemish EPC classification to all regions. This means, for instance, that class G houses in Wallonia are reclassified into class F in our analysis.

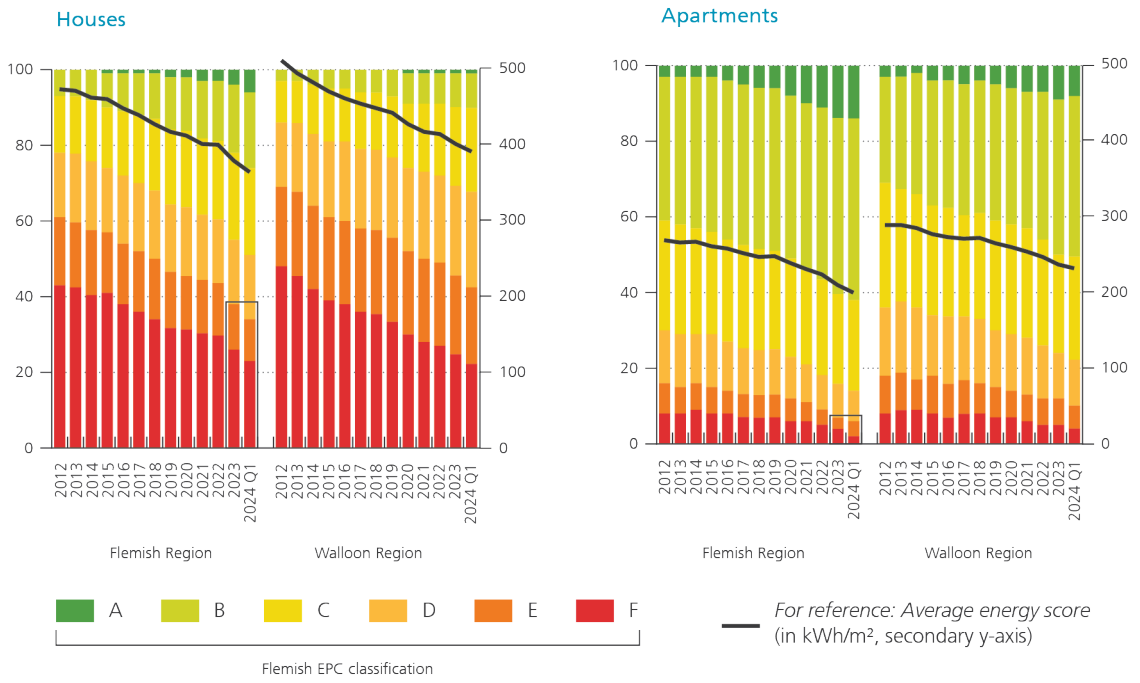
Grouping of energy scores by energy class and regional map of Belgium

Figure 1



Distribution of sold houses and apartments by EPC class[1]
(as a %)

Figure 2



[1] The share of dwellings subject to the Flemish renovation obligation is marked with a black rectangle.

In 2023, the Flemish Region introduced a renovation obligation for homebuyers, obliging purchasers of the most energy-inefficient homes, meaning those with a class E or F EPC, to renovate their dwelling within five years from purchasing the property so as to achieve at least a class D EPC (i.e. an energy score of maximum 400 kWh/m²). This first renovation obligation for homebuyers in the world – implemented with strong credibility and enforcement features (see Section 4) – has made Flanders a pioneering case internationally. At the same time, the EPC class D minimum target remains far from the long-term regional objectives for the building stock, and its adequacy has been debated in the public and policy arena, with views differing on ambition relative to longer-term goals versus feasibility and affordability for homebuyers.

This Flemish renovation obligation mainly affects single-family houses, as the prevalence of class E or F EPCs is much lower for apartments owing to the presence of fewer exterior walls compared to detached houses. Figure 2 shows the distribution of EPC classes and the average energy score for houses and apartments sold in different years and regions. It should be noted that Figure 2 is based on sold dwellings for which an EPC is observed at the time of transaction – the policy relevant population for a transaction triggered obligation – and that the resulting EPC distribution differs from that of the overall housing stock. In the period between 2023 and Q1 2024, about 35% of houses and 7% of apartments sold in the Flemish Region had a class E or F EPC and were thus subject to the renovation obligation. This amounts to 23,124 houses and 2,059 apartments. Finally, a limited number of households seem to have brought forward the purchase or sale of their dwelling with a class E or F EPC to the last quarter of 2022 so as to escape the renovation obligation. Indeed, the share of sold houses with a class E or F EPC jumped from 41% in the third quarter of 2022 to 47% in the last quarter of 2022 before falling to 37% in the first quarter of 2023 and then rising slightly to 39% in the second quarter of 2023.

Finally, Figure 2 also shows that the energy performance of sold dwellings has improved markedly over the past decade, but remains far from meeting the 2050 targets. In Flanders, the share of houses with an E or F EPC fell from 61% in 2012 to 34% in early 2024, while class A rose from virtually zero to 5.6%; for apartments, the share of dwellings with an E or F EPC declined from 16% to 6%, and class A increased from 3% to 14%. A similar improvement was observed in the Walloon Region, although average energy efficiency remains poorer than in Flanders. This improvement in energy efficiency in both regions reflects two main drivers: (i) a growing share of dwellings sold on the secondary market that were built under increasingly stringent new-build energy efficiency standards and (ii) energy renovations of existing homes (see also Section 4.1). In addition, the drop in the share of dwellings with an E or F EPC since 2023 in the Flemish Region is partly also due to the acceleration of sales involving E or F-rated dwellings in late 2022 (see previous paragraph) and possibly the postponement of some household moves to avoid the renovation obligation.

2. Data

We constructed our dataset by combining the universe of residential real estate transactions in Belgium with data on energy performance certificates, asbestos certificates and online real estate listings. Our dataset covers all dwellings sold in Belgium from 2006 to the third quarter of 2024, but our analysis focuses mainly on the period since 2016, for which all data sources (except asbestos certificates) are available.

The dwelling transactions database compiled by the Federal Public Service Finance (FPS Finance) records all sales of homes in Belgium, excluding new builds. It includes the sales price, the date of the notarial deed, the type of transaction (e.g., private sale, public sale or inheritance), a unique parcel identifier, and various dwelling characteristics such as the type of dwelling, the surface area, the age of the building, the number of years since the last officially recorded renovation, and the size of the garden. EPC data were obtained from the regional energy agencies, VEKA (Flemish Region) and SPW Énergie (Walloon Region). They include the energy score of the home, energy efficiency characteristics and the main heating source. We also incorporated asbestos certificate data from the Flemish Public Waste Agency (OVAM). An asbestos certificate has been required for homes sold in the Flemish Region since 23 November 2022. Finally, we used the property listings dataset compiled by Realo, which includes listings data from multiple online platforms and realtors, and thoroughly cleaned the data, to eliminate duplicate listings. This dataset contains, for each property, the initial asking price, the initial listing date and dwelling characteristics such as the energy score, main heating source and the reported building condition.

We merged the EPC, asbestos certificate and online listings databases with the transactions database using the address and the unique identifier (cadastral parcel key) of the property in Belgium. We linked each transaction to the most recent asbestos certificate and EPC prior to the date of sale, complemented by the energy score from the listings database for the small number of dwellings for which EPC matching was not possible. This approach allows excellent matching for houses (with the exception of a small number without a location identifier) but not for apartments as the postal box number for an apartment is defined differently across databases due to the lack of an official system for box numbers in Belgium. As a result, an apartment in the transactions database is often incorrectly associated with the EPC of another unit in the same building, which results in inaccurate matching at unit level given the wide range of energy scores within an apartment building depending on the location of the flat within the building.

We focus our analysis on single-family houses sold in the Flemish and Walloon Regions for several reasons. First and foremost, it is not possible to accurately retrieve the energy score of sold apartments from the available databases (see above). Second, the limited number of apartments with a class E or F EPC (see Section 1) results in a very small sample size. Third, while energy scores vary widely within an apartment building depending on the location of the flat within the building, all owners contribute to the energy renovation of common areas, which include outer walls, the roof, floors and the central heating system. Finally, we excluded the Brussels-Capital Region given the small sample size and the fact that apartments dominate its housing market.

We cleaned the data in several steps. We started with the set of all houses sold on the secondary market in the Flemish and Walloon Regions. This yielded a sample of around 483 000 and 243 000 houses, respectively, for the period from 2016 to Q3 2024. After removing public sales (about 3% in both regions) and transactions that could not be matched with an energy score (about 8% in the Flemish Region and 14% in the Walloon Region), we removed outliers, i.e. observations for which one of the characteristics was above the 99.95th percentile or below the 0.05th percentile and with studentised residuals beyond the range of [-2, 2], following Eurostat's guidelines for outlier removal (Eurostat, 2017). This sample, which is close to the universe of houses sold on the secondary market for the period up to Q1 2024, serves as the basis for our analysis in Figure 2 and Section 4.1. For the difference-in-differences and hedonic regression analyses in Sections 3 and 4.2, we performed several additional steps. We removed transactions that could not be matched with a listing (about 38% in the Flemish Region and 50% in the Walloon Region), as the listings dataset contains the important reported building condition characteristic. We also dropped observations from the transactions dataset with missing values for important dwelling characteristics. We ended up with a sample of around 252 000 and 87 000 houses for the Flemish and Walloon Regions, respectively. In our main analysis, we treat listings for which the building condition variable is missing as a separate category, but provide a robustness analysis in which we exclude these observations. Finally, we perform a robustness analysis for the larger sample, which includes observations that could not be matched with a listing.

3. Impact of the Flemish energy renovation obligation on house prices

This section analyses the impact of the introduction of the Flemish energy renovation obligation on house prices using three separate difference-in-differences specifications. Each specification compares the trend in the prices of Flemish houses with a class E or F EPC (the treatment group) – subject to the renovation obligation as from 2023 – with that of similar houses sold in a comparable economic environment but not subject to this requirement (the control group). This comparison allows us to isolate the impact of the renovation obligation from other house price determinants, so that we can attribute differences in price

trends to the renovation obligation. Each of the three analyses is based on a different specification with a distinct control group, allowing us to test the robustness of the estimated price effect.

In our first specification, we use houses sold in the Flemish Region with a class D EPC as our control group. The main advantage of this specification is that both the control and treatment groups are in the same region, allowing any developments specific to the Flemish housing market and economic environment to be differenced out. However, the price divergence between houses with a class E or F EPC and those with a class D EPC observed since 2023 may not be solely due to the Flemish renovation obligation. It may also partly reflect the increased importance of energy scores in housing markets more broadly – a trend we observe in both the Flemish and Walloon Regions, despite the absence of a renovation obligation in the latter – and which is likely driven by common factors such as higher and more uncertain heating bills since the European energy crisis (see Section 4.2). In addition, this specification does not reveal whether the price difference between Flemish houses with a class E or F EPC and those with a class D EPC is driven solely by a decline in the value of the former or also by an increase in the value of the latter. This upward price effect could result from a shift in demand for houses with a class E or F EPC to more energy-efficient homes, which, coupled with unchanged supply, would lead to a price increase for the latter group. We therefore interpret Specification 1 cautiously and complement it with the cross-region specification and the triple-difference specification.

In our second specification, we use a control group composed of houses with a class E or F EPC sold in the Walloon Region. The advantage of this specification is that it includes houses with exactly the same energy efficiency classes as in the Flemish treatment group, implying that they have been similarly affected by the growing importance of energy scores since 2023. In addition, although the Walloon Region is a distinct housing market with relatively limited interregional mobility due to linguistic and cultural differences and its own region-specific dynamics, developments in most key house price determinants are very similar to those observed in the Flemish Region. First, given that all major Belgian banks operate at the national level and set their credit policies accordingly, financing conditions and mortgage rates have evolved in a largely uniform way in the Flemish and Walloon Regions. Second, household income in both regions has grown at a similar pace due to the country's system of automatic wage indexation and interregional economic linkages, commuting flows and fiscal transfers via the federal government and social security. Third, demographic developments and the number of dwellings per household have evolved in a comparable way in both regions. Fourth, while house prices in the Flemish and Walloon Regions were affected differently by several region-specific changes in fiscal housing policy, the impact of these changes is taken into account in our model. Finally, another advantage of the second specification is that it can analyse the impact of the Flemish renovation obligation on the prices of houses with a class E or F EPC and on houses with a better EPC class separately. For the latter analysis, we use treatment and control groups composed of houses with a class C or D EPC sold in the Flemish and Walloon Regions and perform the same analysis for properties with class A or B EPC.

Our third specification integrates the two preceding specifications by estimating a triple difference (DDD) model, following the framework introduced by Gruber (1994) and formalised by Olden and Møen (2022). This specification compares the evolution of the price difference between dwellings with a class E or F EPC and those with class C or D EPC across the Flemish and Walloon Regions. While common trends in this EPC-related price difference in both regions are likely driven by shared factors – such as the European energy crisis – a more pronounced divergence in Flanders from 2023 onwards can plausibly be attributed to the introduction of the Flemish renovation obligation. Compared to the first specification, the DDD model thus offers a more robust identification strategy to estimate the impact of the Flemish renovation obligation, by controlling for common time-varying factors that have increased the importance of energy scores in both regions. Compared to the second specification, it accounts for region-specific developments, such as changes in fiscal housing policy, that may have affected housing prices in Flanders and Wallonia differently.

Table 1 presents the estimated price impact of the Flemish energy renovation obligation on the treatment group, based on the difference-in-differences analyses. Our findings for the entire post-treatment period indicate that Flemish houses with a class E or F EPC became approximately 1.1% cheaper on average due to the renovation obligation. The price decline of Flemish houses with a class E or F EPC is slightly more pronounced when compared to Flemish houses with a class D EPC (-1.4%) than when compared to Walloon houses with a class E or F EPC (-0.9%) or to the estimate from our triple-difference models (-1.1%). However, this first specification may overstate the policy's effect, as it does not fully account for the broader increase in the importance of energy scores in housing markets since 2023 (see above). All these negative effects are statistically significant across model specifications.

The price effect of the Flemish renovation obligation was, however, not immediate. Instead, our quarterly estimates show that the price effect accumulated gradually throughout 2023, stabilising at around -2% as from the fourth quarter of 2023. For an average house with a class E or F EPC in the year prior to the policy change, this estimated price effect corresponds to approximately €5,800. It should be noted that this price effect comes on top of an already substantial pre-existing price discount for energy-inefficient homes compared to more efficient ones (see Section 4.2). This magnitude is comparable to the findings of Ferentinos, Gibberd, and Guin (2023), who report that the introduction of a minimum energy performance standard for rental properties in England and Wales reduced the prices of the least efficient homes by £5,000–£9,000.

Finally, we find no evidence that the renovation obligation has pushed up the prices of Flemish houses with better EPC classes. Specifically, our comparison of Flemish houses with a class C or D EPC, as well as those with a class A or B EPC to the corresponding Walloon control group suggests that these segments were not substantially impacted by the policy. The estimated coefficients are close to zero and statistically insignificant, indicating that the renovation obligation had no measurable effect on the prices of houses with relatively good energy performance.

Estimated price effect of the Flemish renovation obligation for each difference-in-differences specification[1]

(as a %) Table 1

	1. Flemish Region	2. Flemish Region vs Walloon Region			3. Triple difference Flemish Region vs Walloon Region	
	E+F vs D	E+F	C+D	A+B	E+F vs C+D	E+F vs D
Entire period	-0.014***	-0.009**	0.000	-0.006	-0.011***	-0.011**
Q1 2023	0.010	-0.006	-0.009	-0.020	0.003	-0.004
Q2 2023	-0.010	-0.000	0.006	-0.026**	-0.007	-0.004
Q3 2023	-0.008	-0.001	0.006	-0.007	-0.009	-0.019*
Q4 2023	-0.023***	-0.013*	0.003	0.010	-0.019**	-0.014
Q1 2024	-0.018***	0.005	-0.007	-0.018	0.011	0.013
Q2 2024	-0.023***	-0.015**	0.009	0.013	-0.025***	-0.027**
Q3 2024	-0.029***	-0.035***	-0.007	-0.006	-0.030***	-0.018
Observations	154,403		338,807		219,414	288,373
R-squared	0.790		0.851		0.823	0.838

[1] The table shows the estimated coefficients of the difference-in-difference model, measuring the price impact of the energy renovation obligation on the treatment group for each difference-in-differences analysis. The first row reports the effect over the entire post-treatment period. Quarterly results are estimated using per-quarter variants of the model. The statistical significance of the coefficients is denoted by * (p<0.1), ** (p<0.05) and *** (p<0.01).

4. Potential mechanisms behind the price effect

This section discusses potential mechanisms behind the estimated price effect of the Flemish renovation obligation. We assess that, in general, the impact on house prices of an energy renovation obligation for homebuyers is closely linked to three factors, which can vary across countries and contexts: (i) the policy's credibility and enforcement mechanisms, (ii) whether the minimum energy performance standard is achieved by a large number of homebuyers even in the absence of the obligation, and (iii) the extent to which the renovation cost was already factored into house prices prior to the policy change. The first factor influences the extent to which households and banks take the policy into account in projected future renovation costs. The second factor reflects the binding nature of the energy renovation obligation, which depends on the typical renovation activity of buyers, the overall condition of the housing stock, and the stringency and scope of the renovation obligation – namely, the minimum EPC class to be achieved and the EPC classes subject to the obligation. The third factor determines the degree to which the EPC-related price discount of houses subject to the obligation should increase to reflect the cost of the mandatory energy renovation. Indeed, if homebuyers are required to improve their homes' energy performance, we expect buyers and banks to incorporate the full cost of complying with the obligation into their offers and mortgage conditions.

First, the strong credibility of and enforcement mechanisms for the Flemish renovation obligation explain why the policy has negatively affected the prices of houses with a class E or F EPC. Buyers are well aware that the obligation applies to them and is transferred to the next owner in case of resale, which reinforces its credibility and relevance at the time of purchase. Extensive press coverage has focused on both the obligation itself and the potential administrative fine of up to €200,000 for non-compliance. Moreover, by law, property advertisements must mention any renovation requirement, thereby ensuring transparency for prospective buyers. Banks provide further information to buyers on the renovation obligation during mortgage origination and factor the renovation cost into their credit assessments.

The relatively modest 2% impact of the Flemish renovation obligation on the prices of houses with a class E or F EPC could be attributed to the two other factors. First, the analysis of houses sold twice in Section 4.1 reveals that a majority of buyers of houses with a class E or F EPC were already renovating their properties to at least a class D EPC prior to the introduction of the renovation obligation. As the overall quality of these houses is often poor, renovation works – including energy efficiency improvements – are typically carried out regardless of an obligation and this behaviour is further encouraged by energy-efficiency policies such as mandatory energy efficiency disclosure for sales and rental dwellings, subsidies and renovation coaching (including one stop shops). The renovation obligation therefore does not have much effect on these buyers. Second, as Section 4.2 shows, the price discount for these houses was already substantial before the introduction of the renovation obligation, and the renovation cost appears to have been largely factored into the price.

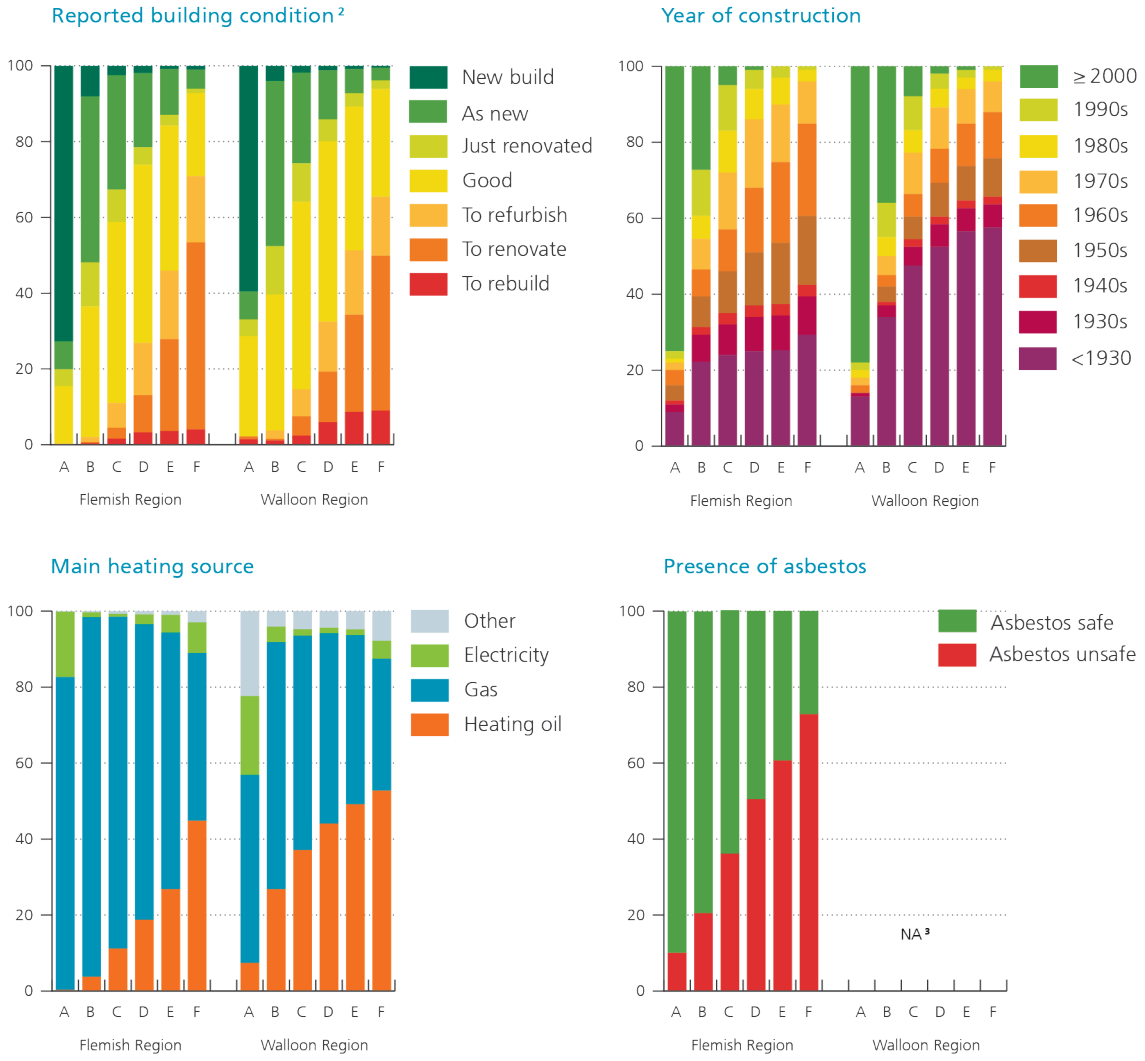
4.1. Pre-obligation energy renovation activity in Flanders

This section discusses energy renovation activity and dwelling characteristics for sold homes with a class E or F EPC and that were not yet subject to the Flemish renovation obligation. We limit our analysis to the period up to Q1 2024, for which our sample comes close to the universe of homes sold on the secondary market (see Section 2).

We first find that the overall quality and comfort of houses with a class E or F EPC is much worse than that of more energy-efficient houses. Figure 3 indeed shows that many houses with a class E or F EPC are in poor condition, old, considered unsafe due to the presence of asbestos and heated with oil.

Quality characteristics of houses sold in 2023 – Q1 2024 per EPC class[1]
(as a %)

Figure 3



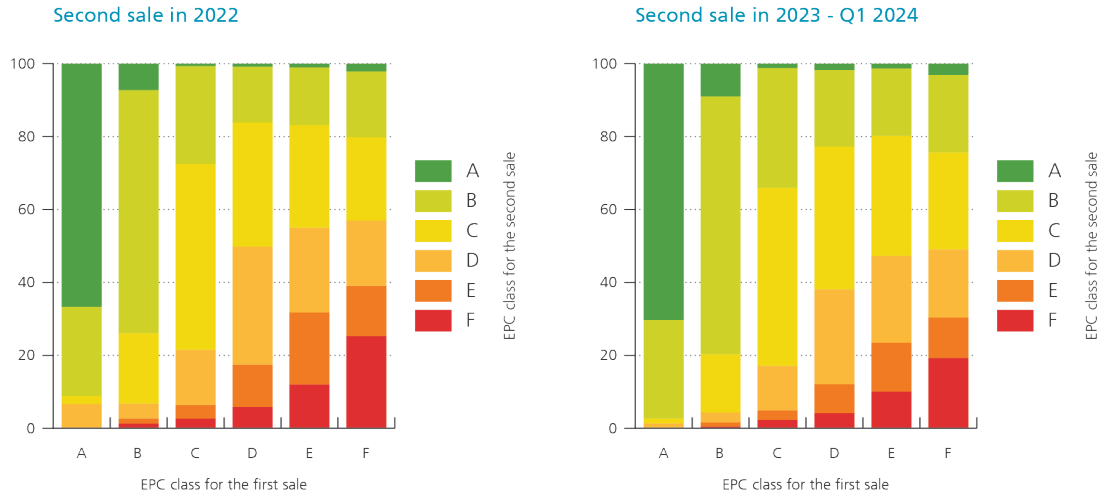
[1] The charts are based on a subsample that excludes observations with a missing value for the displayed variables.
[2] The reported building condition is a subjective assessment of the property by the seller included in the online listing. It should be noted that the share of houses to be rebuilt is underestimated, as most of these dwellings are advertised as a building plot and thus not included in the dataset of sold dwellings.
[3] There is no information on the presence of asbestos for houses in the Walloon Region.

Many buyers of houses with a class E or F EPC undertake renovations to improve energy efficiency and building quality, even without a formal energy renovation obligation. This behaviour is primarily driven by the poor energy performance and overall condition of these houses (see previous paragraph) and is further encouraged by policies such as the EPC certification and mandatory energy efficiency disclosure for sales and rental dwellings (providing energy performance details), renovation coaching (including one-stop shops), subsidies, and insulation and double-glazing standards. Figure 4 illustrates the change in EPC class for the approximately 26,000 Flemish houses that were sold twice, for the first time in the

period 2009–2019 and again in 2022 or 2023–Q1 2024, with at least a five-year interval between sales.[1] For second sales in 2022, we find that 60% of houses initially rated E or F improved to class D or better.[2] Although the timing of upgrades is unknown and some may reflect pre-sale renovations, most appear to be post-purchase. This interpretation is supported by findings in the literature that many buyers of energy-inefficient homes carry out an energy renovation relatively shortly after purchase (see following paragraph). Moreover, additional results (available upon request) show that EPC improvements for houses initially rated E or F often go hand in hand with upgrades in overall building condition, indicating that energy and non-energy renovations are typically integrated into a comprehensive renovation strategy. Finally, although the renovation obligation did not apply to sellers, pre-sale upgrades appear to have gained importance during 2023 and early 2024, as the share of houses initially rated EPC class E or F that improved to class D or better increased to 70%. This increase is likely partly driven by introduction of the Flemish renovation obligation and the increased impact of EPC ratings on house prices (see Section 4.2). However, it may also partly reflect EPC misreporting (see Appendix), and strategic timing of transactions, particularly the acceleration of sales involving E- or F-rated dwellings in late 2022 (see Section 1) as well as the possible postponement of some household moves to avoid the renovation obligation.

Change in the EPC class for Flemish houses sold twice[1]

(EPC distribution for the second sale, broken down by EPC for the first sale, as a %) Figure 4



[1] The charts illustrate the change in EPC class for Flemish houses with multiple recorded sales in the dataset, with at least a five-year interval between them. In particular, they show the distribution of EPC classes for the second sale (as a percentage) broken down by energy class for the first sale (x-axis). The left-hand chart displays houses for which the second sale occurred in 2022, while the right-hand chart depicts those sold for the second time in the period 2023 – Q1 2024. For a small share of repeat sales, the EPC class was lower at the second sale than at the first, likely due to home depreciation, variability among EPC certifiers, or changes in the EPC calculation software.

1 We could accurately analyse the change in energy efficiency only for Flemish houses sold for the second time since 2022. For this group alone, the EPC for the first sale could not be reused for the second sale, meaning the energy score had to be recalculated when the property was resold. Indeed, since January 2022, anyone selling a house in the Flemish Region must, by law, produce an EPC prepared as from 2019. In contrast, for repeat sales in the Flemish Region prior to 2022 and in the Walloon Region, a new EPC was often not produced for the second sale and the initial EPC from the first sale was used, even if renovations had taken place, hence resulting in underestimation of the actual change in energy efficiency.

2 It should be noted that we could only analyse the post-sale change in EPC class for the subset of houses sold twice, and renovation activity may differ for the full set of all sales. We acknowledge that repeat-sales analysis may involve some selection bias, as it covers homes resold within five to sixteen years, although a five-year minimum holding period was applied to limit short-term flips. In addition, the analysis excludes repeat sales of new builds following demolition and reconstruction works, for which data are unavailable and which inclusion would have increased the share of improved EPC ratings.

Our finding that many buyers of energy-inefficient homes carry out an energy renovation relatively shortly after purchase is in line with earlier evidence. First, according to the results of a large-scale housing survey in the Flemish Region, 50% of owner-occupiers made energy-saving improvements between 2002 and 2012, with a higher percentage for homes in poorer condition (Van den Broeck, 2019). The survey also revealed that major renovations are often at least partially completed by the buyer before they move in. Second, a more recent survey of Belgian homeowners conducted between 2018 and 2022 found that young households, which are the most frequent buyers of existing dwellings, are also more likely to perform an energy renovation. Specifically, 36% of homeowners aged 25 to 39 had carried out an energy renovation in the year prior to their participation in the survey, compared with 25% of those aged 40-54 and 20% of those aged 55-74 (Gepts et al., 2025). Furthermore, young homeowners tend to conduct more extensive energy renovations than older homeowners and are more likely to combine energy-efficiency improvements with structural and other renovation works. Finally, our findings on energy renovation activity align with Clara et al. (2026), who observed high renovation activity on the part of both homeowners and landlords for energy-inefficient homes in England and Wales and a further increase in such activity by the latter group as a result of the introduction of minimum energy performance standards for rented residential properties.

4.2. Capitalisation of energy renovation costs into house prices

In order to analyse the capitalisation of energy renovation costs into house prices, this section provides estimated quality-adjusted house prices for each EPC class and region, calculated as the estimated price for a house with average dwelling characteristics.[3] Since the quality-adjusted price for each EPC class is calculated for a house with the same characteristics (with the exception of the energy class), the predicted price difference between classes can be interpreted as the estimated added value of an energy class improvement, while price changes over time can be viewed as the actual change in price of an identical dwelling. However, caution is warranted for several reasons: the estimates are subject to estimation uncertainty; the price differences could still partly reflect differences in characteristics related to quality and comfort that are not controlled for in the dataset; and, finally, the price effect can be dwelling specific.

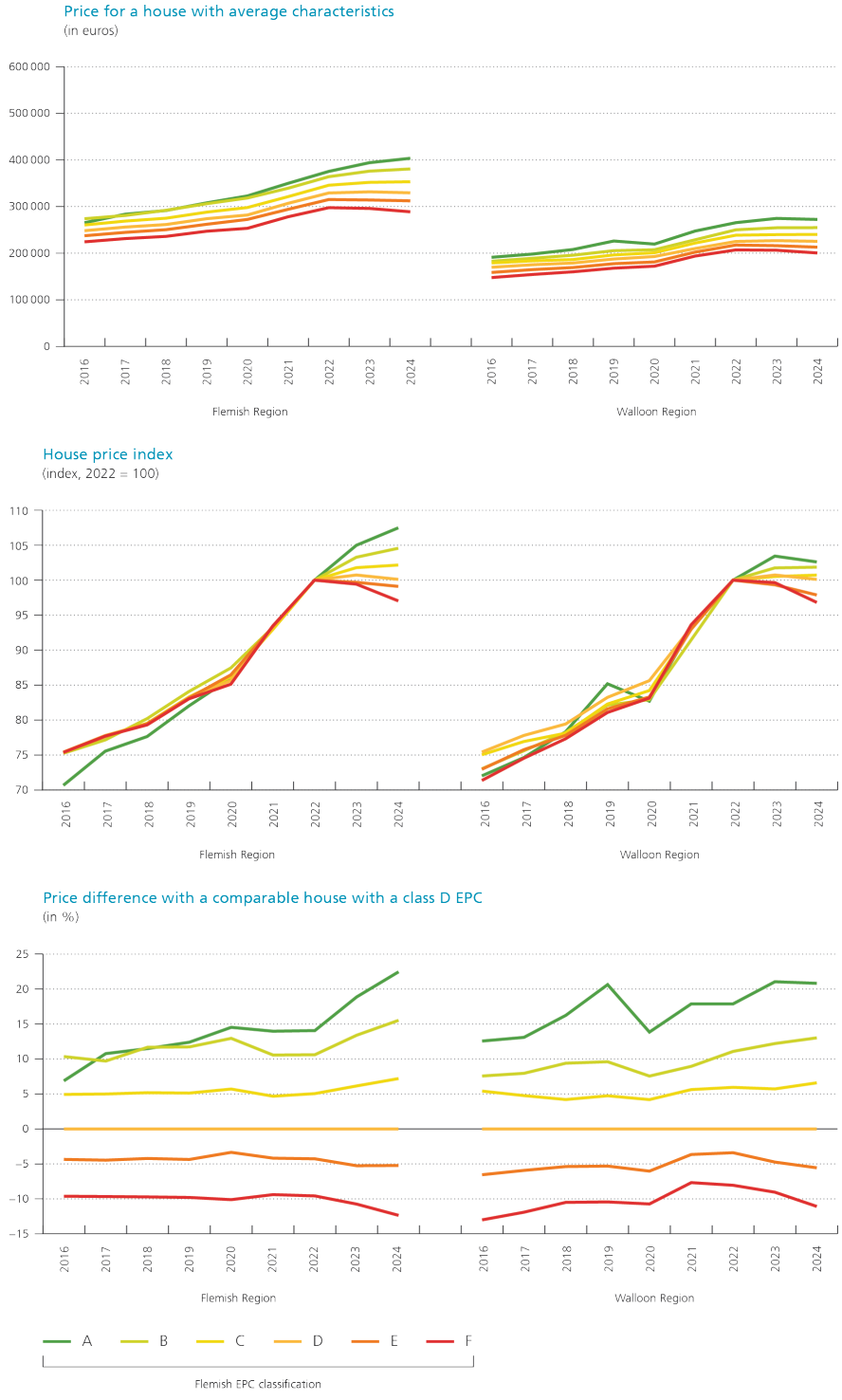
Figure 5 shows the quality-adjusted price (in euros) per EPC class for a house with average dwelling characteristics (top graph), as well as the corresponding price index (using 2022 as the reference year) (middle graph) and the relative price difference (in %) with a comparable house with a class D EPC (bottom graph).

First, our results show that the price discount for houses with a class E or F EPC was already large prior to introduction of the renovation obligation and that the renovation cost appears to have been largely factored into the price. In 2022, the price discount relative to a comparable house with a class D EPC was around 10% for houses with a class F EPC in the Flemish Region, which corresponds to a price difference of around €31 500 for an average Flemish house (see Figure 5, top graph). While accurate estimates of the cost of an energy renovation are lacking, an analysis of a small sample of invoices from recent Flemish energy renovations indicates that the price discount appears to reflect to a large extent the average cost of an energy renovation to a class D EPC. However, it should be noted that the renovation cost can vary widely depending on the dwelling's characteristics, regional and contractor-specific factors, and the technologies and materials used. Costs also depend on whether the energy renovation forms part of a broader refurbishment undertaken for structural or comfort-related reasons, whether the owner performs the work themselves, whether the renovation is part of a collective project, whether subsidies

[3] Unlike average house prices, quality-adjusted prices account for differences in property characteristics. For instance, energy-efficient houses are on average more expensive not only due to their greater energy efficiency but also because they tend to be newer and in better condition.

are taken into account and whether additional expenses are included, such as interior finishing, housing-specific adaptations, waste management and asbestos removal.

Quality-adjusted price per EPC class for a house with average characteristics
(in euros (top graph), as an index (middle graph) and relative price difference (bottom graph)) Figure 5



[1] Estimated for a house with dwelling characteristics equal to the regional average for 2016–2024.

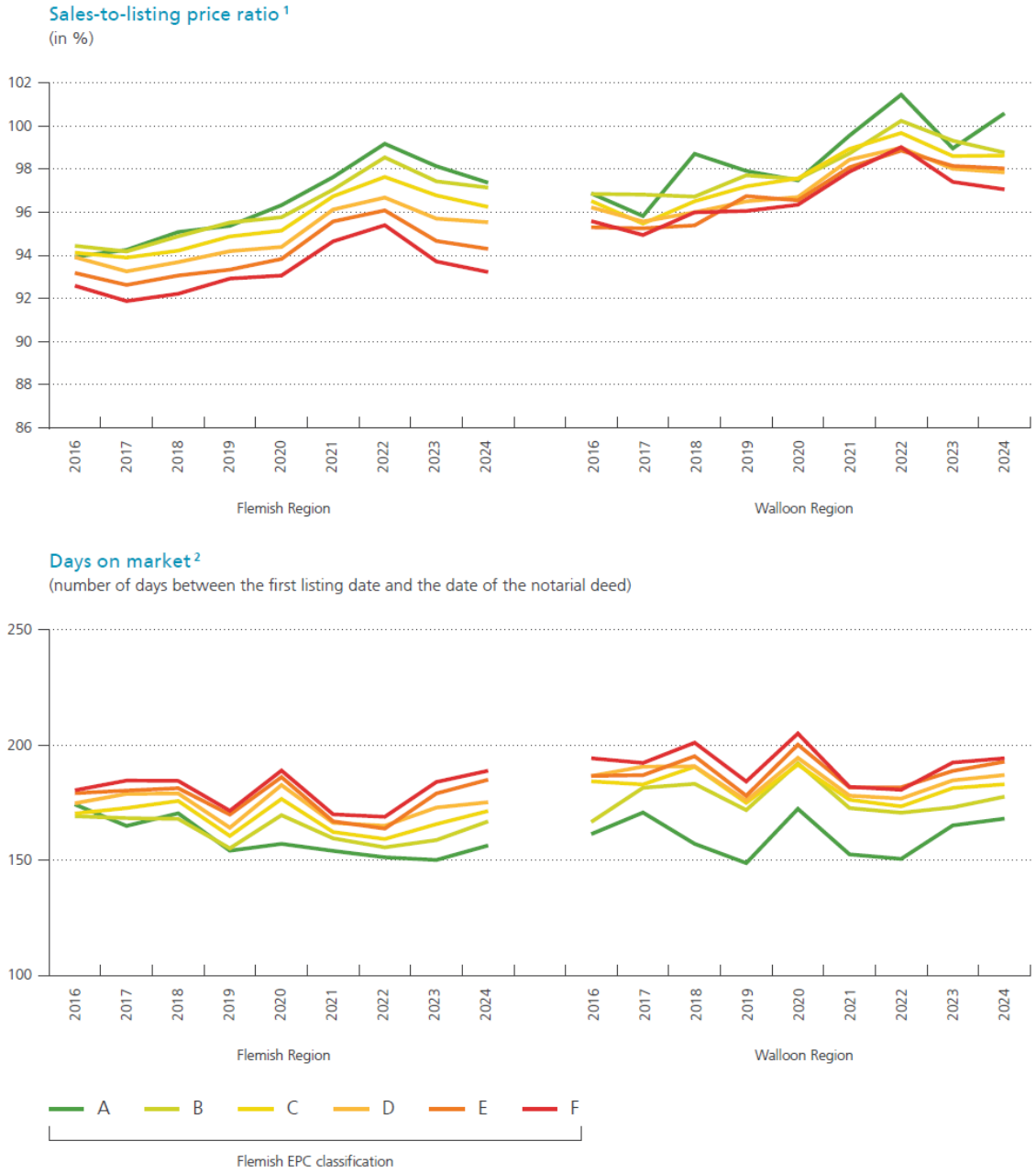
Second, while the energy score has long been an important determinant of house prices, its influence increased markedly in 2023 and the first three quarters of 2024 in the Flemish and Walloon Regions (see Figure 5, bottom graph). From 2016 to 2022, the estimated price premium for houses with a class A, B or C EPC, compared to those with a class D EPC, and the price discount for those with a class E or F EPC remained relatively stable at a sizeable level. On average, these premia and discounts amounted to, respectively, 13%, 11%, 5%, –4% and –10% in the Flemish Region and 16%, 9%, 5%, –5% and –10% in the Walloon Region. EPC-related price differences widened substantially in 2023 and in the first three quarters of 2024. Relative to the 2016–2022 average, the estimated price premium for houses with a class A EPC increased by 9.6 percentage points in the Flemish Region and by 4.8 percentage points in the Walloon Region. The increase in the price premium amounted to 4.4 and 4.1 percentage points for houses with a class B EPC (for the Flemish and Walloon Regions, respectively), 2.1 and 1.6 percentage points for those with a class C EPC, –1.1 and –0.4 percentage points for those with a class E EPC, and –2.7 and –0.7 percentage points for those with a class F EPC. The finding that the price discount for houses with a class E or F EPC increased by around one to two percentage points more in the Flemish Region than in the Walloon Region is in line with the results of our difference-in-differences analysis on the impact of the Flemish energy renovation obligation (see Section 3). The substantial widening of EPC-related price differences has resulted in strongly divergent house price index developments since 2023 (see Figure 5, middle graph). While prices in 2023 and 2024 were at the same level as in 2022 for houses with a class D EPC, they increased for those with a class C EPC, rose even more for those with a class A or B EPC and decreased for those with a class E or F EPC.

This divergence in price developments between EPCs observed since 2023 in the two regions is likely due to the fact that buyers and banks are increasingly taking the energy score into account in their purchase decisions and mortgage conditions. This shift can be attributed to several factors, including the introduction of the Flemish energy renovation obligation (see Section 3), the announcement of increasingly stringent energy renovation requirements in the two regions in the coming years, and higher and more uncertain heating bills since the European energy crisis. Other reasons include the announced future carbon price for heating fuels set by EU ETS2 as from 2027 and a sharp rise in the cost of labour and, especially, building materials, which has made energy renovations more expensive. Furthermore, regulatory developments have also played a role: the EU's Corporate Sustainability Reporting Directive (CSRD) and the EBA's Pillar 3 ESG disclosure requirements, both introduced in 2023, require banks to report on climate-related risks, financed emissions and the energy efficiency of real estate collateral, creating strong incentives for banks to integrate energy performance considerations into their lending and mortgage policies. This has been facilitated by improved data availability, with the share of new mortgage loans for which energy scores are recorded increasing from 39% in 2021 to 67% in 2022, 79% in 2023, and 82% in the first half of 2024 (NBB, 2024a). In practice, many banks now offer preferential mortgage rates for energy-efficient dwellings and incorporate anticipated renovation costs into credit assessments.

Finally, we find that, since 2023, the days on market and sales-to-listing price ratio have also diverged between EPC classes. Figure 6 shows the sales-to-listing price ratio and the days on market for a house with average dwelling characteristics, per EPC class and per region. Together with price data, these liquidity indicators are highly relevant for assessing the impact of climate transition policies on financial stability (ECB/ESRB, 2022; ECB/ESRB, 2023; Foerster et al., 2025). As can be seen, the sales-to-listing price is substantially lower for energy-intensive houses for the entire sample period, especially in the Flemish Region. In addition, the sales-to-listing price ratio is impacted by the housing cycle, with higher values in booming markets due to bidding wars in 2021 and 2022 and lower values since 2023 as a result of mortgage rate hikes and a general cooldown of the housing market. It has decreased more since 2023 for Flemish houses with a class E or F EPC, likely as a result of the energy renovation obligation. The latter two findings are also evidenced by the days on market indicator, which has increased since 2023, especially for Flemish houses with a class E or F EPC.

Sales-to-listing price ratio (top graph) and days on market (bottom graph) per EPC class for a house with average characteristics

Figure 6



[1] The sales-to-listing price ratio is the ratio between the final sales price and the initial listing price.

[2] The term "days on market" as used in this article refers to the period from the first listing date to the date of the notarial deed. This period also includes the time of, on average, about three months between signature of the preliminary sales agreement and the notarial instrument recording the sale.

5. Policy implications

To meet Belgian and EU 2050 energy efficiency and climate neutrality objectives, the vast majority of existing Belgian homes will need to undergo an energy renovation by 2050. This ambitious endeavour will require massive investment and face considerable challenges on both the demand and supply sides (NBB, 2024b). Deep energy renovations require substantial outlays, which many households are unable to finance, for example because they already have an existing loan to service. In addition, as energy-efficiency renovations are labour-intensive, a large increase in the demand for such renovations could be significantly hampered by labour shortages in the construction sector, which could exert upward pressure on prices and lead to higher renovation costs.

We argue that energy renovation obligations for homebuyers, such as the Flemish renovation obligation studied in this paper, can alleviate these challenges and accelerate renovations through four main mechanisms. First, they create financial leeway for buyers to carry out an energy renovation on newly purchased homes. Indeed, as set out in Sections 3 and 4, an energy renovation obligation for homebuyers lowers the prices of energy-inefficient homes, as buyers and banks incorporate the cost of complying with the obligation into their offers and credit assessments. Second, banks are well positioned to inform homebuyers about renovation requirements, as they are typically involved shortly before the sale and maintain a close financial relationship with their clients. This could enable buyers to better anticipate energy renovations, both in terms of cost and planning, and to integrate them into their purchase decisions. Third, a mandatory energy renovation for homebuyers implies that the renovation will take place relatively shortly after purchase of the property, which is a key renovation trigger point. Many buyers of energy-inefficient homes indeed undertake comprehensive upgrades to enhance both the overall quality and energy efficiency of their property, often soon after purchasing and before moving in (see also Section 4.1). Incorporating additional energy-efficiency improvements into a planned renovation can be more practical and cost-effective. For instance, installing floor insulation is more economical when it forms part of a necessary floor replacement and less disruptive when done before occupancy. Fourth, renovation obligations for homebuyers allow renovation deadlines to be spaced out over time based on the transaction date, unlike minimum energy performance standards which impose a uniform deadline on all homes. This phased approach can help alleviate the strain on labour supply in the construction sector.

However, an energy renovation obligation for homebuyers also has redistributive implications. The increase in the price discount of energy-intensive homes as a result of the renovation obligation implies a negative impact on the wealth of their owners. In addition, while it creates some financial leeway for buyers to carry out an energy renovation, the renovation obligation is still a large compulsory investment, on top of the purchase price, for those who were not planning to renovate. This could hamper the accessibility of homeownership for potential buyers without sufficient repayment capacity. This challenge is particularly relevant for lower income buyers, who often live in less energy-efficient homes for affordability reasons and are less likely to undertake renovation works compared to higher-income buyers (Van den Broeck, 2019). For these groups, complementary instruments – such as targeted subsidies, low interest renovation loans, or guarantee schemes – could be considered to help mitigate financing barriers, alongside supply-side policies that expand housing supply and improve housing affordability more generally.

A broader concern – related to minimum energy performance standards in general and the growing emphasis on energy classes – is the increased likelihood of deliberate misreporting of energy scores. In the Appendix, we show substantial bunching of energy scores just below the energy class thresholds in both the Flemish and Walloon Regions, which has strongly increased since 2023, especially for energy scores close to the Flemish renovation obligation threshold. We attribute this phenomenon partly to misreporting, as supported by Lu and Spaenjers (2025) for France. It should however be noted

that bunching primarily concerns energy scores just below the energy class threshold values, which make up a small percentage of total energy performance certificates. Still, while we did not investigate the existence of more generalised EPC misreporting, it seems clear that the growing importance of the energy score for homebuyers, banks and policymakers has increased the risk of misreporting. In particular, an increase in misreporting could be expected based on Goodhart's law, which states that when a particular measure becomes a (policy) target, it will become less effective as people start to game the system to meet the target.

Finally, renovation obligations for homebuyers are insufficient on their own to reach the 2050 climate and energy efficiency objectives. First, the minimum standard required under transaction triggered obligations – such as the EPC class D target in the Flemish case – may remain far below long term regional objectives for the building stock, implying that even dwellings covered by the obligation are not required to reach the long run target level. Second, many dwellings will not be subject to the obligation in the near term, which means that relying solely on transaction-triggered obligations would take many decades to achieve full coverage. Coverage will also expand unevenly across space, growing faster in high turnover market segments and areas than in low-turnover ones. Moreover, the policy may incentivise some households to postpone moving in order to avoid the obligation, potentially reducing household mobility and delaying energy-efficiency investments. Taken together, these considerations underscore the need for complementary measures beyond the transacted segment of the housing stock to accelerate renovations and ensure progress toward 2050 climate goals.

6. Conclusion

This article analyses the impact of the Flemish energy renovation obligation, introduced in January 2023, on house prices. This policy obliges buyers of the most energy-inefficient Flemish homes, i.e. those with a class E or F EPC, to renovate within five years from purchasing the property in order to obtain at least a class D EPC.

We find that the Flemish renovation obligation has had a modest negative impact on the prices of houses with a class E or F EPC. Energy-inefficient houses in the Flemish Region became about 2% cheaper relative to both similar houses in the Walloon Region and to those with a class D EPC in the Flemish Region. This result is consistent across multiple specifications, including a triple difference specification that compares price differentials between EPC classes across both regions. For an average house with a class E or F EPC in the year prior to the policy change, the estimated price effect corresponds to approximately €5,800. The price effect did not materialise immediately following the policy's introduction but instead accumulated gradually over the course of 2023 and remained broadly stable through the first three quarters of 2024.

The reasons for this relatively limited effect of the energy renovation obligation are, first, that a majority of buyers of houses with a class E or F EPC were already renovating their properties to at least a class D EPC prior to its introduction and, second, that the renovation cost was already largely factored into house prices beforehand. More generally, we assess that the impact on house prices of an energy renovation obligation for homebuyers is closely linked to three factors: (i) the credibility and enforcement mechanisms of the policy, (ii) whether the minimum energy performance standard is achieved by a large number of homebuyers even in the absence of the obligation, and (iii) the extent to which the cost of an energy renovation was already factored into house prices prior to the policy change. These factors can vary across countries and depend on the typical renovation activity of buyers, the overall condition of the housing stock, and the stringency and scope of the renovation obligation – namely, the minimum EPC class to be achieved and the EPC classes subject to the obligation.

Our finding that the Flemish energy renovation obligation has slightly lowered the prices of energy-inefficient houses has redistributive implications. First, it implies a modest negative impact on the wealth of the owners of energy-intensive houses. Second, the higher price discount creates a small amount of financial leeway for buyers to carry out an energy renovation, somewhat alleviating the financial burden of the energy and climate transition. However, for those who were not planning to renovate, the renovation obligation results in a large upfront compulsory investment, on top of the purchase price. This could hamper the accessibility of homeownership for potential buyers without sufficient repayment capacity.

Finally, as Flanders is the only region in the world to have introduced an energy renovation obligation for homebuyers, our findings may be of interest to the many other countries that are considering a similar policy. In particular, they are relevant for other EU member states, given that the recently revised Energy Performance of Buildings Directive sets energy efficiency targets for residential building stock to be met by 2030, with a focus on renovation of the worst-performing residential dwellings and the use of minimum energy performance standards as a key potential lever.

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Appendix: Bunching of energy scores below the EPC class thresholds

In this section, we analyse the impact of the Flemish renovation obligation on the bunching of energy scores just below the energy class threshold values. Figure 7 shows the share of each EPC score interval with a width of 5 kWh/m^2 as a percentage of the total number of EPCs for houses sold in the Flemish and Walloon Regions. Like Lu and Spaenjers (2025), we limited our analysis to houses for which only one EPC was available prior to the sale so as to isolate bunching that is likely the result of misreporting. We excluded properties with more than one EPC because, for such properties, the homeowner may have carried out renovation works after having obtained a first EPC in order to move the property's energy score just to the left of the energy class threshold.[4]

We measure bunching by comparing the prevalence of the energy score interval just below the energy class threshold with that just above, which should be about equal in the absence of bunching. It should be noted, however, that a drop in the prevalence of energy scores just above the energy class threshold could in part also be the result of homes not being put up for sale or not being sold after having received an EPC on the wrong side of the threshold.

We observe a strong increase in bunching in the Flemish Region since 2023 and a comparable yet more moderate rise in the Walloon Region. First, given that the Flemish EPC classes were only introduced in 2019, there was no bunching at energy class thresholds in the period 2016–2018. The introduction of the EPC classes led to a small amount of bunching in the period 2019–2021 and in 2022, with 30 to 40% more houses sold with energy score intervals just below the threshold value than just above. Bunching increased strongly in the period 2023–Q1 2024, with energy score intervals just below the threshold two to almost four times more prevalent than those above the threshold. This was most noticeable at the Flemish renovation obligation threshold, between class D and E EPCs. As the EPC was introduced earlier in the Walloon Region, bunching was already present there during the period 2016-2018 and remained constant in 2019–2021 and 2022, with the prevalence of energy score intervals just below the threshold values being about 50% higher. Bunching also increased in the period 2023–Q1 2024, but to a lesser extent than in the Flemish Region.

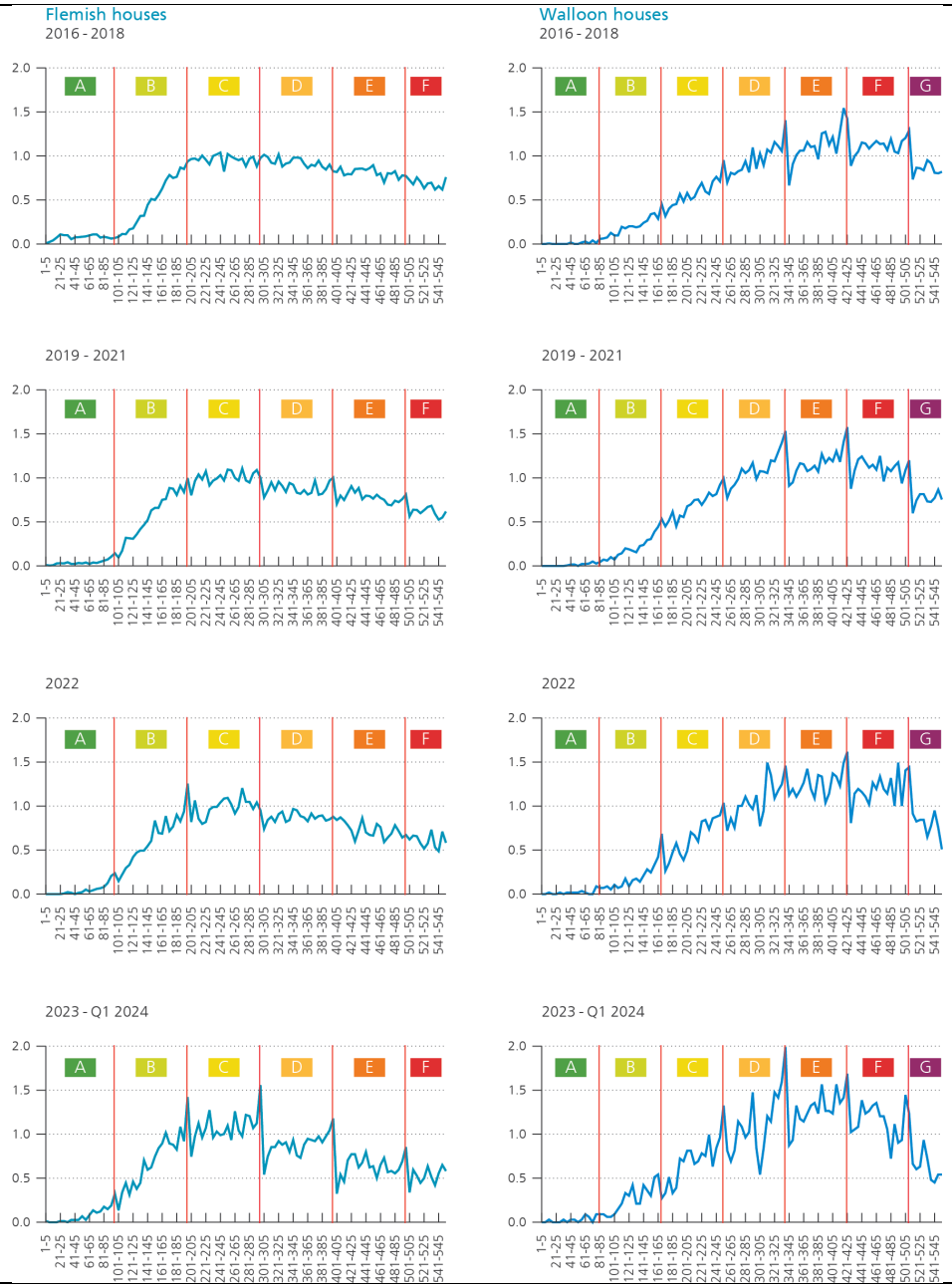
The increase in bunching observed since 2023 can most likely be attributed to the heightened importance of the EPC due to the introduction of the Flemish renovation obligation, the announcement of future renovation requirements in the two regions (see Section 1) and the increased salience of EPC scores in buyer decision-making, mortgage conditions, and broader market dynamics (see Section 4.2).

As we limited our analysis of bunching to houses for which only one EPC was available prior to the sale, this phenomenon likely results in part from misreporting. While bunching could also be the result of genuine renovation works (desirable from a climate-policy perspective) undertaken specifically to move the dwelling just across an energy-class threshold, this is not likely to be the main case for owners without prior knowledge of their property's energy score. However, we cannot rule out last-minute energy efficiency improvements stemming from an initial energy score estimate that was not documented in the EPC database, and Section 4.1 presents some evidence that pre-sale upgrades have become slightly more common since 2023. In addition, the bunching at the threshold between class D and E EPCs in 2023–Q1 2024 may also partly reflect the strategic timing of transactions, particularly the acceleration of sales involving class E or F dwellings in late 2022 (see Section 1) as well as the possible postponement of some household moves to avoid the renovation obligation. While disentangling the relative importance of these

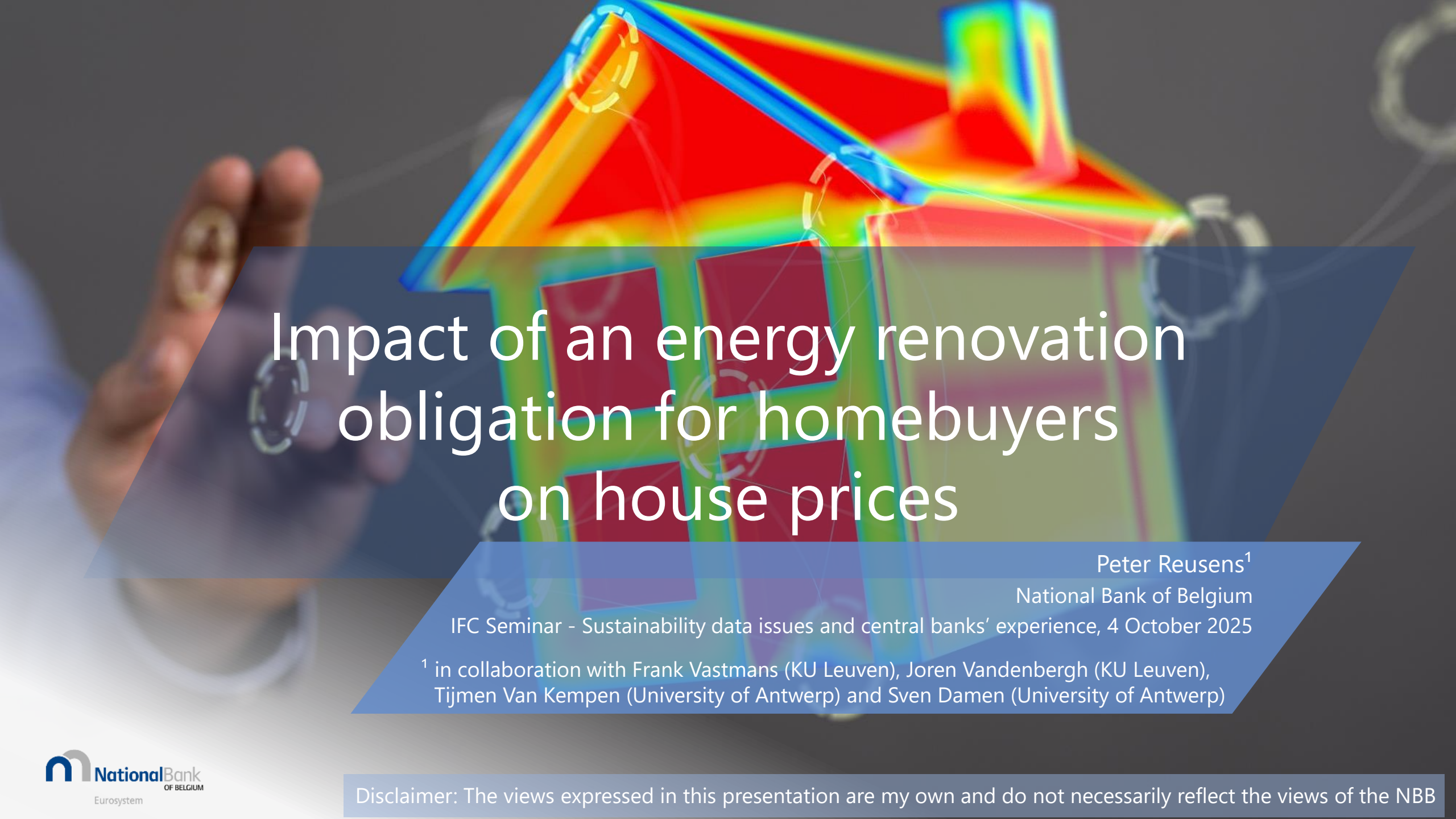
[4] Analysing properties in England and Wales for which more than one EPC had been requested before a sale, Sejas-Portillo, Moro and Stowasser (2025) found that sellers whose properties received an energy score just on the wrong side of the energy class threshold were more likely to improve their rating, which they attributed to last-minute energy efficiency improvements prior to listing the property.

reasons for bunching empirically is not possible with our dataset, our assessment that misreporting plays a role aligns with Lu and Spaenjers (2025) and Civel et al. (2025). Both studies document significant bunching in France and attribute it to misreporting, supported by evidence such as persistent assessor-specific tendencies, software-related variations, deliberate underreporting of dwelling size, and a higher prevalence of bunching in competitive certifier markets.

Prevalence of each energy score interval for houses sold, by EPC issuance year[1]
(as a percentage of the number of houses sold for which only one EPC was available prior to the sale) Figure 7



[1] The vertical lines indicate the energy class thresholds in the Flemish and Walloon Regions, based on the respective energy class definitions from Figure 1. The horizontal axis shows the energy scores, which are grouped in intervals of 5 kWh/m². We omitted very large energy scores (above 550 kWh/m²) from the graphs for the sake of readability.



Impact of an energy renovation obligation for homebuyers on house prices

Peter Reusens[1]
National Bank of Belgium

IFC Seminar - Sustainability data issues and central banks' experience, 4 October 2025

[1] in collaboration with Frank Vastmans (KU Leuven), Joren Vandenbergh (KU Leuven), Tijmen Van Kempen (University of Antwerp) and Sven Damen (University of Antwerp)

National Bank OF BELGIUM
Eurosystem

Disclaimer: The views expressed in this presentation are my own and do not necessarily reflect the views of the NBB



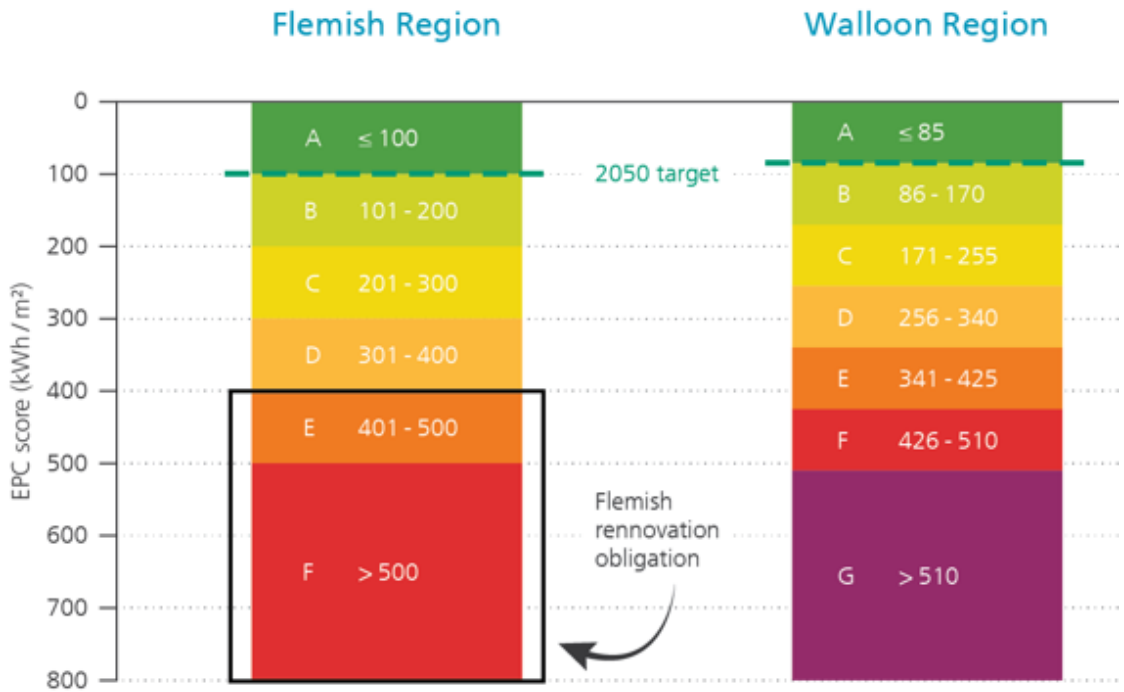
1. Introduction
2. Methodology
3. Results
4. Potential mechanisms
5. Policy implications
6. Bonus topic: Impact of energy efficiency on hedonic house price indices



1. Introduction

Since 2023, homebuyers of Flemish dwellings with a class E or F EPC are obliged to renovate their home to at least a class D level within 5 years

Grouping of energy scores for EPC class purposes[1]



Belgium and its Regions



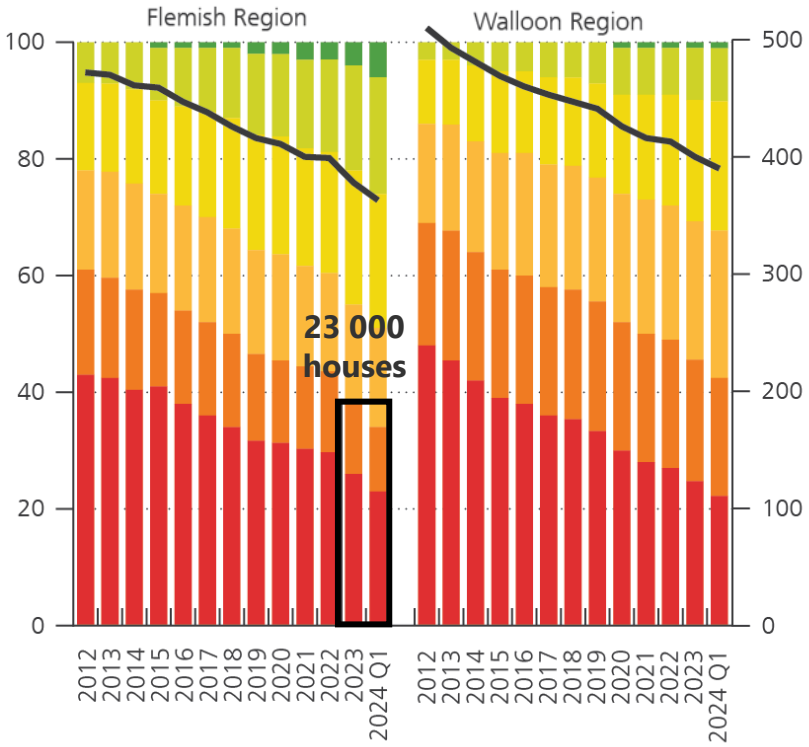
[1] This presentation uses the Flemish Energy Performance Certificate (EPC) classification for both regions for the sake of comparability.

The energy efficiency of sold dwellings has improved over the past decade and the renovation obligation primarily affects houses rather than apartments

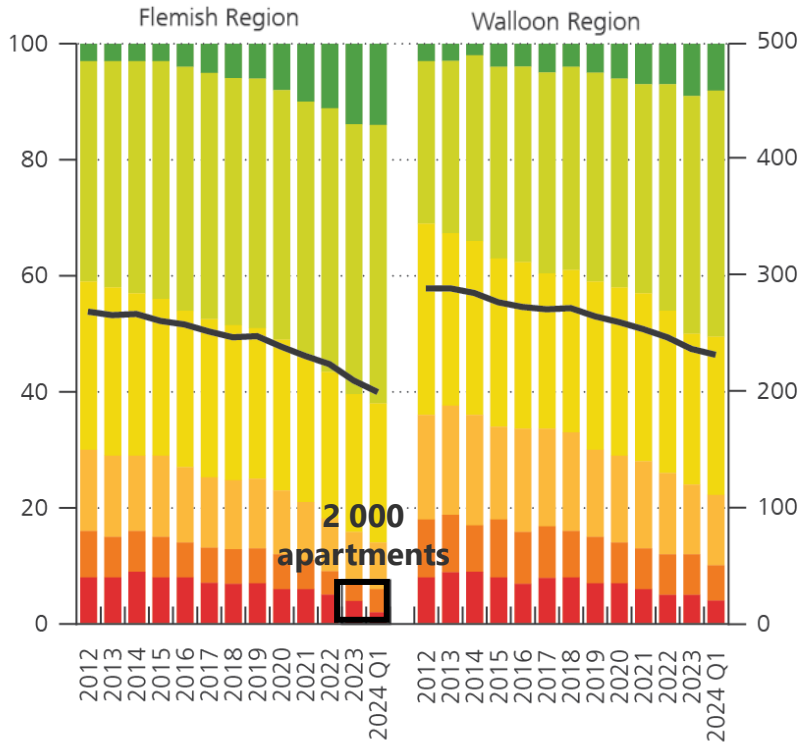
Energy efficiency EPC-score of the sold dwellings[1]

(in % of houses sold (left axis); average EPC in kWh/m²y (right axis))

Houses



Apartments





[1] Note that this energy performance distribution of the sold dwellings is worse than for the entire dwelling stock because (i) new constructions were not included, (ii) overrepresentation of energy-inefficient houses and (iii) the EPC certificate is issued before sale, not reflecting post-sale renovations.

We created a unique dataset, merging all Belgian dwelling transactions to the Energy Performance Certificates, asbestos certificates and online listings

All dwelling transactions (FPS Finance)

- Address (unique identifier)
- Sales price
- Date of sale
- Dwelling characteristics
- 2006 - Q3 2024

Online listings (Realo)

- Address (unique identifier)
- Initial asking price
- Initial listing and delisting date
- Dwelling characteristics
- 2016 - Q3 2024

Unique database



Energy performance certificates (VEKA, SPW, Brussels Environment)

- Address (unique identifier)
- Energy score
- Energy efficiency characteristics
- Main heating source
- 2009 - Q1 2024

Asbestos certificates (OVAM)

- Address (unique identifier)
- Asbestos safety
- Nov. 2022 - Q1 2024
- Flanders only

Main contributions

1. We are the first to examine the impact of a renovation obligation for homebuyers on house prices
   - This Flemish renovation obligation for homebuyers is the first of its kind in the world
   - Limited earlier evidence on minimum energy performance standards, but only for rental dwellings (Clara et al., 2024; Fuerst & Huang, 2023)

2. We provide more accurate estimates of the capitalisation of energy efficiency into house prices
   - Very wide range of estimated energy efficiency price premia in previous literature (see e.g. Copiello & Donati, 2021), due to differences in the time periods and countries analysed, EPC class definitions and omitted variable bias
   - We estimate quality-adjusted house prices for each EPC class, controlling for a large set of dwelling characteristics

3. We provide new insights on the energy efficiency and other characteristics of sold dwellings
   - Unique database merging Belgian dwelling transactions data, energy performance certificates, asbestos certificates and online listings data
   - Useful for the development of national databases on the energy performance of homes and the EU Building Stock Observatory (EC, 2024)



2. Methodology

We estimate the impact of the Flemish renovation obligation on house prices using difference-in-differences analyses

- We compare the trend in prices of Flemish houses with a class E or F EPC (the treatment group) with that of similar houses sold in a comparable economic environment but not subject to the renovation obligation

- We perform three separate analyses, each with a different control group

1. Flemish E+F vs D	✅ Same region 🟡 Similar EPC classes, but a general increased EPC importance may still confound results 🟡 Cannot isolate potential upward price effect of the policy on EPC D houses
2. Flemish E+F vs Walloon E+F	🟡 Similar economic context, but regional shocks may still confound results ✅ Same EPC class ✅ Can isolate policy impact on E+F, C+D, A+B EPC classes
3. Triple-Difference Flemish E+F vs C+D vs Walloon E+F vs C+D	✅ Controls for regional shocks ✅ Controls for common EPC-specific shocks 🟡 Cannot isolate potential upward price effect of the policy on Flemish EPC C+D houses

Difference-in-differences models

1. Flemish E+F vs D

$$\log(p_{it}) = \gamma R_{i,t}^{EF} + \delta_t + \delta_{EPC} + \sum_{k=1}^{K} \beta^k x_{it}^k + \epsilon_{it} \quad (1)$$

2. Flemish E+F vs Walloon E+F

$$\begin{aligned}\log(\tilde{p}_{it}) = {} & \gamma_{AB} R_{i,t}^{AB} + \delta_{t,AB} + \delta_{Flanders,AB} \\ & + \gamma_{CD} R_{i,t}^{CD} + \delta_{t,CD} + \delta_{Flanders,CD} \\ & + \gamma_{EF} R_{i,t}^{EF} + \delta_{t,EF} + \delta_{Flanders,EF} + \delta_{EPC} + \delta_{Fiscal} + \sum_{k=1}^{K} \beta^k x_{it}^k + \epsilon_{it}\end{aligned} \quad (2)$$

3. Triple-Difference

Flemish E+F vs C+D

vs

Walloon E+F vs C+D

$$\log(p_{it}) = \gamma R_{i,t}^{EF} + \delta_{Flanders,EF} + \delta_{t,Flanders} + \delta_{t,EF} + \delta_t + \delta_{EPC} + \sum_{k=1}^{K} \beta^k x_{it}^k + \epsilon_{it} \quad (3)$$

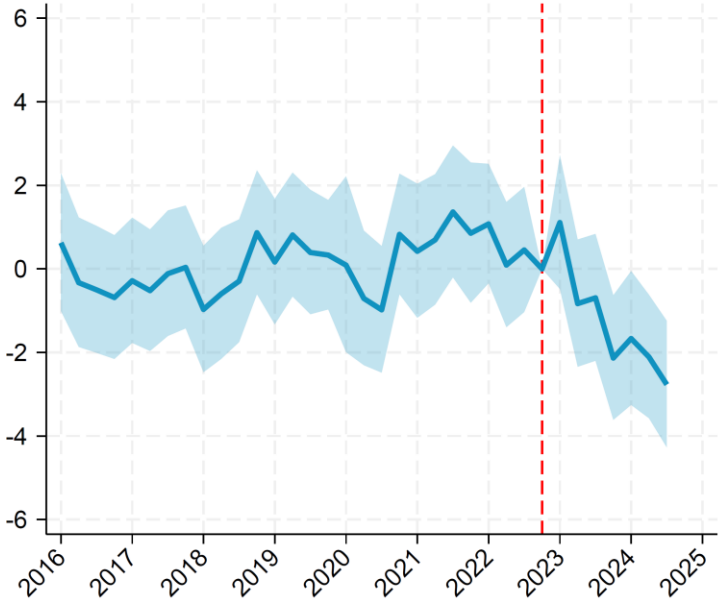


3. Results

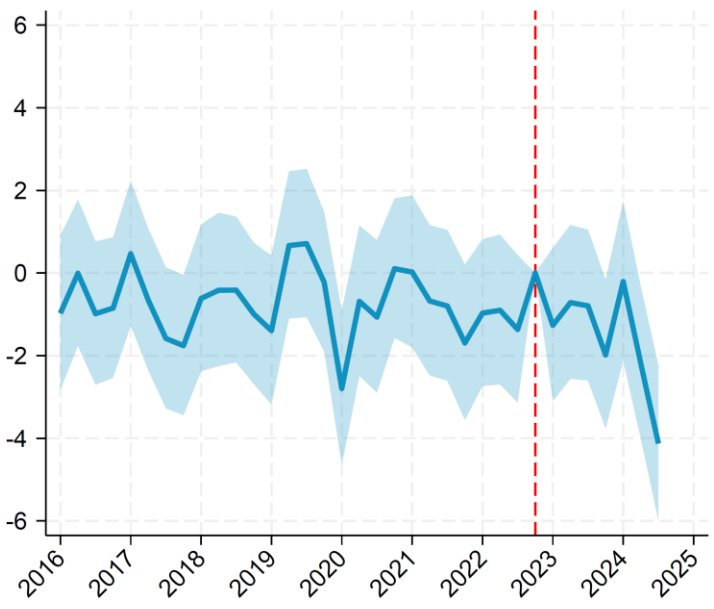
Price trends in the treatment and control groups were very similar prior to introduction of the renovation obligation

Difference in price trends (relative to Q4 2022) between the treatment group and the control group
(in percentage points)

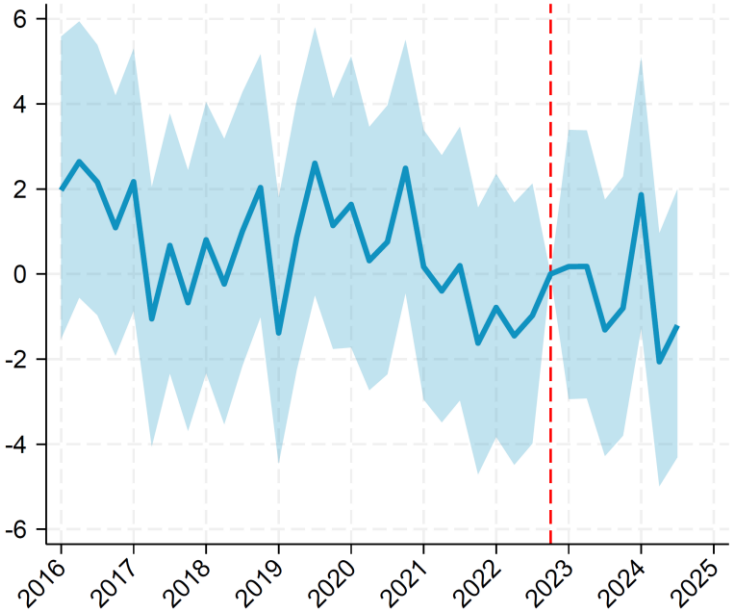
1. Flemish E+F vs D



2. Flemish E+F vs Walloon E+F



3. Triple-Difference



Flemish renovation obligation had a modest negative impact on prices of houses with a class E/F EPC and no price impact on the better energy scores

Estimated impact of the Flemish renovation obligation for each difference-in-differences analysis

	1. Flemish Region	2. Flemish Region vs Walloon Region			3. Triple difference
	E+F vs D	E+F	C+D	A+B	
Entire period	-0.014***	-0.009**	0.000	-0.006	-0.011***
	(0.003)	(0.004)	(0.003)	(0.005)	(0.004)
Q1 2023	0.001	-0.006	-0.009	-0.020	0.003
Q2 2023	-0.001	-0.000	0.006	-0.026**	-0.007
Q3 2023	-0.008	-0.001	0.006	-0.007	-0.009
Q4 2023	-0.023***	-0.013*	0.003	0.010	-0.019**
Q1 2024	-0.018***	0.005	-0.007	-0.018	0.011
Q2 2024	-0.023***	-0.015**	0.009	0.013	-0.025***
Q3 2024	-0.029***	-0.035***	-0.007	-0.006	-0.030***
Observations	*154 403*		*338 807*		*288 273*
R-squared	*0.790*		*0.851*		*0.838*



4. Potential mechanisms

We assess the house price impact of a renovation obligation for homebuyers to be closely linked to three factors, which can vary from case to case

1. **The credibility and enforcement mechanisms of the policy**
   → Big administrative fines for non-compliance, extensive media coverage, legal ad disclosures and information provision by banks reinforced buyer awareness and credibility of the Flemish renovation obligation

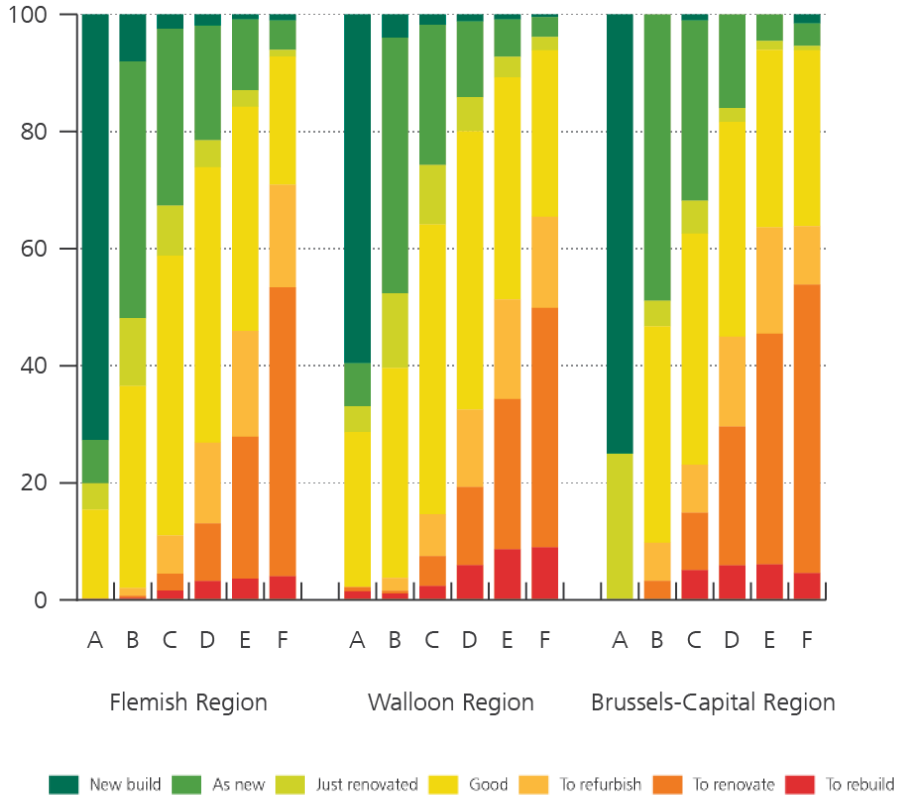
2. **Whether the energy standard is met by many homebuyers even without a mandate**
   → A majority of Flemish buyers of houses with a class E or F EPC were renovating their properties to at least a class D level in any case. The renovation obligation as such does not change much for these buyers

3. **Extent to which the energy renovation cost was factored into house prices before the policy change**
   → The price discount for Flemish E/F houses was large beforehand as the renovation cost seems to have been largely factored into the price

The overall quality and comfort of homes with a class E or F EPC are much worse than for more energy-efficient dwellings

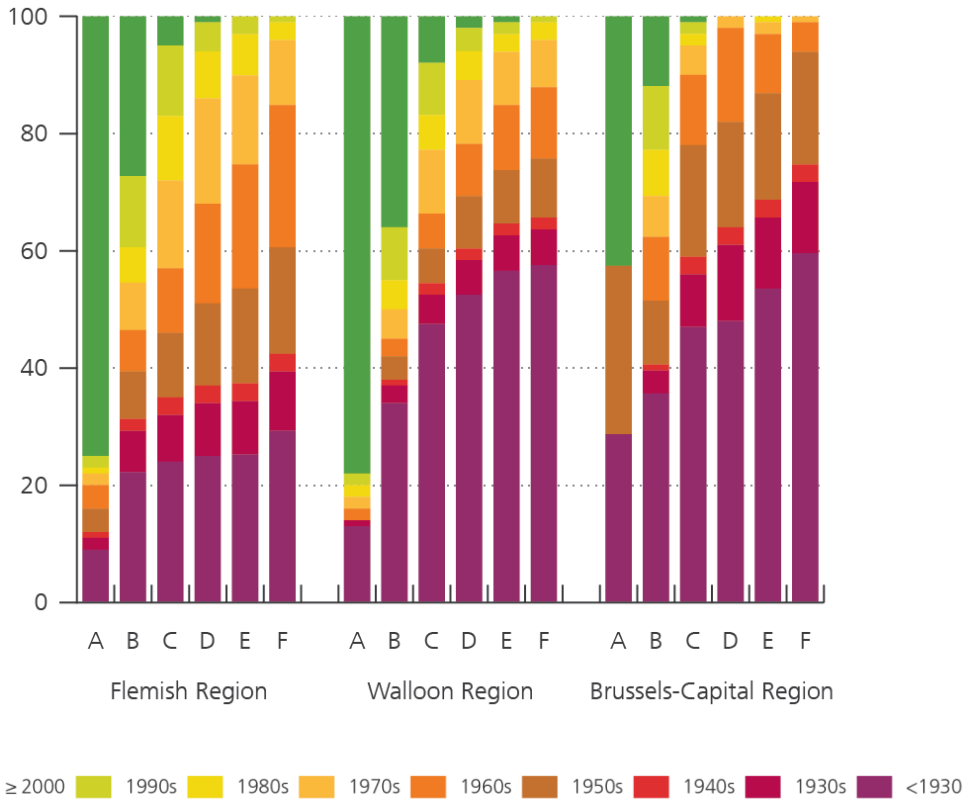
Reported building condition

(in % of houses sold in 2023-2024Q1)



Year of construction

(in % of houses sold in 2023-2024Q1)

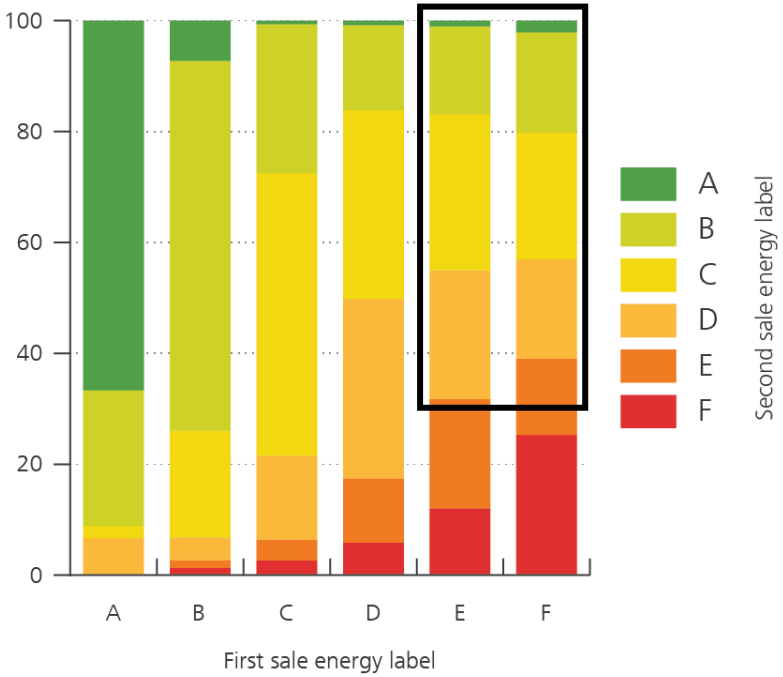


Due to their poor quality, a majority of buyers of houses with a class E or F EPC were renovating their homes to at least a class D level in any case

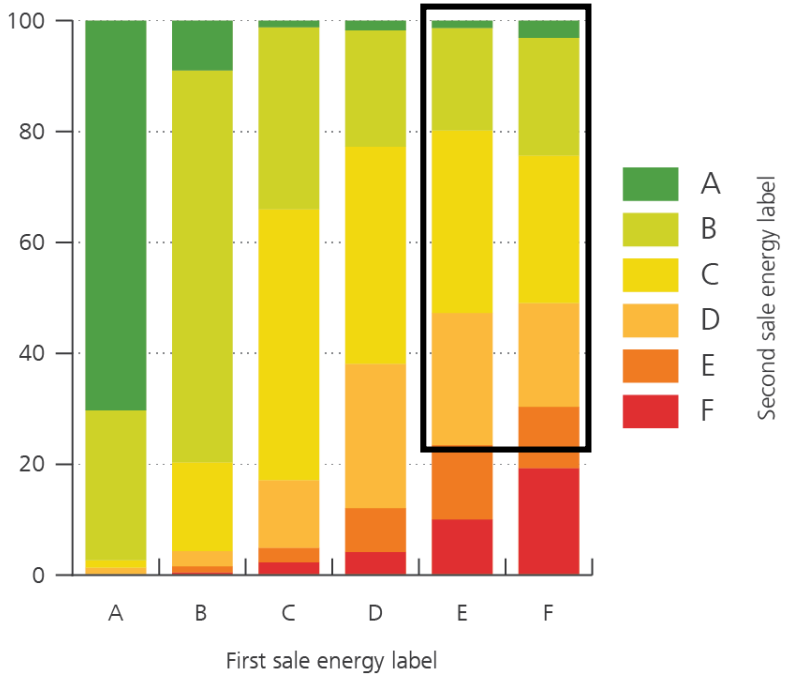
Change in the EPC class for Flemish houses sold twice[1]

(EPC distribution for the second sale, broken down by EPC for the first sale, as a %)

Second sale in 2022



Second sale in 2023 – Q1 2024



[1] The charts illustrate the change in the energy class for the Flemish houses with multiple recorded sales in the dataset, with at least a five-year interval between sales. We could accurately analyse the improvement in energy efficiency only for Flemish houses sold for the second time since 2022. For this group alone, the EPC for the first sale could not be reused for the second sale, meaning the energy score had to be recalculated when the property was resold.

Quality-adjusted house prices per EPC class: methodology

- Motivation for quality adjusted prices: energy-efficient houses are on average more expensive not only due to their greater energy efficiency but also because they tend to be newer and in better condition

- Hedonic regression model

$$\log(p_{it}) = \delta_t + \sum_{z=1}^{5} \alpha_t^z EPC_{it}^z + \sum_{k=1}^{K} \beta^k x_{it}^k + \varepsilon_{it}$$

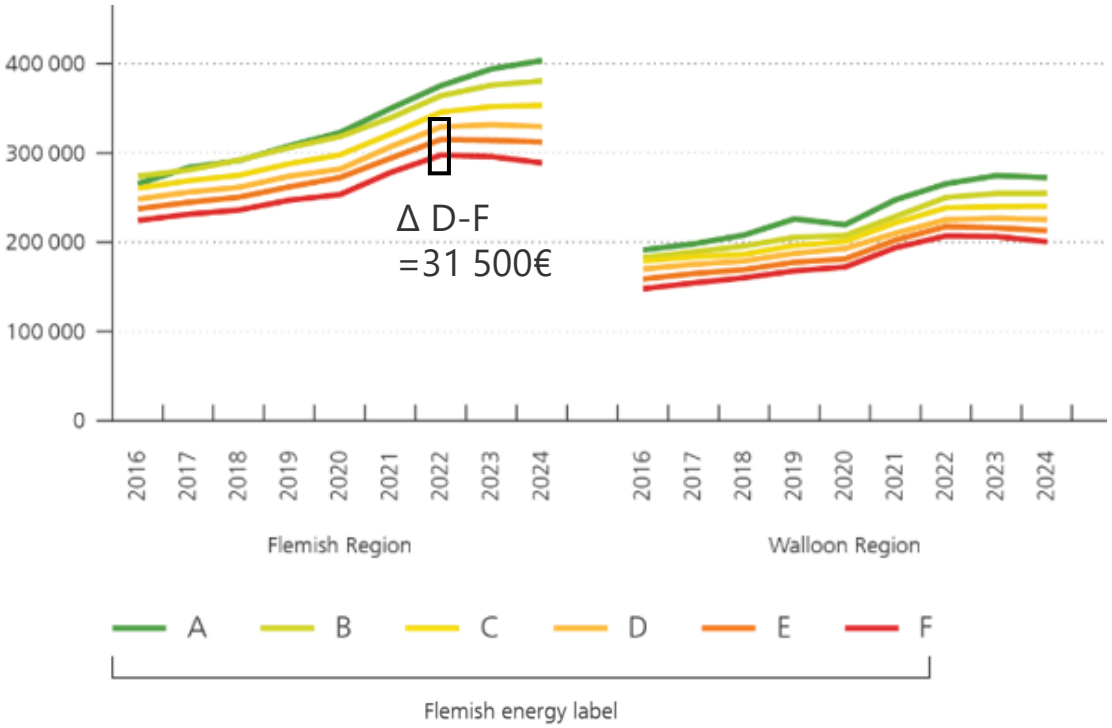
- Estimated quality adjusted price for a house with energy class *z* and average dwelling characteristics $\bar{x}^k$ (e.g. age, dwelling type, reported building condition, house size and location)

$$P_t^z = \mathrm{e}^{(\hat{\delta}_t + \hat{\alpha}_t^z + \sum_{k=1}^{K} \hat{\beta}^k \bar{x}^k)}$$

- Price difference between EPC classes can be interpreted as the estimated added value of a class improvement (but caution is advised due to estimation uncertainty, omitted variable bias and dwelling specific factors)

Price discount for houses with a class E/F EPC was already large prior to the renovation obligation and it largely corresponded to the renovation cost[1]

Quality-adjusted price per EPC class
for a house with average characteristics
(in euro)

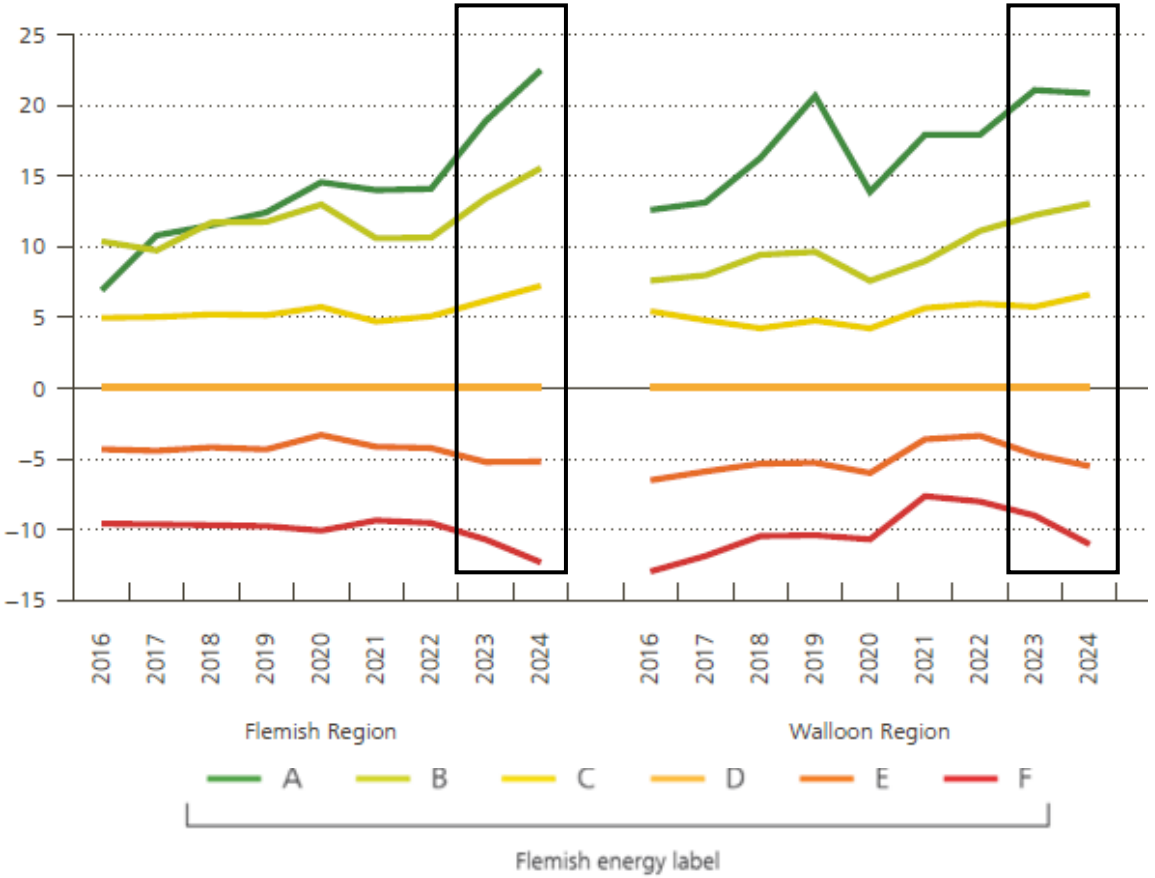


[1] While accurate estimates of the cost of an energy renovation are lacking, an analysis of a small sample of invoices from recent Flemish energy renovations indicates that the price discount appears to reflect to a large extent the average cost of an energy renovation to a class D level. However, it should be noted that the renovation cost can vary widely from dwelling to dwelling.

Beyond the Flemish renovation obligation, the energy score has gained importance in both regions since 2023 due to several additional factors

Price difference vs. comparable house with class D EPC[1]

(in %)



Factors behind the increased EPC price impact

Buyers and banks are increasingly taking the energy score into account in their purchase decisions and mortgage conditions as a result of:

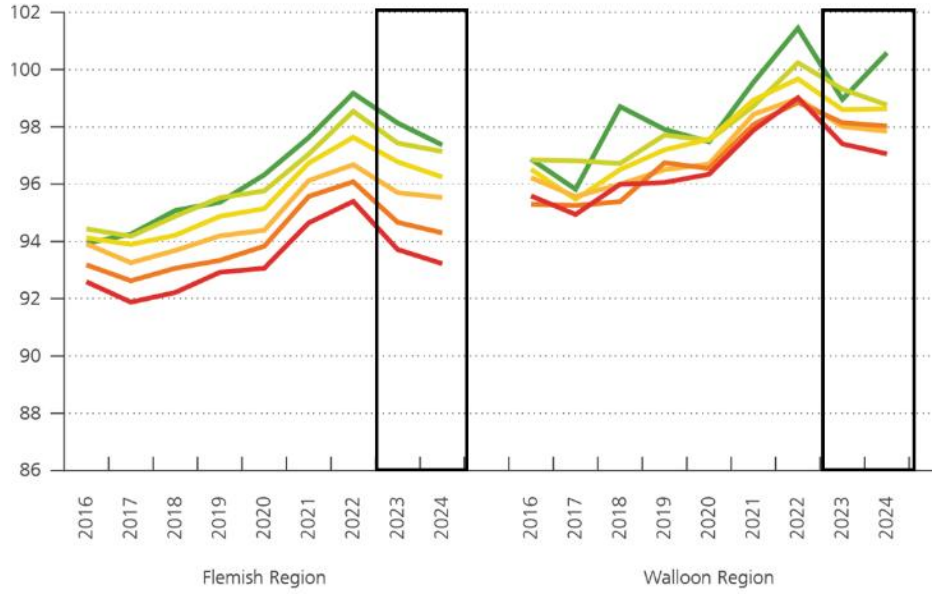
- Higher and more uncertain energy bills
- The future carbon price for heating fuels
- Higher renovation costs
- (Future) renovation obligations
- Better collection of energy scores by banks

[1] Our study estimates the price difference between homes with a different EPC class, while holding all other housing characteristics constant (e.g., age, condition of the home, size and location). Still, our results should be interpreted with caution as we could not control for quality characteristics that are not included in the dataset.

The sales-to-listing price ratio has decreased and houses are on sale for longer since 2023 (due to the rent increase) and the impact was largest for the energy inefficient houses

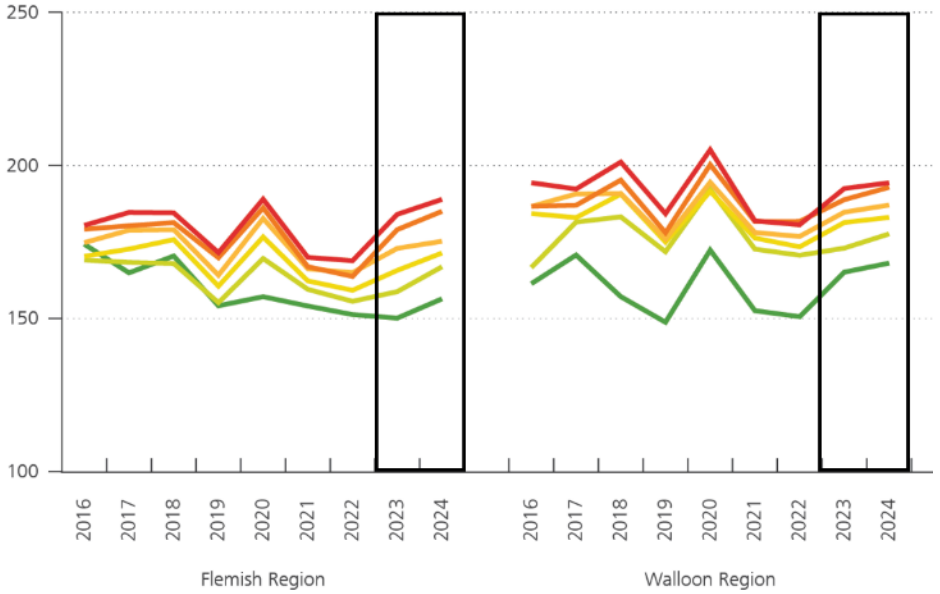
Sales-to-listing price ratio[1]

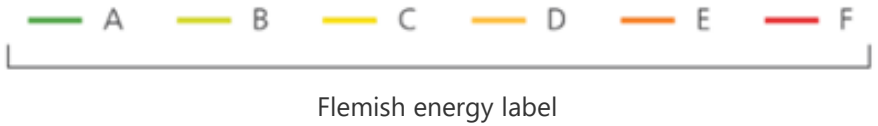
(in %)



Days on market[1]

(number of days between the first listing and the notarial deed)





[1] Estimated for a house with dwelling characteristics equal to the regional average for 2016–2024.

5. Policy implications



Energy renovation obligation for homebuyers: benefits and downsides

- Meeting EU 2050 energy efficiency and climate goals —requiring renovations of most existing homes— faces major hurdles: labour shortages, affordability issues, and limited homeowner interest

- An energy renovation obligation for homebuyers could somewhat alleviate these impediments in several ways
  - Slightly lowers purchase prices of inefficient homes, giving buyers financial room to invest in energy renovations
  - Leverages banks' role to inform buyers on renovation obligations
  - Aligns with natural renovation timing, as buyers often upgrade homes shortly after purchase
  - Ensures that energy renovations will take place (as it is mandatory)
  - Staggers renovation deadlines over time (vs. a uniform MEPS deadline), helping to alleviate labour shortages

- Potential downsides
  - Lowers property values for current owners of inefficient homes
  - The renovation obligation is a large compulsory investment for those who were not planning to renovate
    → This could hamper accessibility of home ownership for buyers without sufficient repayment capacity
  - The increased policy importance of EPC classes may exacerbate EPC-misreporting following Goodhart's law (next slide)

Increase in bunching just below energy class thresholds (partially due to misreporting[1]), which can be attributed to the increased importance of the EPC since 2023

Prevalence of each energy score interval of sold houses, by year of issuance of the EPC in the Flemish Region[2]

(as a percentage of the number of houses sold for which only one EPC was available prior to the sale)



Sources: FOD Financiën, VEKA, own calculations.

[1] Lu & Spaenjers (2025) observed significant bunching in France from 2013 to 2020 and attributed it to misreporting, supported by additional evidence.

[2] The horizontal axis shows the energy scores, which are grouped in intervals of 5 kWh/m². The vertical lines indicate the energy class thresholds.



Conclusion

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Conclusion

- We are the first to examine the impact of a renovation obligation for homebuyers on house prices
- We find that the Flemish renovation obligation has had a minor negative impact on the prices of E/F houses
- Reasons why the price impact was not larger
  - A majority of buyers of houses with a class E or F EPC were renovating their properties to at least a D level in any case
  - The price discount for these houses was large beforehand (renovation cost was already largely capitalised in the price)
- This slightly higher price discount of houses with class E and F EPC creates some financial leeway for buyers to carry out an energy renovation, but it also has redistributive implications
- As Flanders is currently the only region worldwide having introduced an effective renovation obligation for homebuyers, our findings are key for the many other countries that are contemplating similar policies

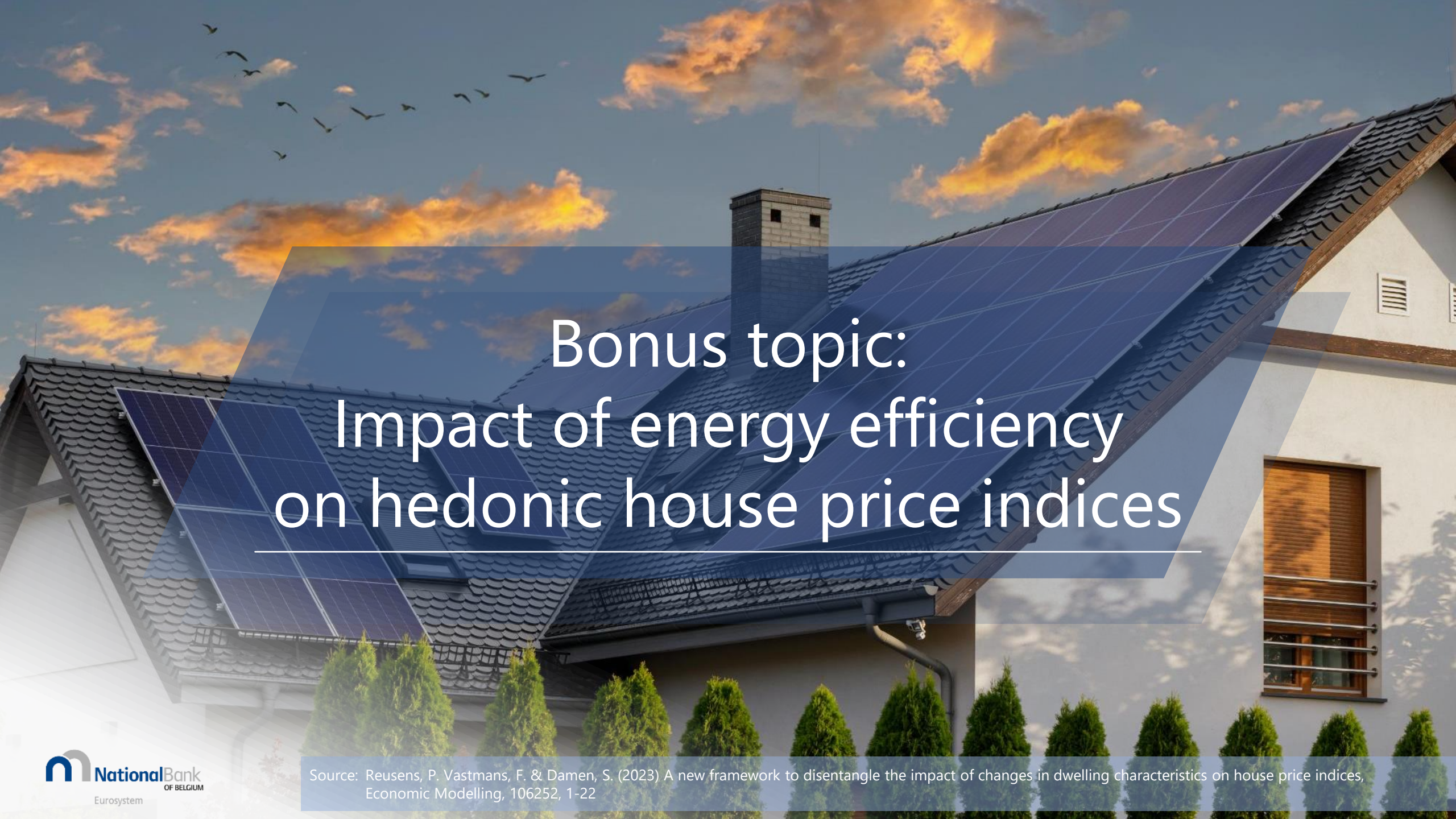
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- Reusens, Vastmans, Vandenbergh, van Kempen and Damen (2025) Impact of the Flemish energy renovation obligation on house prices NBB Economic Review 2025 1

- Reusens, P. Vastmans, F. & Damen, S. (2023). A new framework to disentangle the impact of changes in dwelling characteristics on house price indices, *Economic Modelling*, 106252, 1-22

Contact: peter.reusens@nbb.be





Bonus topic: Impact of energy efficiency on hedonic house price indices

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Eurosystem

Source: Reusens, P. Vastmans, F. & Damen, S. (2023) A new framework to disentangle the impact of changes in dwelling characteristics on house price indices, Economic Modelling, 106252, 1-22

Unlike average house prices, hedonic house price indices correct for changes over time in the quality of the houses sold

Houses sold in Period 1 (illustrative example)



Houses sold in Period 2



Our paper proposes a new framework to disentangle and quantify the contribution of each individual dwelling characteristic to the quality change

- Standard log-linear hedonic regression model with changing coefficients

$$log(p_{it}) = \delta_t + \sum_{k=1}^{K} \beta_t^k x_{it}^k + \varepsilon_{it} \quad for\ i = 1, \ldots, N_t\ and\ t = 0, \ldots, T$$

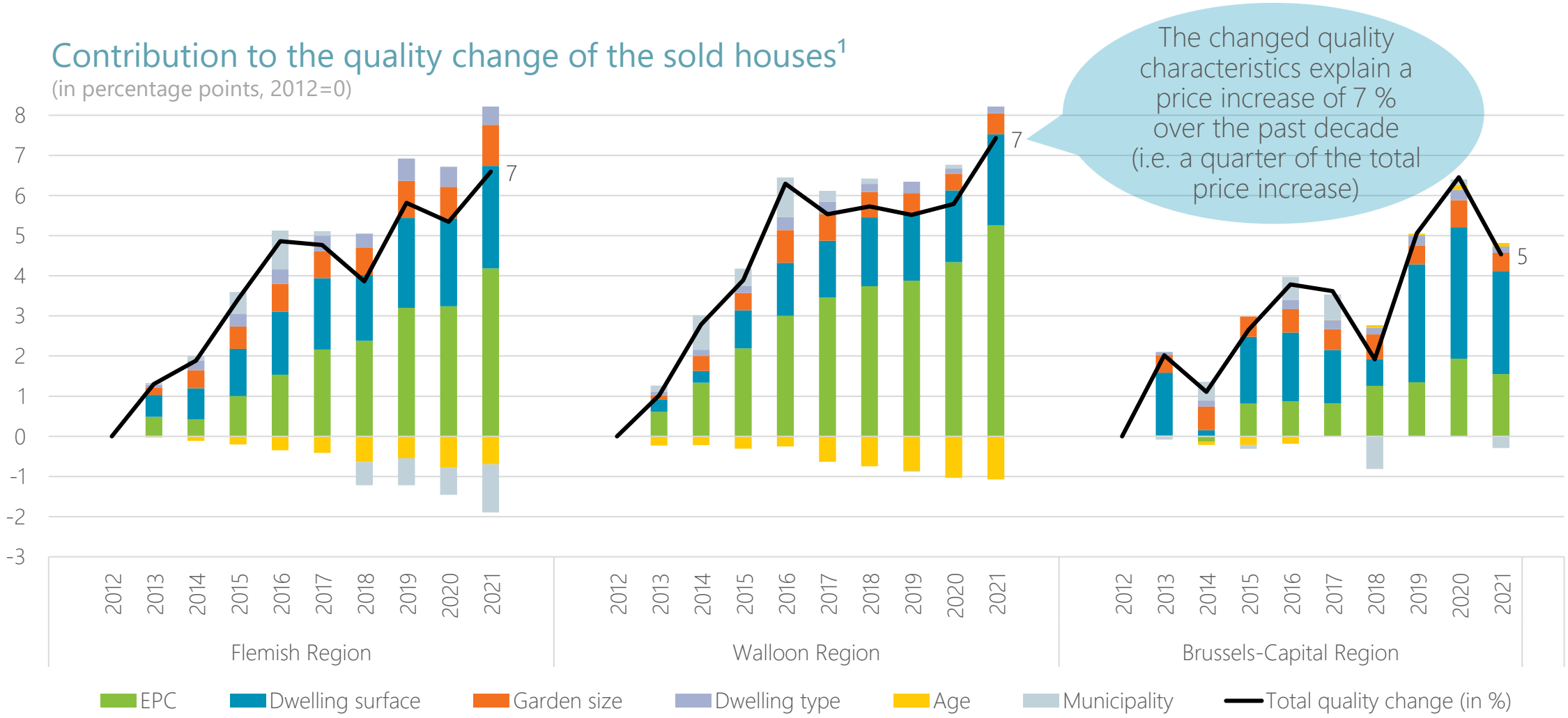
- Decomposition of the average price index as the product of the hedonic price index and the quality change

$$\frac{\prod_{i=1}^{N_t} p_{it}^{\frac{1}{N_t}}}{\prod_{i=1}^{N_0} p_{i0}^{\frac{1}{N_0}}} \approx I_t \prod_{k=1}^{K} [1 + \hat{\beta}_{0t}^k (\bar{x}_t^k - \bar{x}_0^k)]$$

Contribution of variable *k* to the quality change

Geometric mean price index | Hedonic price index | Hedonic quality change

The quality of the houses sold has improved over the previous decade, mostly driven by improved energy efficiency (as well as larger dwelling sizes)



[1] The quality of the houses sold should be broadly interpreted as the value of their dwelling characteristics. Note also that apartments are excluded and that our years are shifted backwards by 2 quarters (e.g. our year "2021" corresponds to the period 2020Q3-2021Q2).

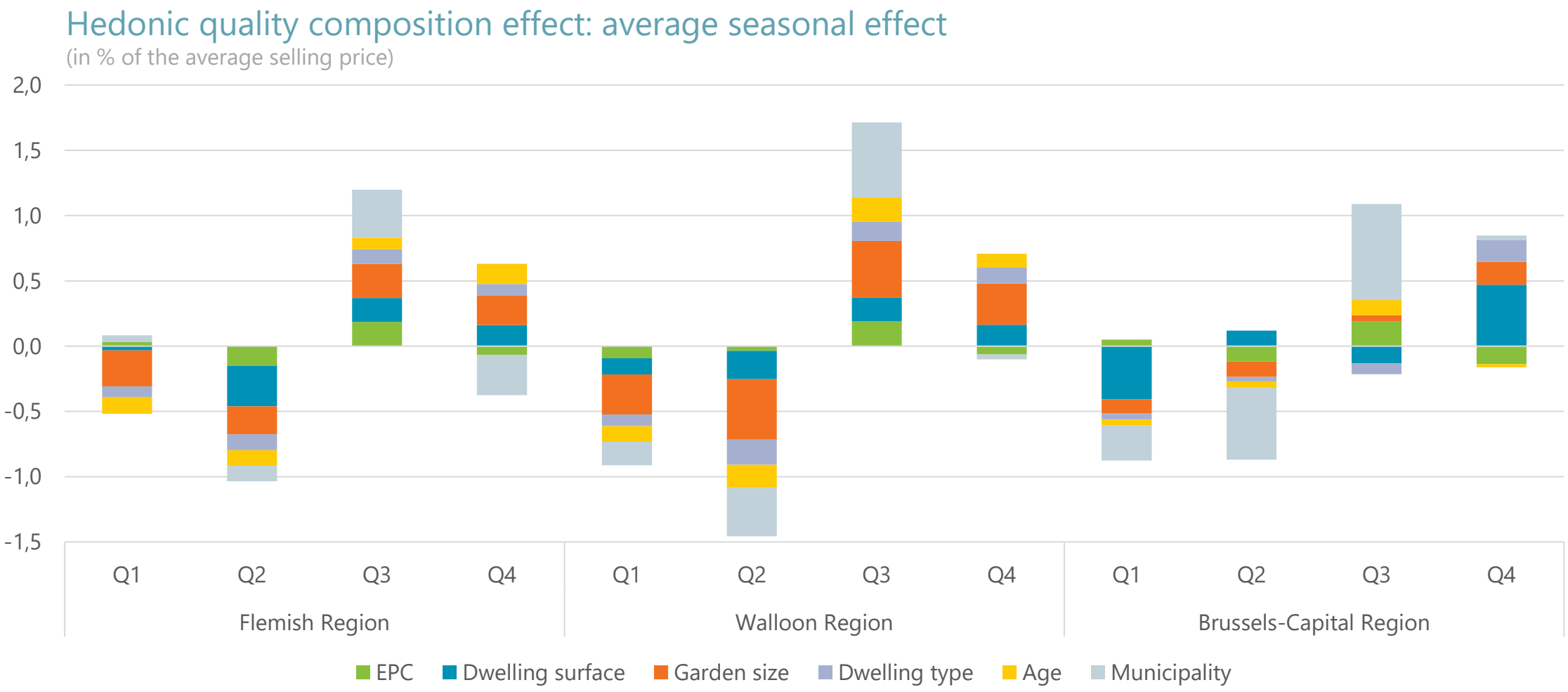
The hedonic house price index has risen 7% less over the past decade compared to average sales prices and it is less subject to (seasonal) fluctuations

Average and hedonic house price indices for the Belgian Regions

(index 2011Q3-2012Q2=100, nominal prices)



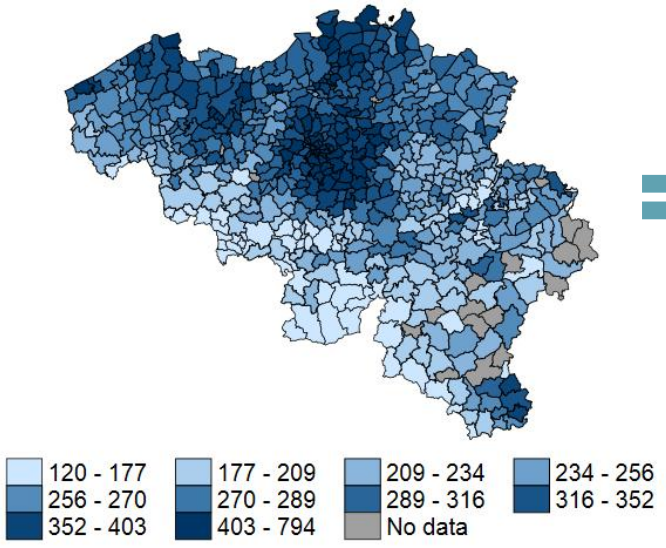
Seasonal pattern in hedonic quality change mainly reflects that dwelling and garden size is on average higher in Q3 and Q4 (sales of the Spring-Summer)[1]



[1] As the notary deed take place about 3 months before the sales agreement, the actual sale of the houses takes place about one quarter earlier.

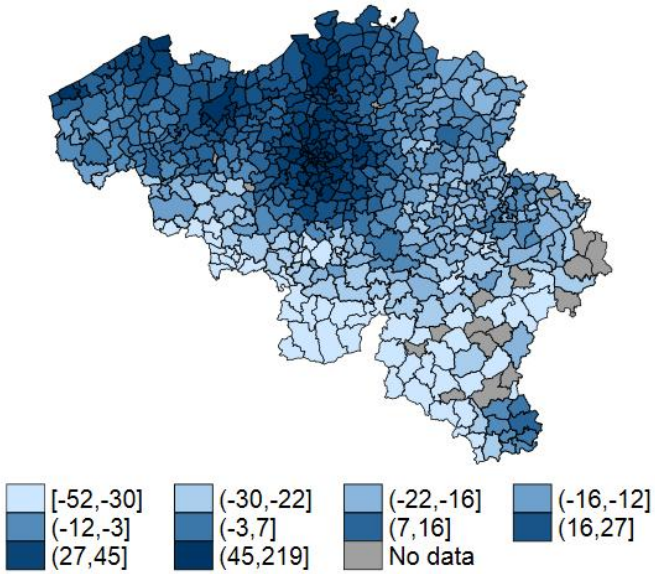
Average house prices of municipalities differ mainly due to location effect but to a lesser extent also due to quality characteristics (e.g. city houses are smaller)

Average house price in 2021[1]
(in '000 €)



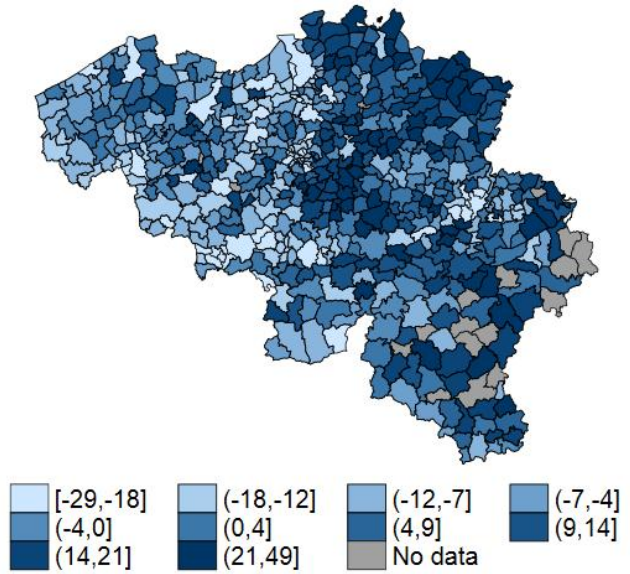
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Price difference due to location
(% difference compared to the average municipality)

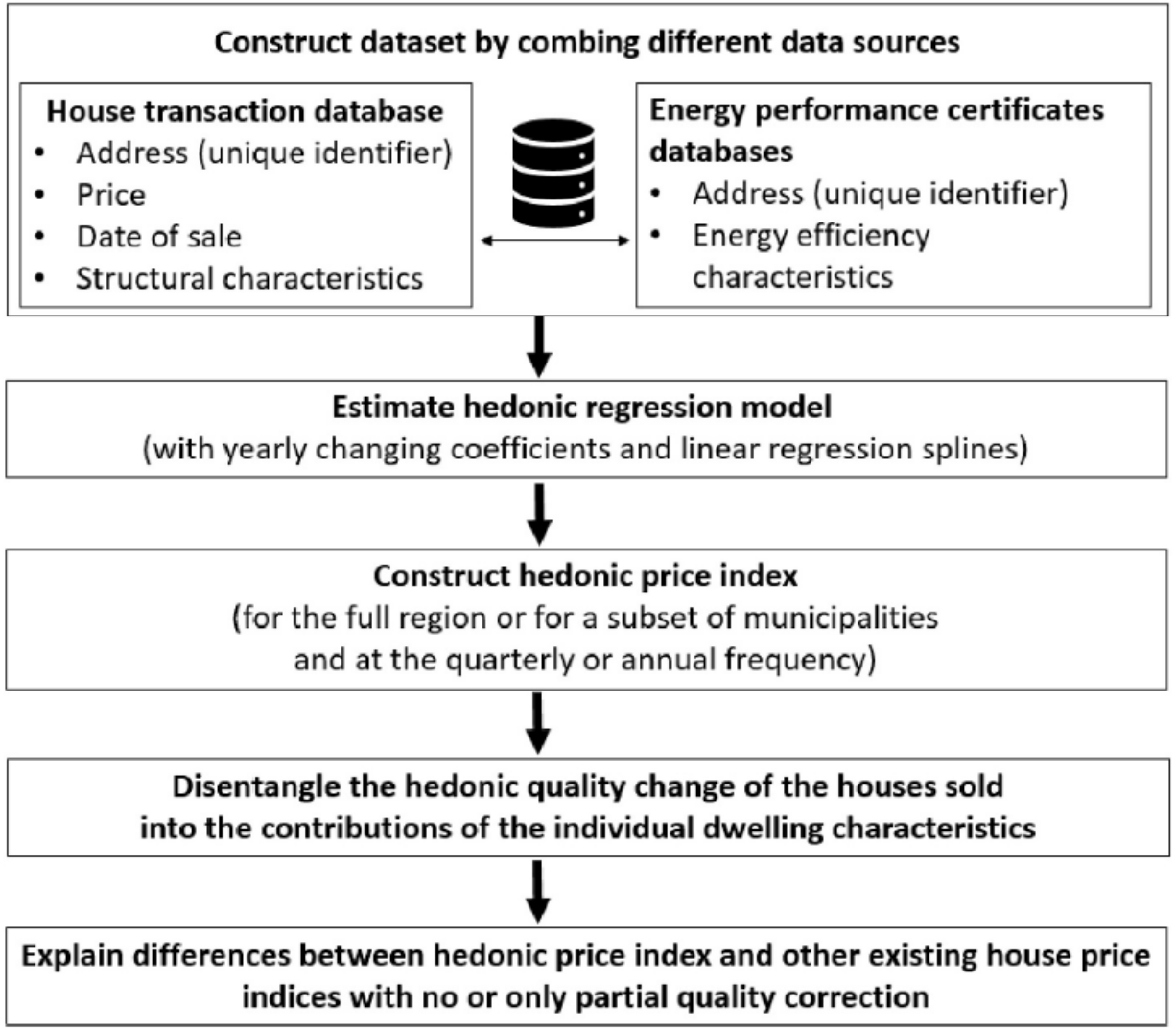


+

Price difference due to quality
(% difference compared to the average municipality)



Practical roadmap for the construction and interpretation of hedonic house price indices



Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Quantitative projection of sukuk demand in Malaysia and the potential of sustainable sukuk to bridge expected supply-demand gap

Muhammad Nadzif bin Ramlan
and Abdul Haq bin Mohaidin,
Central Bank of Malaysia

This contribution was prepared for the seminar. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC or the other central banks and institutions represented at the event.

Quantitative projection of sukuk demand in Malaysia and the potential of sustainable sukuk to bridge expected supply-demand gap[1]

Muhammad Nadzif bin Ramlan[2], Abdul Haq bin Mohaidin[3]

Abstract

Malaysia has firmly positioned itself as a prominent hub in Islamic finance, with sukuk (Shariah-compliant bonds) serving as a cornerstone of its financial ecosystem. This paper investigates the forecasting of long-term sukuk demand in Malaysia, a market that now surpasses the size of the domestic conventional bond market. Employing a quantitative approach based on historical bid-to-cover ratios from issued sukuk as benchmark, the study forecasts sukuk demand over a 10-year horizon and compares the projection against the anticipated sukuk supply. The paper also examines the potential of sustainable sukuk to bridge the expected demand-supply gap, amid their growing prominence in the market. The analysis is further contextualised by anecdotal evidence, including growing appetite from sizeable domestic institutional investors and emerging drivers that are expected to maintain the growth of sustainable sukuk such as alignment with national agenda. The findings aim to provide insights on the adequacy of current sukuk issuance rates in meeting future market demand.

Keywords: Malaysia, Islamic Finance, Sukuk, Islamic Bond, Demand-Supply Dynamics, Fixed Income Securities, Quantitative Forecasting, Sustainable Sukuk, Green Sukuk

JEL classification: C53, G12, G17, H63, Q56

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[2] Associate Analyst at Islamic Finance Department, Bank Negara Malaysia. Currently pursuing Doctoral degree in Quranic studies with a focus on influence of canonical recitations (*Qira'at*) in Islamic jurisprudence including Islamic finance principles.

[3] Manager at Islamic Finance Department, Bank Negara Malaysia.

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1. Introduction

Islamic finance has progressed from a niche alternative into an increasingly recognised component of the global financial landscape, driven by ethical imperatives and robust growth dynamics. Global Islamic finance assets reached about USD6 trillion in 2024, marking a notable 21 percent year-on-year growth, and are projected to rise to an estimated USD9.7 trillion by 2029 – underscoring the industry's sustained double-digit expansion despite prevailing market volatility (ICD-LSEG, 2025). This expansion reflects the industry's resilience and appeal: by emphasising risk-sharing structures, asset-backed instruments, and social welfare objectives, Islamic finance has attracted a diverse investor base seeking both stability and ethical alignment. Underpinning this growth is the *Maqāṣid al-Sharīʿah*[4] framework, which fulfills the higher objectives of Shariah – preserving religion (*dīn*), life (*nafs*), intellect (*'aql*), lineage (*nasb*), and wealth (*māl*)[5] and thus ensures that financial products promote communal well-being and justice rather than mere profit maximisation (Bin Bayyah, 2018).

At the forefront of this transformation stands Malaysia, which has retained the top position in the Islamic Finance Development Indicator (IFDI) 2025 for the 13th consecutive year (ICD-LSEG, 2025). As at end-July 2025, Malaysia's Islamic banking assets reached RM1,583.3 billion – 38.7 percent of total banking assets – while Islamic financing stood at RM997.7 billion, accounting for 47.5 percent of total loans and financing and growing by 8 percent year-on-year. Within the broader financial system, Malaysia's Islamic capital market has expanded to RM2,634 billion, representing about 64 percent of the domestic capital market, signalling the central role of Shariah-compliant intermediation in mobilising funds. This leadership is underpinned by robust Shariah governance as well as facilitative legal and regulatory frameworks that collectively position Malaysia as a principal incubator of Islamic financial innovation.

Within the dynamic Islamic financial markets, sukuk have emerged as the flagship instrument in meeting both public and private financing needs. Globally, outstanding sukuk surpassed approximately USD1 trillion in 2024, with annual sukuk issuance reaching USD254.3 billion and recording an 11 percent year-on-year increase, confirming sukuk's shift from a niche product to an increasingly mainstream funding tool (ICD-LSEG, 2025). Malaysia remains one of the world's largest sukuk markets, commanding an estimated 33.9 percent share of global sukuk outstanding as at end-July 2025. Domestically, sukuk amounts to RM1,402 billion, or 63.6 percent of Malaysia's outstanding debt securities. As sustainable finance gains traction worldwide, Malaysia has also pioneered sustainable sukuk[6], illustrating how sukuk can align Shariah objectives with environmental and social imperatives. Against this backdrop of robust growth and innovation, a detailed examination of demand-supply dynamics and the potential for sustainable sukuk to bridge emerging gaps is both timely and essential for policymakers and market participants.

[4] Higher Objectives of Islamic Law. Jurists such as al-Raysūni defined it as "the goals for which the Shariah was instituted in order to realise the welfare of His servants" (Muhammad Yusrī Ibrāhīm, 2013). Securities Commission Malaysia (2023) further contextualised this concept within the Islamic capital market (ICM) as an overarching, principle-based framework that goes beyond procedural Shariah compliance, emphasising the promotion of *maslahah* (human welfare) through the twin objectives of serving benefits and preventing harm (*jalb al-masālih wa dar' al-mafāsid*). In the ICM context, this is operationalised through six aspirations -Humanity; Justice and Benevolence; Clarity and Transparency; Flexibility and Innovation; Fiduciary and Accountability; Accessibility and Inclusivity -which guide financial activities towards equitable growth, ethical conduct, and sustainable socio-economic impact.

[5] Maqāṣid al-Sharīʿah for wealth category are influenced by five elements: circulation, clarity, preservation, establishment, and justice.

[6] Sustainable sukuk include Sustainable and Responsible Investment (SRI) and SRI-linked sukuk as outlined by Securities Commission Malaysia and ASEAN Green, Social, Sustainability and Sustainability-linked Bond as outlined by ASEAN Capital Market Forum (ACMF). Much like in the European Union, these frameworks are very much aligned with United Nations Sustainable Development Goals (SDG).

2. Literature Review

Foundational Insights on Sukuk

Sukuk, derived from the Arabic word for *certificate,* in its simplest form are certificates of equal value that evidence undivided ownership or investment in the assets based on Shariah principles and concepts[7]. Sukuk are structured to avoid interest (*ribā*), uncertainty (*gharar*) and speculation (*maysir*) – key prohibitions in Islamic finance. Sukuk serve as Islamic capital market instruments designed to meet the financing needs of fund seekers, including government and corporations that require large-scale Shariah-compliant funding. Sukuk have been documented as an effective tool for resource mobilisation (Jobst et al., 2008); they are often structured to mimic the economic outcome of fixed income instrument such as bonds, offering regular returns to investors and repayment of principal at maturity. The main reason for this convergence to bond-like instruments - considering similar risk-reward structures and features - is that the bond market plays a pivotal role in the broader financial markets and economy (Bahari et al., 2016, Sairally et al., 2017). Nonetheless, as the sukuk market develops and matures, its features have evolved to include distinct characteristics, particularly through the adoption of various financial contracts tailored to diverse economic needs across different regions of the world. For example, sale-based sukuk (based on the contract of *Murābaḥah*, *Salam*, *Istisnāʿ*), lease-based sukuk (based on the concept of *Ijārah*), partnership-based and agency (based on the concept of *Muḍārabah*, *Mushārakah* and *Wakālah*), or any combination thereof. Further innovation introduces capacity sukuk, which utilises 'business capacity' of respective companies (such as airtime by telcos, rights to travel by airlines) as intangible underlying assets (Djafri et al., 2023). Table 1 provides further details on the foundational differences between conventional bond and sukuk.

Comparison between bond and sukuk instruments — Table 1

Aspect	Bond	Sukuk
Nature	Represent interest-bearing debt obligation of the issuer	Represent proportionate ownership in Shariah compliant assets, usufructs, services, or profit-sharing venture or financial asset, or any combination
Issuer	Any issuer	Any issuer engaged in business activities which are permissible under Shariah rulings
Investor base	Conventional	Islamic and conventional investors
Issuer-investor relationship	Debtor-creditor	Sale, lease, partnership, agency or combination
Returns to investors	Interest on loan	Profit from sale, rent from lease, profit sharing from investment activities/service
Principal repayment by issuer	Return of principal at maturity is irrevocable, regardless of the profitability of funded project	In sale-based and lease-based structures, the return of principal is guaranteed. However, in principle, there is no ex-ante fixed obligation of capital repayment for partnership-based sukuk structure
Underlying assets	Not applicable	Shall comply with Shariah requirements, can represent both debt and non-debt assets.
Utilisation of proceeds	No specific requirements	Proceeds must be utilised to finance Shariah-compliant activities

[7] Definition by Malaysia's Securities Commission. In the Malaysia, the Shariah principles and concepts shall be endorsed by the Securities Commission's Shariah Advisory Council.

Pricing	Pricing based on credit rating of issuer and term and conditions, usually a spread over a reference interest rate	Pricing depends on the structure of the sukuk. For non-recourse asset-backed sukuk, pricing is based on the asset. For sukuk structured based on fixed income and debt-creating contracts, pricing is typically similar to bond pricing.
Tradability	Sale of debt	Dependent on the nature of underlying assets

Sukuk are now issued in multiple currencies across the globe. They have become increasingly mainstream in their traditional homes in the Middle East (e.g. Saudi Arabia, UAE, Turkiye, Iran, Qatar, Bahrain, Kuwait) and Southeast Asia (e.g. Malaysia, Indonesia), while also expanding into non-traditional markets such as the United Kingdom, France, Luxembourg, Hong Kong, South Africa and the United States.

Brief History of Sukuk Development in Malaysia

Malaysia's sukuk journey began with the issuance of the Government Investment Certificate (GIC) in 1983, aimed at providing an avenue for short-term liquidity management and long-term investment for Islamic financial institutions during the period. These were later replaced by Malaysian Government Investment Issues (MGII), laying the foundation for the development of the domestic Islamic capital market. The first corporate sukuk was later issued in Malaysia in 1990 by Shell MDS Malaysia (Sairally et al., 2017). Several decades later, Malaysia's sukuk market has grown exponentially and has demonstrated a positive impact on economic growth (Abrorov, 2020). Sukuk have been instrumental in financing major infrastructure projects in Malaysia, including commuter and rapid transit system, airports, highways and buildings. Notably, Merdeka 118, Malaysia's most recent skyscraper and the second tallest building in the world, was also funded through sukuk.

Malaysia is the ideal dataset for this study, hosting a mature Islamic capital market alongside the conventional bond market. This dual financial system, governed by the Financial Services Act (2013) and the Islamic Financial Services Act (IFSA) 2013, enables a fair and meaningful comparison between the two vibrant markets.

Recent Studies on Sukuk Forecasting

In the sukuk and Islamic finance forecasting literature, time-series models such as ARIMA and its seasonal variant SARIMA are widely used as baseline benchmarks before moving to more complex specifications. For example, Rosadhillah and Ülev (2024) forecast Turkey's sovereign sukuk outstanding with ARIMA and then examine its relationship with inflation and the exchange rate using Granger causality, Their study is useful for the present paper because it treats sukuk outstanding as a time-series object whose own past dynamics must first be modelled before macro-financial linkages are assessed. However, since their model is ARIMA rather than SARIMA/SARIMAX, it is best read as support for the univariate benchmark stage.

Seasonal and calendar-sensitive extensions are relevant where monthly or quarterly financial series display recurring patterns. In Islamic economies, this is especially important because religious-calendar and business-cycle effects can affect financial and monetary series. Riazuddin and Khan (2005) worked on extending standard ARIMA modelling to incorporate Islamic calendar effects in monthly currency-in-circulation in Pakistan and found that such effects were strongly pronounced. This supports the broader rationale for testing seasonal structures before adding further macro-financial variables, especially where issuance and investment activity may be influenced by recurring fiscal, religious or corporate funding windows.

A second strand of the literature uses causality testing to identify whether macroeconomic variables contain genuine predictive content for sukuk markets. The methodological foundation is Toda and Yamamoto (1995), whose augmented VAR approach allows inference in levels even when variables may be integrated or cointegrated. In sukuk-specific applications, Echchabi, Aziz and Idriss (2016) applied the Toda–Yamamoto Granger non-causality test to major sukuk-issuing countries and found evidence of directional causality running from sukuk to GDP and gross capital formation in the pooled sample, although not for Saudi Arabia and the GCC separately. More recently, Baykut (2024) applied the Toda–Yamamoto causality test to Turkish sukuk data and showed that the dollar exchange rate and deposit interest rates have causal relationships with the size of sukuk issuance, while ARDL model is used to quantify short- and long-term relationships of sukuk returns with respect to other macroeconomic variables. Together, these studies justify a design where causality testing is positioned between a univariate benchmark and a multivariate forecasting model, serving as an econometrically robust filter for selecting macro-financial drivers.

Once candidate drivers are identified, another body of work moves from univariate ARIMA/SARIMA to multivariate time-series models with exogenous regressors - ARIMAX/SARIMAX, ARDL, VAR and related frameworks - to improve forecast accuracy. In Islamic banking, Aryani, Aidi, and Syafitri (2018) used ARIMAX and regression with ARIMA errors approaches to relate Islamic bank profitability to macroeconomic predictors such as benchmark interest rate, inflation and exchange rates. The result was noted vigilantly as its reported model performance comparison did not provide a clean general claim that ARIMAX always outperforms ARIMA.

Parallel to these econometric developments, a growing literature experiments with machine-learning and hybrid models to capture potential non-linearities in sukuk and Islamic-finance series. Hila et al. (2019), for instance, studied sukuk investment forecasting using artificial-neural-network-based algorithms and report lower forecast errors than those obtained from simple moving-average benchmarks, highlighting the ability of ANN architectures to pick up complex patterns in sukuk returns. Çetin and Metlek (2021) applied a multilayer feed-forward ANN to to forecast Turkish sovereign sukuk prices with dollar index, volatility index, geopolitical risk index, S&P MENA sukuk index and Eurobond prices as input variables. These studies show the potential of machine-learning models in sukuk forecasting, but they also highlight a trade-off: whilst ANN-based models may capture complex patterns, they are less transparent than SARIMA/SARIMAX specifications when the purpose is to explain the role of macro-financial drivers in a policy-oriented setting.

Taken together, the literature supports a stepped methodological strategy for sukuk demand–supply analysis. First, a SARIMA model can be used to establish a transparent baseline forecast that captures own-dynamics and seasonality in sukuk demand or sukuk supply, following common practice in sukuk and macro-financial forecasting. Second, Toda–Yamamoto causality testing can be employed – following the logic of Toda and Yamamoto (1995), Echchabi, Aziz and Idriss (2016), and Baykut (2024) - to screen macro variables and identify those with statistically significant causal influence on sukuk series. Third, a SARIMAX specification can be estimated that embeds only the causally relevant macroeconomic drivers, thereby preserving the parsimony and interpretability of SARIMA whilst allowing selected exogenous variables to improve conditional projections. This sequence provides a literature-anchored rationale for moving from SARIMA to TY-MWALD screening, followed by SARIMAX in a sukuk supply-demand forecasting framework.

3. Methodology

Data Collection and Consideration

This study uses monthly open-tender issuances of Malaysian sukuk and conventional bonds from 2000Q1 to 2025Q2, combined with quarterly macro-financial variables.

We focus on open-tender auctions, which account for about 46% of Malaysia's debt securities market. Open tenders provide market-driven prices and quantities, as a broad investor base competes on yields and allocation, thus providing "true" demand for ringgit sukuk and bonds. By contrast, private placements are negotiated bilaterally with a select group of investors and may be influenced by multiple factors such as relationship between dealers, information asymmetries, negotiation dynamics, or national-interest considerations. Open tender issuances by sovereign issuers establish the reference yield curve, which serves as a common benchmark for pricing privately placed instruments of similar tenor. Taken together, these factors make open tender issuances a more reliable proxy for overall market conditions.

The dataset originates from Malaysia's Fully Automated System for Issuing/Tendering (FAST), a local system that facilitates primary issuance of all debt securities instruments which is accessible through public platforms such as Bond Pricing Agency Malaysia (BPAM) Bondstream application and various industry market reports. The final dataset comprises 869 open-tender issuances across diverse sectors. Of these, 655 are sovereign and 214 are corporate issues, and within the same sample, 491 instruments are conventional bonds while 378 are Shariah-compliant sukuk. This construction allows us to compare sukuk and conventional bonds, and sovereign and corporate segments, under a common auction mechanism.

To explain and forecast sukuk demand–supply dynamics, we link these issuance data to a set of macro-financial covariates. Malaysia's benchmark interest rate, Overnight Policy Rate (OPR), is taken from Bank Negara Malaysia's official data download and captures the monetary-policy stance; it is available from 2004 onwards, so regressions that include OPR naturally begin later than the full sukuk/bond sample. The 12-month fixed-deposit rate of commercial banks is obtained from government record, OpenDOSM, and Bank Negara Malaysia's published statistics, and measures the opportunity cost of holding deposits relative to sukuk and bonds. The USD-Malaysian Ringgit (MYR) exchange rate comes from the Federal Reserve Bank of St. Louis (FRED series DEXMAUS) and reflects external conditions and currency risk that may affect foreign participation in Malaysia's debt markets.

We proxy domestic risk sentiment and relative asset attractiveness using the Malaysia's benchmark stock market index, FTSE Bursa Malaysia KLCI (FBMKLCI, via Investing.com). FDI inflows, outflows and net flows are drawn from OpenDOSM's balance-of-payments data and capture external financing conditions and real-sector investment. Conventional bond demand and supply, which are a part of the overall dataset, provide a direct conventional benchmark for sukuk demand and supply. Finally, we require a long, consistent measure of the domestic business cycle. For 2015Q1–2025Q2, we use official quarterly real GDP at constant prices from OpenDOSM. For 2000Q1–2014Q4, where quarterly real GDP is not available in a directly usable form, we construct a model-based quarterly series using an unrestricted mixed data sampling (U-MIDAS) regression anchored to annual real GDP growth from the World Bank.

The resulting quarterly GDP growth series thus combines observed data (2015 onward) with U-MIDAS-based backcasts (pre-2015). We use the extended series primarily as a control for the macroeconomic cycle; key results are checked against the shorter post-2015 sample where quarterly GDP is fully observed.

Assumptions

In addition, the forecast relies on several broad assumptions. It presumes a stable political and policy environment over the next decade, with no major policy reversal or regulatory changes that could drastically disrupt the Malaysia's financial market. This includes the continuity of Shariah regulations and governance, whereby the current centralised Shariah authority called the Shariah Advisory Council (SAC) remains intact. Economic growth and benchmark interest rate are assumed to follow a historically predictable path within the range of 1.75%-3.50% and exclude the occurrence of any black swan events that could trigger global market shocks. Non-resident holdings of Ringgit-denominated sukuk, which currently averaged around 3.6% of outstanding sukuk and remained lower than conventional counterparts, are assumed to stay broadly unchanged over the next 10 years, consistent with historical pattern. The forecast does not factor in potential upsides from increased foreign participation that may result from ongoing market initiatives to attract foreign funds into the domestic market.

Diagnostics, Forecast Techniques and Variable Screening

Model diagnostics and differencing

We first determine the order of differencing required to obtain a stationary representation of sukuk demand and supply. This is necessary because SARIMA and SARIMAX models require the stochastic component of the series to be stationary after the appropriate non-seasonal and seasonal transformations.

(a) Unit-root and stationarity tests

We use the Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests as complementary checks on stationarity. The ADF test uses a unit-root null hypothesis, whilst the KPSS test uses a stationarity null hypothesis. Taken together, both tests provide a more reliable basis for identifying the integration order of the series.

Augmented Dickey-Fuller (ADF) test

For a series y_t, the ADF regression is specified as:

$$\Delta y_t = \alpha + \beta t + \phi y_{t-1} + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \varepsilon_t$$

where $\Delta y_t = y_t - y_{t-1}$, t is a deterministic time trend, and p is the number of augmentation lags included to account for serial correlation in the residuals. If the deterministic trend is not included, the term βt is omitted. The hypotheses are:

- Null: $H_0: \phi = 0$ (unit root, non-stationary).
- Alternative: $H_1: \phi < 0$
  (stationary or trend-stationary, depending on deterministic specification)

Rejection of H_0 indicates that the series being tested does not contain a unit root under the selected deterministic specification.

Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

The KPSS test takes the opposite null: that the series is level- or trend-stationary. Let $\hat{u}_t$ denote the residuals from this regression, and define the partial sum process as:

$$S_t = \sum_{i=1}^{t} \hat{u}_i$$

The KPSS statistic is:

$$KPSS = \frac{1}{T^2\hat{\sigma}^2}\sum_{t=1}^{T} S_t^2$$

where T is the sample size and $\hat{\sigma}^2$ is a consistent estimate of the long-run variance of $\hat{u}_t$. Large values of the statistic lead to rejection of the stationarity null.

Using ADF together with KPSS allows the integration order to be triangulated. ADF tests whether the series contain a unit root, whereas KPSS tests whether the series is stationary around the relevant deterministic component. This combined approach motivates the non-seasonal differencing decision, while the seasonal differencing decision is supported separately by monthly plots, autocorrelation functions and residual diagnostics.

Results:

- In levels, both sukuk demand and sukuk supply display strong persistence and upward trends. Under the relevant deterministic specifications, the ADF tests fail to reject the unit-root null at conventional levels, while KPSS tests reject the stationarity null. This provides evidence that both series are non-stationarity in levels.
- In first differences, the ADF tests reject the unit-root null and the KPSS tests no longer reject stationarity for both series.

Taken together, these outcomes indicate that both sukuk supply and sukuk demand are integrated of order one, $I(1)$, justifying one non-seasonal difference ($d = 1$) in all subsequent SARIMA and SARIMAX models.

(b) Seasonal behaviour and residual autocorrelation

Monthly plots and autocorrelation functions show a pronounced 12-month seasonal pattern in both sukuk demand and sukuk supply. To address this seasonal structure, we apply a seasonal difference at period $s = 12$:

$$\nabla_{12} y_t = (1 - B^{12}) y_t,$$

where B is the backshift operator, so that:

$$B^{12} y_t = y_{t-12}$$

and therefore:

$$\nabla_{12} y_t = y_t - y_{t-12}$$

The combined non-seasonal and seasonal differencing transformation is:

$$\omega_t = (1 - B)(1 - B^{12}) y_t$$

where $(1 - B)$ applies the first non-seasonal difference and $(1 - B^{12})$ applies the seasonal difference. This corresponds to:

$$d = 1, \qquad D = 1, \qquad s = 12$$

For the pure SARIMA specification, this transformation is applied to the endogenous issuance series. In the SARIMAX specification, the same integration orders are imposed on the endogenous series, whilst the treatment of exogenous regressors follows the selected SARIMAX framework.

After differencing, we examine the residual autocorrelation using Ljung-Box Q statistic:

$$Q(m) = n(n+2)\sum_{k=1}^{m}\frac{\hat{p}_k^2}{n-k}$$

where n is the sample size, $\hat{p}_k$ is the residual autocorrelation at lag k, and m is the maximum lag tested. The null hypothesis is that there is no residual autocorrelation up to lag m. For fitted SARIMA and SARIMAX models, the statistic is assessed with degrees of freedom adjusted for the estimated dynamic parameters.

Results:

- The combined non-seasonal and seasonal differencing transformation, ($d = 1,\ D = 1,\ s = 12$), removes visible seasonality from both sukuk series.
- For candidate SARIMA models estimated on ω_t, Ljung–Box tests at lags 12 and 24 do not reject the null of no residual autocorrelation for sukuk demand and sukuk supply, indicating that the differenced models capture the main dynamics of the series and do not leave systematic autocorrelation in the residuals.

(c) Order selection via information criteria

Among the differenced models, parsimonious lag orders are selected using the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC):

$$\mathrm{AIC} = -2\hat{\ell} + 2k$$

$$\mathrm{BIC} = -2\hat{\ell} + k\ln n$$

where $\hat{\ell}$ is the maximised log-likelihood, k the number of estimated parameters, and n is the effective sample size. Lower values of AIC and BIC indicate a better balance between model fit and parsimony, with BIC applying a stronger penalty for additional parameters.

Results:

- For both sukuk demand and sukuk supply, the information criteria favour low-order MA dynamics with no non-seasonal AR terms, and a single seasonal MA term at lag 12.
- The preferred specification that balances fit and parsimony for both sukuk demand and sukuk supply in both SARIMA and SARIMAX is $(0,1,2)(0,1,1)_{12}$.

Main forecasting technique: SARIMA and SARIMAX

Let y_t denote the sukuk demand or sukuk supply. Using the backshift operator B, where $By_t = y_{t-1}$, the non-seasonal and seasonal differences are defined as follows:

- $\nabla y_t = (1-B)y_t$
- $\nabla_s y_t = (1-B^s)y_t$

For monthly data, $s = 12$, so that:

$$\nabla_s y_t = (1-B^s)y_t = y_t - y_{t-12}$$

The differencing structure and order selection identified in the diagnostic stage are then carried over when exogenous variables are added in the SARIMAX models. This ensures that the sukuk demand and sukuk supply equations share a common, well-diagnosed time-series backbone, whilst allowing macro-financial drivers to enter the forecasting framework.

Seasonal Autoregressive Integrated Moving Average (SARIMA)

A general Seasonal ARIMA model, SARIMA $(p,d,q)(P,D,Q)_s$ can be written as:

$$\Phi(B)\Phi_s(B^s)(1-B)^d(1-B^s)^D y_t = \Theta(B)\Theta_s(B^s)\varepsilon_t$$

where:

- $\Phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ is the non-seasonal AR polynomial;
- $\Phi_s(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{P_s}$ is the seasonal AR polynomial;
- $\Theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$ is the non-seasonal MA polynomial;
- $\Theta_s(B^s) = 1 + \Theta_1 B^s + \cdots + \Theta_Q B^{Q_s}$ is the seasonal MA polynomial;

and ε_t is a white-noise error.

This framework captures short-term persistence, seasonal patterns and shocks in a single, relatively parsimonious structure.

SARIMA with exogenous regressors (SARIMAX)

To quantify how macro-financial drivers affect issuance, we extend the model to include exogenous variables. The SARIMAX model can be represented as a regression with SARIMA errors:

$$y_t = \beta' x_{t-1} + u_t$$
$$\Phi(B)\Phi_s(B^s)(1-B)^d(1-B^s)^D u_t = \Theta(B)\Theta_s(B^s)\varepsilon_t$$

where x_{t-1} is a vector of lagged, standardised exogenous variables (e.g. OPR, 12-month fixed-deposit rate, 10-year Malaysian Government Securities (MGS) yield, conventional bond demand and bond supply, USD/MYR, quarterly real GDP growth), and the vector β contains the associated coefficients. Lagging x_t by one period aligns the regressors with the information set available at auction time and reduces simultaneity concerns. SARIMAX therefore preserves the interpretability of SARIMA while allowing the marginal contribution of macro-financial drivers to be assessed in the sukuk and bond demand and supply equations.

Model-agnostic directionality screening: Toda-Yamamoto MWALD

We screen candidate drivers using the Toda–Yamamoto (TY) modified Wald causality test. The TY approach has two advantages:

- It can be applied to variables that may be integrated or cointegrated, provided the maximum order of integration is accounted for;
- and it enables standard Wald-type inference by by estimating an augmented VAR in levels.

Let $Z_t = (y_t, x_t)'$ stack sukuk demand/supply with a candidate macro-variable (e.g. OPR). We estimate the lag-augmented VAR:

$$Z_t = c + \sum_{i=1}^{k+d_{max}} A_i Z_{t-i} + u_t$$

where k is the optimal lag length of the underlying VAR in levels, d_{max} is the maximum suspected integration order among the variables, and u_t is a vector of innovations.

To test whether x_t Granger-causes y_t, we test the joint null hypothesis that the coefficients on the first k lags of x_t in the y_t equation are zero. The additional d_{max} lags are included to secure the asymptomatic distribution of the test statistic but are not included in the causality restrictions.

Let $\hat{\beta}$ be the stacked VAR coefficient vector and R the restriction matrix such that $R\beta = 0$ encodes the null hypothesis of "no causality from $x_t$to y_t". The TY modified Wald statistic is:

$$W = (R\hat{\beta})'[R\widehat{Var}(\hat{\beta})R']^{-1}(R\hat{\beta})$$

which is asymptotically distributed as $W \sim \boldsymbol{\chi}_{\boldsymbol{q}}^{\boldsymbol{2}}$ under the null, with q as the number of restrictions.

For each candidate macro variable, a bivariate TY test is conducted with sukuk (or bond) demand/supply. Variables that exhibit statistically significant unilateral or bilateral causality are retained as exogenous regressors in the SARIMAX models; variables that do not are excluded. This model-agnostic screening helps ensure that only predictive directional content are fed into the final forecasting equations.

Forecast-accuracy metric: Mean Absolute Scaled Error (MASE)

To compare forecast performance across sukuk and bond models, we use the Mean Absolute Scaled Error (MASE) proposed by Hyndman and Koehler (2006). MASE is scale-free and is therefore suitable for comparing forecast accuracy across series with different magnitude.

For a seasonal monthly series with period $s = 12$, let $e_t = y_t - \hat{y}_t$ denote the forecast error. The in-sample mean absolute error of the seasonal naïve benchmark as:

$$MAE_{\text{naïve}} = \frac{1}{T-s}\sum_{t=s+1}^{T}|y_t - y_{t-s}|$$

where the seasonal naïve benchmark forecast is:

$$\hat{y}_t^{\text{naïve}} = y_{t-s}$$

and the absolute scaled errors is:

$$q_t = \frac{|e_t|}{MAE_{\text{naïve}}}$$

thus, the MASE over a forecast horizon of length H is:

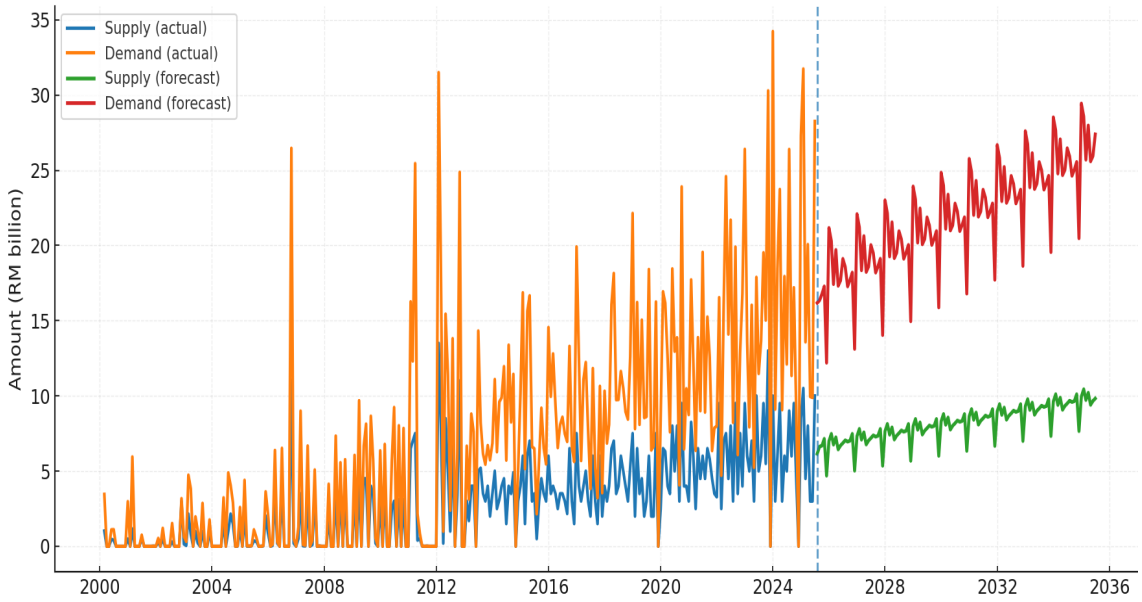
$$MASE = \frac{1}{H}\sum_{t=1}^{H}|q_t|.$$

Values below one indicate that a model improves on the seasonal naïve benchmark, and values above one indicate weaker forecast performance than the seasonal naïve benchmark.

4. Preliminary Results

Seasonal Autoregressive Integrated Moving Average (SARIMA)

SARIMA baseline forecast for sukuk issuance supply-demand (2025-2035) Chart 1



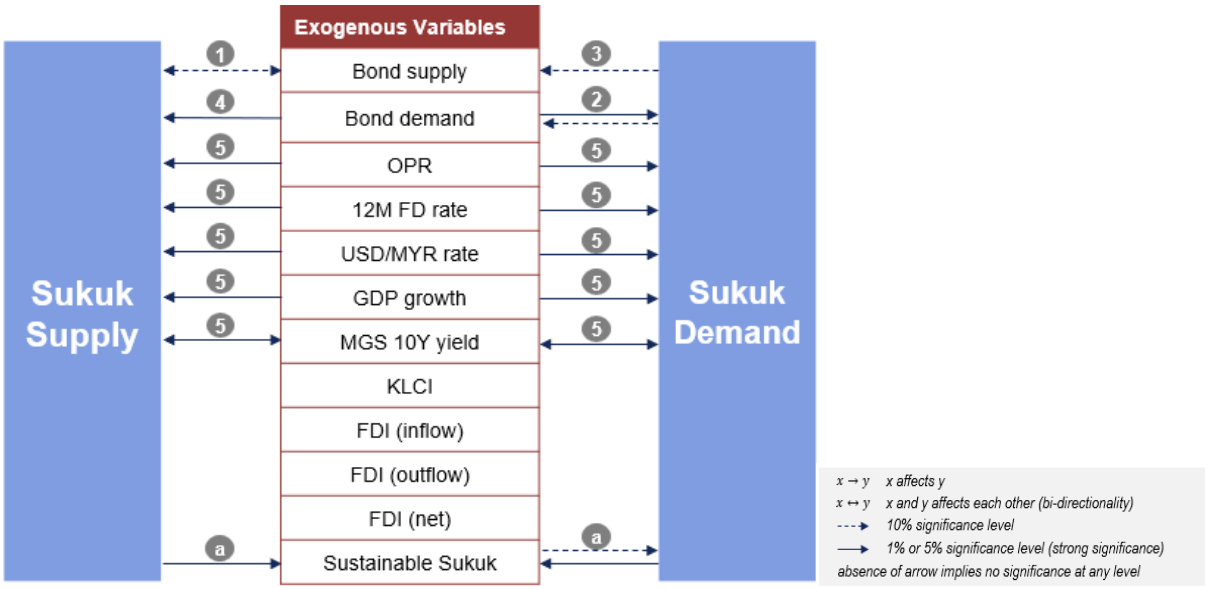
As a first step, sukuk supply and demand are modelled separately using a univariate Seasonal ARIMA specification. Based on the diagnostics in Section 4.1, we apply one non-seasonal and one seasonal difference at period 12, and select a low-order MA structure. The resulting baseline for both sukuk supply and sukuk demand is SARIMA(0,1,2)(0,1,1)$_{12}$. The intercept is set to zero; the transformed series fluctuates around zero without an imposed deterministic drift after differencing, therefore the forecasts are driven purely by the estimated stochastic components.

Using this SARIMA specification, we generate 10-year forecasts for sukuk supply and sukuk demand. The model produces a constant BTC stabilising at about 2.78 over both horizons at the end of 5-year and 10-year forecast. In other words, the purely endogenous SARIMA model effectively assumes that sukuk demand will scale proportionally with sukuk supply, yielding a constant auction coverage ratio.

To judge whether this baseline is adequate, we evaluate in-sample fit using the Mean Absolute Scaled Error (MASE) relative to a seasonal naïve benchmark y_{t-12}, following Hyndman and Koehler (2006). For sukuk supply, MASE ≈ 1.41, and for sukuk demand, MASE ≈ 1.58; these results show that the univariate SARIMA does not fully capture the dynamics of sukuk supply and demand. Taken together the constant BTC around 2.78 and MASE > 1 for both series, this motivates extending the model to include exogenous macro-financial variables. In the next step, these candidate drivers are screened using the Toda–Yamamoto modified Wald (TY-MWALD) causality tests, and the selected variables are incorporated in a SARIMAX framework.

Toda-Yamamoto Modified Wald Test (TYMWALD test)

Directionality of variables via TYMWALD test — Chart 2



To justify the choice of regressors, we use bivariate Toda–Yamamoto modified Wald (TY-MWALD) causality tests between each candidate external variable and sukuk supply and sukuk demand. For every pair (y_t, x_t) where y_t is sukuk supply or demand and x_t is a candidate driver, we estimate a lag-augmented VAR in levels with maximum integration order set to one and then test, via the MWALD statistic, whether lags of x_t jointly Granger-cause y_t. Variables that exhibit statistically significant causality at conventional levels are retained as exogenous regressors in the SARIMAX models; those that do not are excluded.

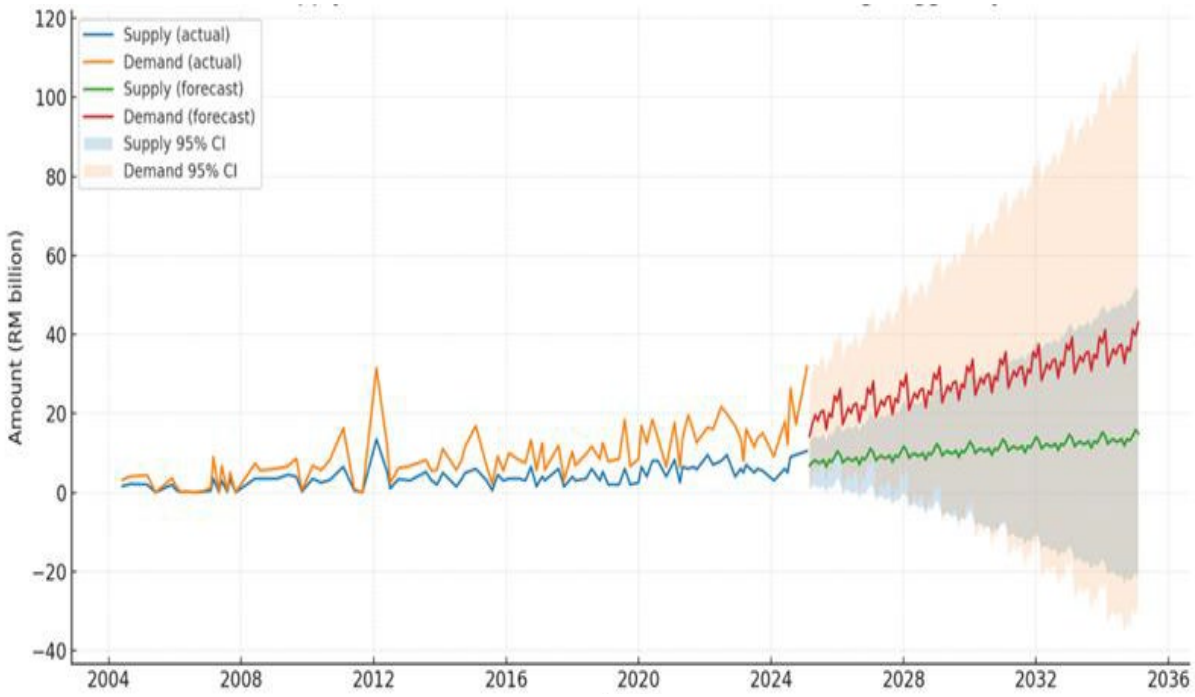
The tests show strong mutual dependence between sukuk and conventional markets. Sukuk supply and bond supply Granger-cause each other, as issuance in one segment often prompt adjustments in the other. Similarly, sukuk demand and bond demand are mutually causal, reflecting portfolio rebalancing tendencies between sukuk and conventional bonds. There is also unidirectional spillover from sukuk demand to bond supply (interpretable as investors' preference for Shariah-compliant instruments influencing funding choices and reducing bond issuance) and from bond demand to sukuk supply (conventional investors are also able to buy sukuk, so swings in bond demand transmit to more sukuk issuance).

Among the macro-financial variables, the TY-MWALD tests support the benchmark interest rate OPR, the 12-month fixed-deposit rate, the USD/MYR exchange rate, quarterly real GDP growth and the 10-year MGS yield. All aforementioned indicators show predictive content for sukuk supply and sukuk demand, with particularly strong bi-directional causality between sukuk variables and the 10-year MGS yield, underlining the benchmark role of long-term government instrument yields. An additional variable, sustainable sukuk issuance, is found to Granger-cause sukuk demand and to be itself influenced by sukuk demand and supply, though it is ultimately excluded from the forecasting equations because the available data start only in 2017, creating a much shorter and structurally different sample than the main dataset (from 2000). By contrast, the FTSE KLCI index and FDI measures (inflow, outflow and net) show no robust causal link with sukuk supply or demand in the TY-MWALD tests and are therefore excluded. The final

SARIMAX models for sukuk supply and sukuk demand thus include only the external variables for which the TY-MWALD procedure provides clear evidence of predictive power.

5. Analysis

SARIMAX forecast on Malaysian Sukuk Issuance Supply-Demand (2025-2035) Chart 3



Note: Both sukuk supply and demand are modelled using SARIMAX(0,1,2)(0,1,1)$_{12}$ with exogenous variables (MGS10Y, OPR, 12-month FD rate, USD/MYR, quarterly real GDP YoY, conventional bond supply and bond demand) lagged one month and standardised on the training window (2004-09 till 2025-02) due to absence of OPR data from 2000-early 2004.

Building on the SARIMA backbone, we estimate SARIMAX(0,1,2)(0,1,1)$_{12}$ models for sukuk demand and sukuk supply, adding exogenous variables selected through the TY-MWALD screening procedure. The SARIMAX model is specified as a regression with SARIMA errors:

$$y_t = \beta' Z_{t-1} + u_t$$

$$(1-B)(1-B^{12})u_t = \theta(B)\Theta(B^{12})\,\varepsilon_t$$

where y_t denotes sukuk demand or sukuk supply, Z_{t-1} is the lag-1 standardised vector of exogenous variables, and u_t is the regression error component that follows the selected seasonal ARIMA structure.

The exogenous vector is given by:

$$Z_{t-1} = [MGS10Y_{t-1}, OPR_{t-1}, FD_{t-1}, FX_{t-1}, QGDP_{t-1}, Bond\ D_{t-1}, Bond\ S_{t-1}]'$$

with $\theta(B) = 1 + \theta_1 B + \theta_2 B^2$ and $\Theta(B^{12}) = 1 + \Theta_1 B^{12}$. All exogenous variables are lagged by one period to better match the information set available at issuance time and to reduce simultaneity concerns.

The SARIMAX forecasts indicate a widening gap between projected sukuk demand and supply over 2025–2035. Conditional on the assumed macro-financial paths, demand for ringgit-denominated

sukuk is projected to roughly triple by 2035, with the point forecast reaching about RM42 billion and the upper bound of the forecast interval approaching RM100 billion in more favourable scenarios. By contrast, sukuk supply is expected to grow only gradually. As a result, the forecast bid-to-cover (BTC) ratio, defined as forecast demand over forecast supply, rises from around 2.10 times in 2025 to about 2.89 times by 2035, implying a widening demand–supply gap and intensifying competition among investors for Shariah-compliant paper.

Model diagnostics suggest that the inclusion of exogenous drivers delivers improved forecast performance relative to the univariate SARIMA baseline. Residual Ljung–Box tests at lags 12 and 24 do not reject the null of no autocorrelation, indicating that the SARIMAX specifications adequately capture remaining serial dependence. Using MASE relative to the seasonal naïve benchmark y_{t-12}, the average scaled errors fall below one for both series (0.898 for sukuk supply and 0.885 for sukuk demand), showing that the SARIMAX models now outperform the seasonal naïve benchmark and improve on the earlier SARIMA fits. Overall, the results suggest that macro-financial conditions, particularly the benchmark interest rate, long-term government yields, deposit rates, exchange rate movements, GDP growth, as well as conventional bond market conditions contain useful predictive information for realistic projections of Malaysia's future sukuk demand–supply balance.

Scenario-unit coefficient of exogenous variables — Chart 4

Dependent Variable	Scenario-Unit Impact	Exogenous Variable	Scenario-Unit Impact	Dependent Variable
Sukuk supply	+ RM2.18 bn	Bond supply (+RM10 bn)	+ RM4.95 bn	Sukuk Demand
	+ RM0.25 bn	Bond demand (+RM10 bn)	+ RM0.33 bn	
	+ RM0.77 bn	OPR (+25 bps)	+ RM1.10 bn	
	- RM2.68 bn	12M FD rate (+25 bps)	- RM5.17 bn	
	+ RM0.36 bn	USD/MYR rate (+0.10 USD appreciates)	+ RM0.89 bn	
	+ RM0.12 bn	GDP growth (+ 1.0 pps)	+ RM0.30 bn	
	- RM0.82 bn	MGS 10Y yield (+ 50 bps)	- RM1.33 bn	

Note: Exogenous variables are standardised using training-window means and standard deviations before estimation. The reported values convert the standardised SARIMAX coefficients into scenario-unit effects using $\hat{\beta}_j^{(z)}\left(\frac{\Delta x_j}{\sigma_j}\right)$*, where* Δx_j *is the reported change in the original variable. The estimates show the model-implied change in the transformed monthly sukuk issuance series,* $\omega_t = (1-B)(1-B^{12})y_t$*, associated with selected changes in each lagged driver, holding other regressors constant. These coefficient effects should be interpreted as conditional predictive associations rather than structural causal impacts.*

The pattern of SARIMAX coefficients is consistent with how sukuk behave in the wider fixed-income literature. First, the positive coefficients on sukuk supply and demand to conventional bond supply and demand reflects that both instruments tap a common pool of investors and are often priced off similar benchmarks. Event-study and portfolio studies show that markets tend to treat sukuk and conventional bonds as closely related claims: stock-price reactions to sukuk and bond announcements are similar across various situations (Godlewski, Turk-Ariss & Weill, 2011; Alam, Hassan & Haque 2013), and adding sukuk to conventional bond portfolios mainly reshapes, rather than transforms, the risk–return profile (Raei & Çakır, 2007). This supports our interpretation that stronger overall fixed-income appetite, captured by higher conventional bond supply and demand, raises issuance and demand for sukuk rather than crowding them out.

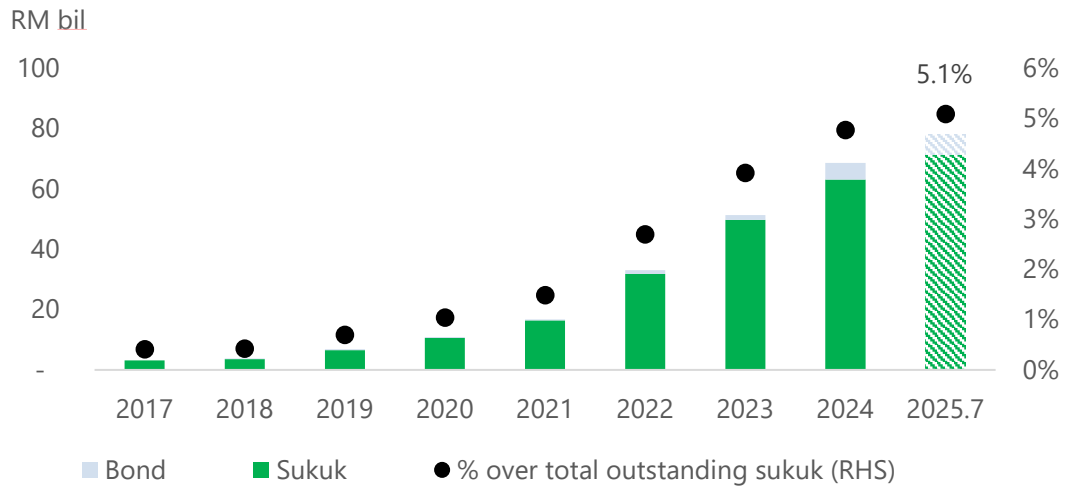
Second, the negative coefficients on 12-month fixed deposit rates and long-term government yields on sukuk issuance and demand is in line with evidence that higher interest-rate levels or wider interest-rate spreads dampen sukuk market development due to weaker issuance appetite and lower investor risk appetite, particularly to longer tenor instruments. Cross-country GMM studies find that larger interest-rate spreads (lending minus deposit or interbank rates) are significantly and negatively related to sukuk market size, as higher borrowing costs deter new issues (Said & Grassa, 2013; Smaoui & Khawaja, 2017). Conceptual models for GCC countries similarly highlight interest rates as a key macro factor shaping sukuk financing decisions (Al-Raeai, Zainol, & Abdul Rahim, 2018). Our finding that increases in the benchmark interest rate OPR are associated with modestly higher sukuk activity fits this logic: short-term policy tightening lifts expected yields, making new sukuk relatively more attractive than existing papers, even as very high long-term or deposit rates eventually restrain issuance and demand.

Third, the positive coefficients on GDP growth accord with the broader literature that links larger or faster-growing economies to deeper sukuk markets. Empirical work shows that economic size and income per capita are among the strongest predictors of sukuk market development (Smaoui & Khawaja, 2017; Basyariah, Kusuma & Qizam, 2021; Najib & Sa'adah, 2025), as stronger growth generates more investment projects and supports domestic investor bases. Studies on the growth effects of sukuk also find that sukuk market development and real GDP growth reinforce one another over the long run (Smaoui & Nechi, 2017; Yıldırım, Yıldırım & Diboglu, 2020), consistent with our interpretation that higher contemporaneous GDP growth goes hand in hand with higher sukuk issuance and demand.

Finally, the positive coefficient on ringgit depreciation (higher USD/MYR) on ringgit sukuk activity is consistent with research that emphasises exchange rate and currency-risk channels in both sukuk and local-currency bond markets. Cross-country studies identify the exchange rate and its volatility as significant determinants of sukuk market development, often with adverse effects when currency risk is high (Said & Grassa, 2013; Basyariah, Kusuma & Qizam, 2021; Al-Raeai et al., 2018). At the same time, BIS and IMF work on emerging-market local-currency bond markets shows that exchange-rate movements strongly influence local-currency bond risk premia and can encourage borrowers to shift away from foreign-currency borrowing to avoid balance-sheet mismatches (Burger & Warnock, 2006; Hofmann, Shim, & Shin, 2020; Grigorian, 2019). Taken together, these findings support our reading that a weaker ringgit heightens FX risk and encourages both issuers and investors to favour local-currency, Shariah-compliant sukuk.

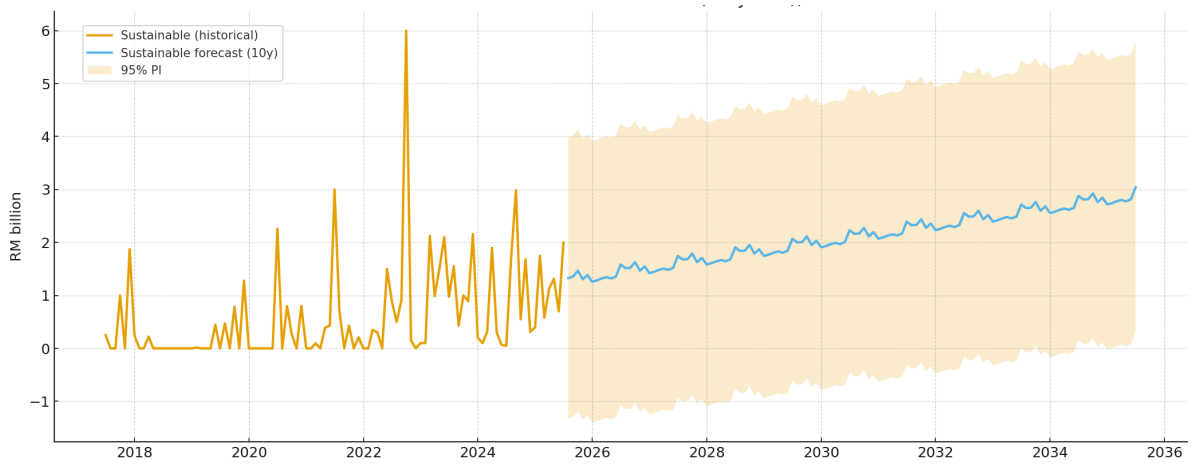
6. Potential of Sustainable Sukuk to Fill the Demand-Supply Gap

Malaysia's outstanding sustainable debt securities (2017-2025) Chart 5



Earlier, the study presented a forecast estimate that the demand-supply gap of Malaysia's sukuk to widen in the coming 10 years. At the same time, the study also observed that sustainable sukuk growth is rapidly expanding in the Malaysia's market, presenting timely opportunities to bridge the stated gap. The market share is currently still minimal at 5.1% of the overall outstanding domestic debt securities market, yet 5-year CAGR shown impressive growth of 57%.

SARIMA Sustainable sukuk forecast (2025-2035) Chart 6



Though MASE value is 1.26, SARIMA is proven the best forecasting model compared to others (e.g. ARIMA, Holt-Winter method etc.) for the particular dataset. Earlier diagnostics confirmed its model to be SARIMA $(0,1,2)(0,1,1)_{12}$.

The same forecast model is then utilised to estimate the projection of sustainable sukuk growth, and the finding suggests that if Malaysia's market managed to sustain this growth in the same 10-year

period, sustainable sukuk is estimated to reach RM3.04 billion – sufficient to plug earlier estimated demand-supply gap of RM2.95 billion. The estimate however is ambitious due to severely limited time horizon since the first ever sustainable sukuk was issued in 2017[8], giving merely 8-years data for the forecast. Nonetheless, the presence of multiple growth drivers in the Malaysia's domestic market signals that the current momentum could be maintained. The drivers include:

1. **Alignment with national agenda** – with Malaysia's clear target and commitment to achieve net-zero emission by 2050. The government have also identified the necessary infrastructure and initiatives through climate roadmaps (e.g. National Energy Transition Roadmap, NETR) and the required funding to operationalise the plan. The market is foreseeing high potential for these initiatives to be funded by sustainable sukuk, judging from wide availability, familiarity to the instrument and proven track records.

2. **Facilitative regulatory landscape** – the financial sector authorities are actively providing conducive ecosystem to sustainable sukuk to thrive, including tax incentives, capacity building programmes and issuance of frameworks & industry guides.

3. **Integration of ESG into investment mandate** - institutional investors, domestic and foreign, are increasingly integrating ESG into their investment strategy and mandate, in line with the growing awareness on climate risks and social equity.

4. **Broader range of issuers** – which includes multilateral development banks, local councils, corporates. Notably, an education institution in Malaysia has ventured to issue green sukuk in 2018 to construct a solar power plant and transmission infrastructure.

Beyond these market and policy drivers, sustainable sukuk also has a deeper normative basis within Islamic finance. Quran 30:41 warns about human-induced corruption (*fasād*) in the created order, "Corruption has spread on land and sea as a result of what people's hands have done, so that He/We[9] may cause them to taste the consequences of some of their deeds and perhaps they might return to the Right Path". Al-Farrā' (2006) exegeted *fasād* in this context as encompassing drought on land and the drying up of resources at sea as a consequence of humanity's misconduct, whereby hardship in this world functions as a corrective prompt to repentance. In contemporary terms, this linkage between moral failure, environmental disruption and economic hardship provides a theological rationale for designing instruments such as sustainable sukuk that actively mitigate environmental damage and support social well-being, rather than amplifying the deterioration caused by unsustainable patterns of production and consumption.

In this light, the projected expansion of Malaysia's sustainable sukuk market is not merely a market-based funding solution, but part of a wider call to reverse corruption by directing capital towards projects that restore balance (*iṣlāḥ*)[10] in society and the environment. This aligns with MIFC Leadership Council's aspiration where Islamic finance is expected to generate positive and sustained impact on lives, livelihoods, economics and societies. By financing renewable energy, low-carbon infrastructure and socially beneficial projects, sustainable sukuk contribute to a mode of development that is more consistent

[8] https://www.sukuk.com/article/malaysia-launches-the-worlds-first-green-sukuk-6361/

[9] Among the ten canonical recitations (*Qira'at*), two authentic readings for the word لِيُذِيقَهُمْ refer to the interchangeability of God's pronouns "He" and "We" (لِنُذِيقَهُمْ) both complying with the standardised Uthmani script; the former (most of the reciters) keeps the third-person flow of the surrounding verses and emphasises on the occurrence of the consequences itself; the latter (read by Qunbul from Ibn Kathīr in one form and Rauḥ from Yaʿqūb) expresses God speaking about Himself in the plural of grandeur, heightening the sense of justice and the greatness of the Divine act. Both readings converge on the same meaning: the hardship and corruption people experience on Earth is a divinely governed consequence of their own wrongdoings, intended to cue their return to righteousness. Refer to Ibn Ghalbūn (2017); Muhannā, (2022), and Sanad (2023) for more details.

[10] Refer to MIFC Leadership Council (2024) Position Paper, "Establish Islah through Islamic Finance". https://mifclc.com/main/wp-content/uploads/2024/06/MIFC_Position-Paper.pdf

with the Quranic vision of responsible human agency on earth, while remaining fully integrated with the broader sukuk market architecture.

7. Challenges and opportunities

i. **Inconsistency in sukuk issuance data frequency** – monthly sukuk issuances is not consistently available. Within the 25-year dataset, there were months of nil issuance. Impairment of consistent data pattern could adversely impact the robustness of forecasts and accuracy of predictions.

ii. **Limitations on sustainable sukuk forecast** – dataset horizon is severely limited. Sustainable sukuk was only first issued in 2017, compared to the overall sukuk dataset available from early 21st century. Its limited data timeline renders it incompatible with the overall SARIMAX model. Sustainable sukuk are also currently offered exclusively through private placement, which necessitates its exclusion from the overall sukuk forecast.

iii. **Limited benchmarking on sukuk issuance forecasting** – There are limited studies conducted on forecasting of sukuk in both industry and academia. This gap underscores the need for more rigorous research and data-driven analysis to establish benchmarks and improve predictive methodologies in the sukuk market.

8. Conclusion

Sukuk demand in Malaysia is forecasted to triple within the next decade, and expected to widen the existing demand-supply gap as well as increase competition among investors seeking for the Shariah-compliant investment instrument in the domestic market.

The study finds SARIMA is inadequate to project the forecast accurately, hence necessitating exogenous variables in the said projection through SARIMAX. The study also incorporates exogenous variables including conventional bonds supply and demand, benchmark interest rate OPR, 12-month fixed deposit rate by commercial banks, USD-MYR exchange rate, quarterly GDP growth and MGS 10-year yield.

Anecdotal evidence is also supportive of the forecast, with expectations of growing appetite from major institutional investors with Shariah-compliant investment mandates. For example, Malaysia's Employees Provident Fund (EPF) – the 5th largest pension fund in Asia – recorded an 11% increase in contribution size driven by wage growth and an increased workforce size.[11]

Nevertheless, sustainable sukuk is forecasted to bridge the demand-supply gap within the same period, should the current rapid growth rate be sustained. The estimate is supported by multiple drivers in the Malaysia's market, such as alignment with national agenda, facilitative regulatory support, enhanced integration of ESG considerations into investment strategies and institutional investors' mandates as well as broader range of issuers in the sustainable sukuk segment.

[11] https://www.kwsp.gov.my/en/w/epf-declares-630-dividend-for-simpanan-konvensional-and-630-for-simpanan-shariah-In

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10. Annex

Constructing a long quarterly GDP series using U-MIDAS adapted annual benchmarking

Official quarterly real GDP for Malaysia is available only for the more recent period. To avoid discarding early sukuk and bond observations, we extend quarterly GDP series back to 2000Q1 using U-MIDAS adapted annual benchmarking.

The procedure is adapted from U-MIDAS literature, rather than applied as textbook U-MIDAS nowcasting model because the task is to backcast a higher-frequency quarterly GDP path from lower-frequency annual information. We therefore use the unrestricted lag structure of U-MIDAS as a transparent bridge equation, while annual consistency is imposed through a separate benchmarking step. The U-MIDAS framework, developed by Foroni, Marcellino and Schumacher (2011), is useful in this context as it allows mixed-frequency relationships to be modelled without imposing restrictive lag-polynomial assumptions. In our setting, , by assigning unrestricted coefficients to each lag. In our case, we let $GDP_{q,t}$ denote quarterly real GDP growth and $GDP_{a,\tau}$ denote annual real GDP growth. For the period where both official quarterly and annual growth rates are available, we estimate the following bridge equation:

$$GDP_{q,t} = \alpha + \sum_{j=0}^{K} \beta_j GDP_{a,\tau(t)-j} + \varepsilon_t$$

where $\tau(t)$ maps quarter t to its corresponding calendar year, $GDP_{a,\tau(t)-j}$ denotes appropriately aligned annual real GDP growth and its lags, and β_j are freely estimated lag coefficients. The model is estimated by ordinary least squares using the period where quarterly GDP data are available. The estimated coefficients are then applied to annual GDP growth observations for 2000-2014 to generate preliminary quarterly GDP growth backcasts for 2000Q1 – 2014Q4.

Because an unrestricted bridge regression does not automatically guarantee that the generated quarterly path aggregates consistently to the observed annual growth rates, we impose a separate annual benchmarking step. This ensures that the backcast quarterly series preserves the official annual macroeconomic path, while the intrayear quarterly profile is informed by the relationship estimated over the period where quarterly GDP data are available. The resulting quarterly GDP growth series therefore extends the macroeconomic control variable back to 2000Q1 without discarding early sukuk and bond observations, whilst maintaining consistency with observed annual GDP growth.

Why MASE is preferred and not RMSE / MAPE?

Hyndman and Koehler (2006) introduced scaled errors and proposed MASE as a general-purpose accuracy for comparing forecast performance across different time series. The idea is to normalise each model's forecast errors by the in-sample MAE of a simple benchmark (here, the seasonal naïve benchmark), so that:

- **Scale-free comparability**. Because both the numerator and denominator are in the same units, MASE is independent of scale and can be used to compare forecast accuracy across series (e.g. sukuk vs bonds, demand vs supply) that differ in level and volatility.
- **Robustness with zeroes and intermittent data**. Percentage-based measures such as MAPE or sMAPE divide by actual values and can become undefined or unstable when observations are near or close to zero. MASE avoids this problem because the scaling denominator is based on the in-sample absolute error of the benchmark forecast, except in unusual cases where the benchmark error is exactly zero.

- **Clear interpretation relative to a realistic benchmark**. Using the seasonal naïve as the reference makes interpretation straightforward:
    - MASE < 1: better than seasonal naïve benchmark;
    - MASE = 1: no gain over seasonal naïve benchmark;
    - MASE > 1: worse than seasonal naïve benchmark.
- **Support in the forecasting literature.** Subsequent work (e.g. Franses, 2016) shows that MASE integrates well within formal tests of equal forecast accuracy and behaves better than several alternative criteria in simulations, reinforcing its status as a recommended standard when comparing forecasting methods.

Interpreting SARIMAX coefficients and scenario-unit effects

SARIMAX as regression with ARIMA errors

In this setting, the SARIMAX model is interpreted as a regression model with seasonal ARIMA errors:

$$y_t = \beta_0 + \beta' Z_{t-1} + u_t$$
$$(1-B)(1-B^{12})u_t = \theta(B)\Theta(B^{12})\,\varepsilon_t$$

where y_t denotes monthly sukuk demand or supply, Z_{t-1} is the vector of lagged exogenous variables, and u_t is the regression error component following the selected seasonal ARIMA structure.

The specification follows the dynamic-regression treatment of SARIMAX as regression with ARIMA errors, where the regression component captures the conditional association between the sukuk issuance and the lagged exogenous regressors, whilst the ARIMA component models serial dependence in the regression errors (Hyndman & Athanasopoulos, 2021). This is also consistent with the state-space SARIMAX implementation in *statsmodels*, which treats exogenous variables OLS-type regressors within a regression within SARIMA errors framework (Seabold & Perktold, 2010).

Standardising exogenous variables and recovering "scenario-unit" effects

For numerical stability and comparability, the SARIMAX models are estimated with standardised exogenous variables,

$$z_{j,t-1} = \frac{x_{j,t-1} - \mu_j}{\sigma_j}$$

in which μ_j and σ_j are the training-window mean and standard deviation of exogenous variable x_j. The estimated coefficient $\hat{\beta}_j^{(z)}$therefore measures the model-implied change in y_t measured in RM billion, associated with one standard deviation change in x_j, holding other regressors constant and accounting for the seasonal ARIMA error structure. This is consistent with the standard regression-scaling logic that dividing predictors by their standard deviations places heterogenous variables on a common scale, though such scaling does not by itself establish causal interpretation (Gelman, 2008).

Because standardisation is a linear transformation, the implied original-scale coefficient is:

$$\hat{\beta}_j^{(original\ scale)} = \frac{\hat{\beta}_j^{(z)}}{\sigma_j}$$

yet Chart 4 reports effects for selected economically meaningful changes, hence the applied reported quantity is scenario-unit effect:

$$\widehat{Scenario\ effect}_j(\Delta x_j) = \hat{\beta}_j^{(z)}(\frac{\Delta x_j}{\sigma_j})$$

Δx_j is the selected change in the original variable, such as as +25 basis points in OPR" or +RM10 billion in conventional bond supply on sukuk issuance. This use of standardised exogenous variables is appropriate when SARIMAX/ARIMAX models include heterogenous macro-financial predictors measured in different units, such as interest rates, exchange rates, GDP growth and currency denominations. The reported values should therefore be interpreted as conditional, model-implied scenario-unit effects, not structural causal impacts. Recent applied SARIMAX/ARIMAX forecasting studies incorporate diverse exogenous information into their forecasting frameworks; Lei, Chen, and Chu (2025) used SARIMAX model for gaming tourism destination demand by incorporating heterogeneous external information such as gaming revenue, weather, transportation, exchange rates, holidays and seasonality. Vonitsanos, Kanavos, and Mylonas (2025) similarly developed a context-enriched ARIMAX-deep learning framework for Bitcoin price forecasting, market capitalisation and moving averages to enrich the model inputs.

Quantitative Projection of Sukuk Demand in Malaysia and The Potential of Sustainable Sukuk to Bridge Expected Supply-Demand Gap

Muhammad Nadzif bin Ramlan and Abdul Haq bin Mohaidin
Bank Negara Malaysia

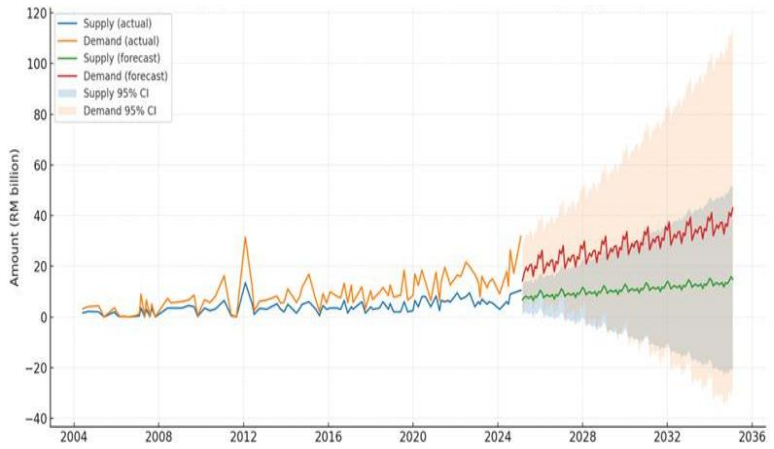
Seminar by De Nederlandsche Bank (DNB) and the BIS's Irving Fisher Committee (IFC)
Sustainability data issues and central banks' experience
Amsterdam, Netherlands
4 October 2025

The views expressed in this presentation are those of the authors and not necessarily those of Bank Negara Malaysia.

Executive summary: Demand for Malaysia's sukuk forecasted to triple in the next decade, widening existing demand-supply gap

Sukuk demand projected to triple by 2035

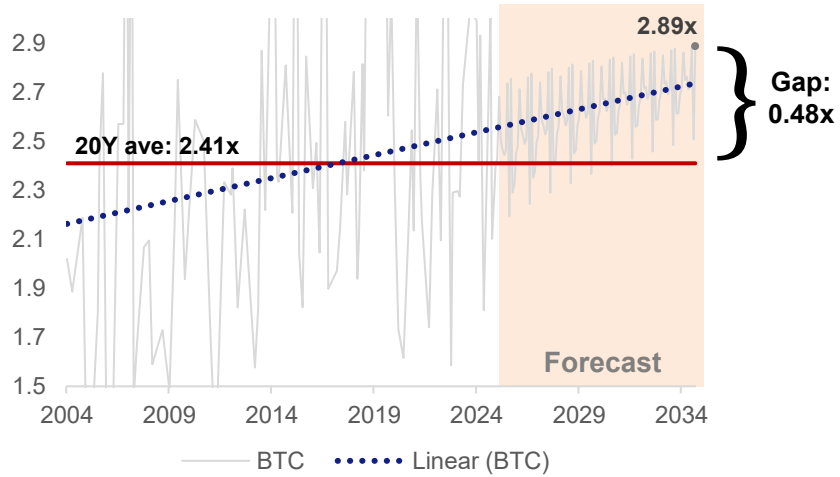
Malaysia's sukuk issuance supply-demand forecast (2025-2035)



Demand for Ringgit-denominated sukuk is projected to triple in size to RM42 billion by 2035. In contrast, demand for conventional bonds is expected to moderate during the same period. Tested and utilised forecast models include Seasonal Autoregressive Integrated Moving Average (SARIMA), Toda-Yamamoto Modified Wald Test (TY-MWALD) and SARIMA with exogenous variables (SARIMAX).

Widening the demand-supply gap even further

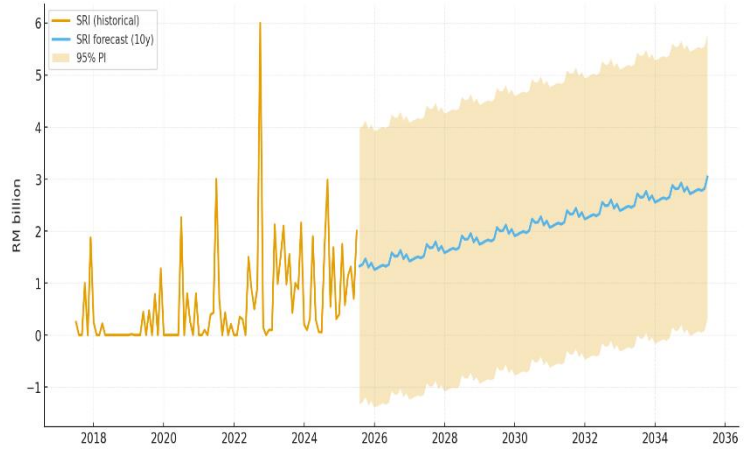
Malaysia's sukuk bid-to-cover ratio (2004-2035)



Sukuk bid-to-cover ratio (BTC) expected to rise higher than 20-year average (2.41x), as demand outpaces supply. This signals increasing competition among investors for limited Shariah-compliant sukuk issuances.

Nevertheless, sustainable sukuk could bridge the expected gap

Malaysia's sustainable sukuk issuances forecast (2025-2035)



Should sustainable sukuk maintain its current rapid growth, the issuance is forecasted to reach up to RM3 billion in the next same period of 10 years, sufficient to address the projected demand-supply gap (BTC 0.48x, or RM2.95 billion). BTC will gravitate back towards 20Y average if this materialise.

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Other forecast: ICD-LSEG's Islamic Finance Development Report 2024 forecasts that global sukuk is set to grow at 12% (CAGR 2023-2028). Similarly, our model forecasts sukuk issuances (sukuk supply green line in LHS chart) to grow at 12% (5Y CAGR).

Sustainability definition: Malaysia is mainly guided by Securities Commission Malaysia's Sustainable and Responsible Investment (SRI) Framework 2019 that are aligned with United Nations Sustainable Development Goals (SDGs). The EU similarly adopted the SDGs through its Taxonomy Regulation 2020, setting out overarching conditions for bonds to qualify as environmentally sustainable.

Presentation Outline

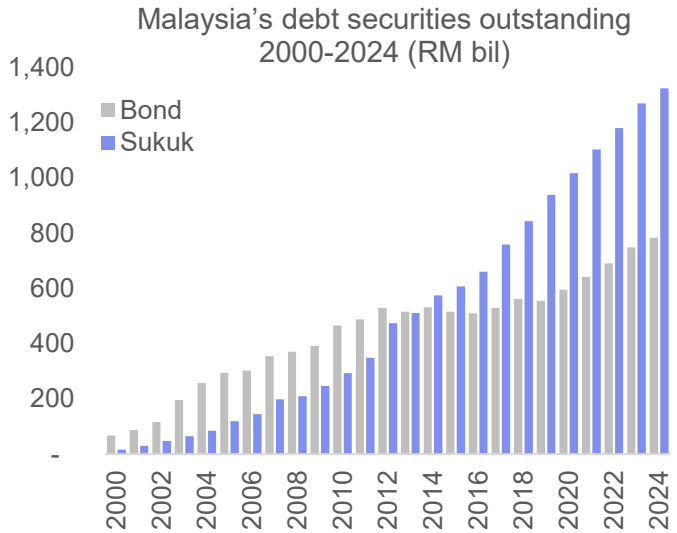
1. Introduction
2. Methodology
3. Analysis: Forecast findings
4. Analysis: Sustainable sukuk to bridge the gap
5. Limitations and Challenges
6. Conclusion

Appendices

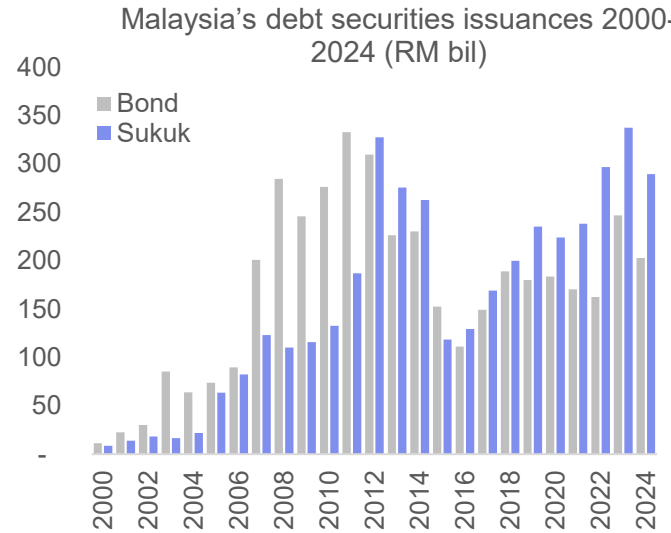
1. Literature review
2. Dataset and assumptions
3. Comparison with bond

Introduction: Islamic finance in Malaysia

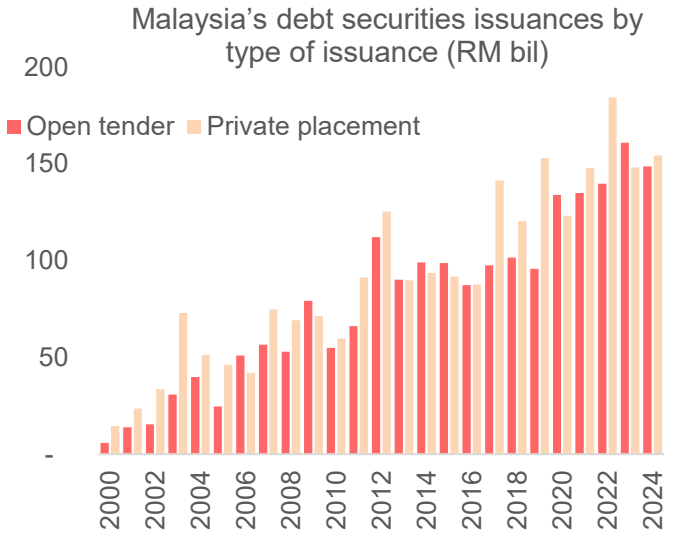
- Islamic finance has evolved from a niche alternative into a cornerstone of the global financial system, driven by ethical imperatives and robust growth dynamics. Underpinning this growth is the **Maqaṣid al-Sharīah (**higher objectives of Islamic law): preserving religion (*dīn*), life (*nafs*), intellect (*'aql*), lineage (*nasb*), and wealth (*māl*); objectives within wealth are five – circulation, clarity, preservation, establishment, and justice (Bin Bayyah, 2018).
- Globally, the Islamic financial services industry – covering capital market, banking and takaful – experienced growth in 2024, achieving a strong 14.9% year-on-year increase and reaching total assets of USD3.88 trillion; of which global outstanding sukuk surpassed USD900 billion (Islamic Financial Services Board, May 2025).
- Malaysia is home to the most developed Islamic finance market, ranked first globally for 12th consecutive year by the Islamic Finance Development Indicator (IFDI) 2024 released by ICD-LSEG. For sukuk market in particular, Malaysia has the largest share in the global market at 33.2% as at end-July 2024 (Ministry of Finance Malaysia, 2024).
- Within its unique dual financial system where Islamic and conventional system run in parallel, Islamic market comprised approximately 64% of Malaysia's domestic capital market (Securities Commission Malaysia, 2025), and anticipated to maintain its growth momentum—a trend observed since the early 21st century.



CAGR (2000-2024): Bond 10.8%; Sukuk 20.3%



CAGR (2000-2024): Bond 12.8%; Sukuk 15.7%



CAGR (2000-2024): Open tender 14.5%; private placement 10.3%

Introduction: Comparison between sukuk and conventional bonds

Sukuk industry has dominantly advanced in Malaysia's dual financial system, despite structural differences in comparison to conventional bonds:

Bond	Aspect	Sukuk
Represent interest-bearing debt obligation of the issuer	**Nature**	Represent proportionate ownership in Shariah compliant assets, usufructs, services, or profit-sharing venture or financial asset, or any combination
Any issuer	**Issuer**	Any issuer engaged in business activities which are permissible under Shariah rulings
Conventional	**Investor base**	Islamic and conventional investors
Debtor-creditor	**Issuer-investor relationship**	Sale, lease, partnership, agency or combination
Interest on loan	**Returns to investors**	Profit from sale, rent from lease, profit from investment activities/service
Return of principal at maturity is an irrevocable, irrespective profitability of funded project	**Principal repayment by issuer**	In sale-based and lease-based structures, the return of principal is guaranteed. However, in principle, there is no ex-ante fixed obligation of capital repayment for partnership-based sukuk structure
Not applicable	**Underlying assets**	Shall comply with Shariah requirements, can represent both debt and non-debt assets.
No specific requirements	**Utilisation of proceeds**	Proceeds must be utilised to finance Shariah-compliant activities
Pricing based on credit rating of issuer and term and conditions, usually a spread over a reference interest rate	**Pricing**	Pricing depends on the structure of the sukuk. For non-recourse asset-backed sukuk, pricing is based on the asset. For sukuk structured based on fixed income and debt-creating contracts, pricing is typically similar to bond pricing.
Sale of debt	**Tradability**	Dependent on the nature of underlying assets

Methodology: Diagnostics, forecast techniques & variable screening

Model diagnostics

Augmented Dickey-Fuller:

$$\Delta y_t = \alpha + \beta t + \phi y_{t-1} + \sum_{i=1}^{p} \psi_i \Delta y_{t-i} + \varepsilon_t$$

Kwiatkowski-Phillips-Schmidt-Shin:

$$S_t = \sum_{i=1}^{t} \hat{u}_i$$

$$KPSS = \frac{1}{T^2 \hat{\sigma}_u^2} \sum_{t=1}^{T} S_t^2$$

Ljung-Box portmanteau Q:

$$Q(m) = n(n+2) \sum_{k=1}^{m} \frac{\hat{p}_k^2}{n-k}$$

Akaike/Bayesian Info Criterion:

$$\text{AIC} = -2\hat{\ell} + 2k$$
$$\text{BIC} = -2\hat{\ell} + k \ln n$$

MASE (scale-free), benchmarked to seasonal naïve with s = 12:

$$MASE = \frac{\frac{1}{H}\sum_{t=1}^{H} |y_t - \hat{y}_t|}{\frac{1}{T-s}\sum_{t=s+1}^{T} |y_t - y_{t-s}|}$$

- **ADF-KPSS triangulation: In first differences, n**on-rejection for ADF, vice-versa for KPSS renders *d* = 1
- **Seasonality and residual whiteness:** Seasonal unit-root behaviour, but no autocorrelation at m=12/24
- **Parsimonious model:** Lower AIC/BIC preferred, BIC imposes stronger penalty, promoting more stable models
- **Scale-free accuracy:** MASE < 1 means the model is better the seasonal naïve forecast at s = 12

Main forecasting technique

Seasonal Autoregressive Integrated Moving Average (SARIMA):
AR: $\Phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$, $\Phi_s(B^s) = 1 - \Phi_1 B^s - \cdots - \Phi_P B^{P_s}$

MA: $\Theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$, $\Theta_s(B^s) = 1 + \Theta_1 B^s + \cdots + \Theta_Q B^{Q_s}$

No intercept/drift retained in the selected specification

SARIMA with exogenous variable (SARIMAX): Let Z_{t-1} be the lag-1 standardized exogenous vector:

$$Z_{t-1} = [MGS10Y_{t-1}, OPR_{t-1}, FD_{t-1}, FX_{t-1}, QGDP_{t-1}, Bond\ D_{t-1}, Bond\ S_{t-1}]'$$

Overall model with no intercept: $w_t = \beta' Z_{t-1} + u_t,\ u_t = \theta(B)\Theta(B^{12})\varepsilon_t$

- **Chosen baseline:** SARIMA (0,1,2)(0,1,1)$_{12}$, implying no AR terms, $d = 1, D = 1$, two non-seasonal MA terms, one seasonal MA terms
- **Residual diagnostics**: Ljung-Box tests at 12 and 24 check whether residual correlation remains after fitting
- **Regressand**: Sukuk demand and sukuk supply, transformed as : $w_t = (1-B)(1-B^{12})y_t$
- **SARIMAX regressors:** TY MWALD-selected variables enter with 1-month lag, standardised using training-window mean and standard deviation

Model-agnostic directionality screening

Augmented VAR in levels (avoid pretest bias):

$$Z_t = c + \sum_{i=1}^{k+d_{max}} A_i Z_{t-i} + u_t$$

Test restrictions only on first k lags; additional d_{max} lags are included but untested

Modified Wald statistics (valid with unit roots/cointegration):

$$W = R(\hat{\beta} - r)' \left[R\widehat{Var}(\hat{\beta})R'\right)^{-1}[R(\hat{\beta}) - r] \sim \chi_q^2$$

- **Candidate pool:** OPR*, 12M fixed deposits rate by commercial banks, quarterly GDP growth, 10-year MGS yield, conventional bond demand, conventional bonds supply, USD/MYR rate, FBM KLCI, FDI inflow, FDI outflow, FDI net flow
- **Toda-Yamamoto Modified Wald Test (TY MWALD) screening** – identify variables with predictive directional content for sukuk demand-supply
- **Retained SARIMAX drivers:** OPR, 12M FD rate, Quarterly GDP growth, 10MGSY, conventional bond demand, conventional bond supply, USD/MYR

**Latest data is mid-2004; other variables are dated since 2000.*

Methodology: Establishing forecast baseline and determining external factors

SARIMA as baseline forecast model

- Baseline model for Seasonal Autoregressive Integrated Moving Average (SARIMA): (p, d, q)(P, D, Q)h = $(0,1,2)(0,1,1)_{12}$
- Seasonal differencing and Moving Average (MA) terms are applied.
- $c \neq 0$, no intercept/drift as it would act like a deterministic trend. After differencing, the series fluctuates around zero without imposed drift.

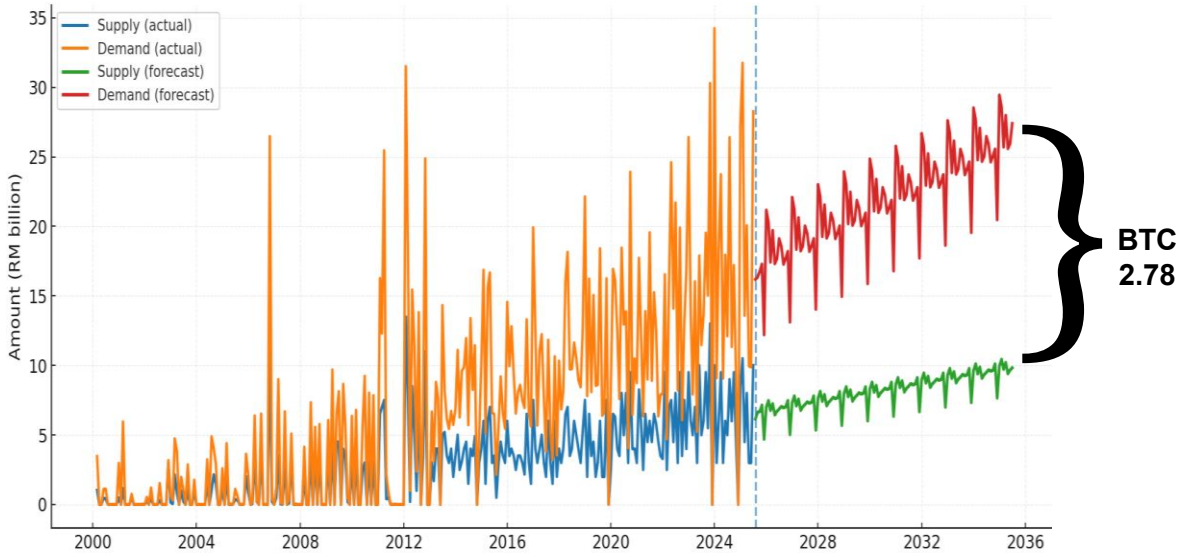
Observations:

a) Sukuk bid-to-cover (BTC) under SARIMA forecast shows constant value of 2.78 throughout 5-year and 10-year forecast horizon.

b) Mean Absolute Scaled Error (MASE) for both Supply and Demand > 1 (1.41, 1.58 respectively). This means its forecast is worse than seasonal naïve benchmark.

c) Refinement is needed, leading to utilisation of TY-MWALD to consider for exogeneity.

Baseline forecast for sukuk issuance supply-demand



Choosing external factors via Toda-Yamamoto Modified Wald Test

Exogenous variables tested and accepted

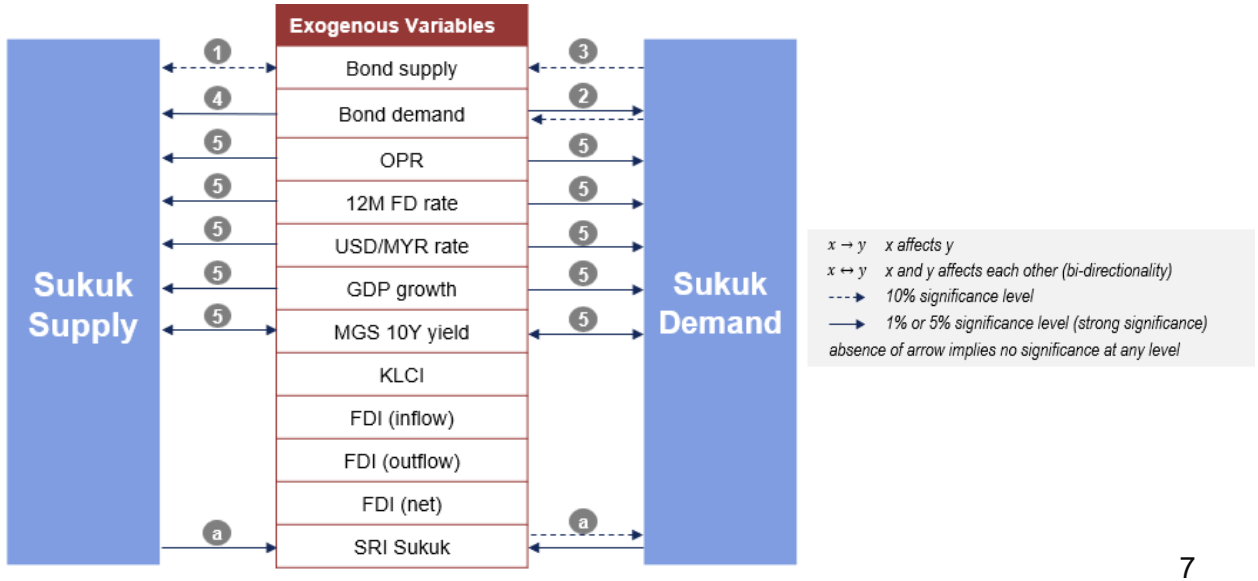
1. Sukuk and bond supply affects each other, since the supply of one may prompt adjustment in the other.
2. Similarly on the demand side, sukuk and bond demand affect each other, since a surge in demand for one may lead to rebalancing away from the other.
3. Sukuk demand affects bond supply, potentially due to strong investor preference for Shariah-compliant instruments influencing bond issuers to reduce issuance of bond.
4. Bond demand affects Islamic supply, likely since conventional bond buyers are also able to buy sukuk, causes spillover to sukuk market and influence sukuk supply decision.
5. Other variables are well expected to strongly affect both sukuk supply and demand, i.e. OPR, FD rate, FX rate, GDP growth & benchmark MGS 10Y yield. Strong bi-directionality in MGS 10Y yield.

Exogenous variable tested and accepted, but unable to be applied

a. SRI Sukuk to influence Sukuk demand, while being affected by both Sukuk demand and supply. To be excluded due to severe data limitation (dataset starts from 2017, while others from 2000).

Exogenous variables tested and rejected

KLCI and FDI (tested individually for inflow, outflow and net) are not significant variables.

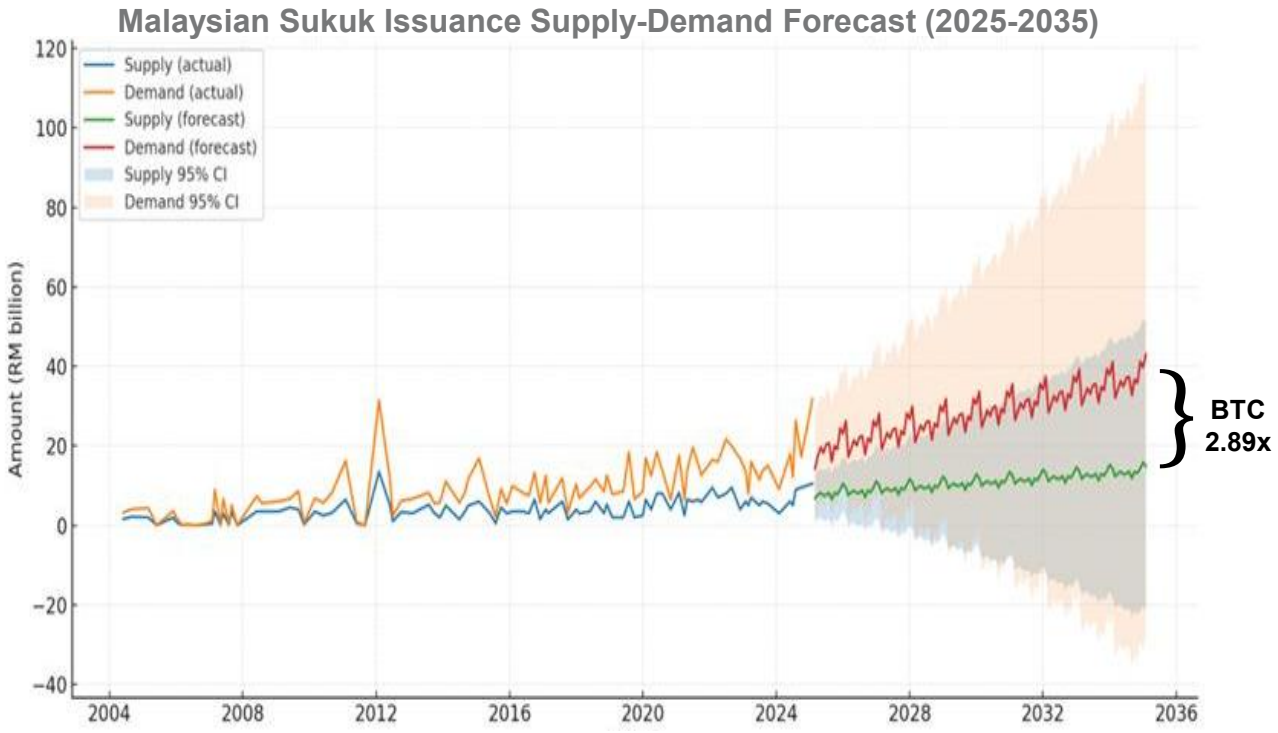


Analysis: Demand for Malaysia's sukuk forecasted to triple in the next decade, widening existing demand-supply gap

Model equation

$$w_t = \beta' Z_{t-1} + \theta(B)\Theta(B^{12})\varepsilon_t$$

$$Z_{t-1} = [MGS10Y_{t-1}, OPR_{t-1}, FD_{t-1}, FX_{t-1}, QGDP_{t-1}, Bond\ D_{t-1}, Bond\ S_{t-1}]'$$



- Accuracy metric: MASE value for Supply and Demand are 0.896, 0.885. This means that the model's average error is smaller than the naïve baseline.
- The same model applies with seasonal differencing (D=1, s=12) and non-seasonal differencing (d=1)
- Ljung-Box at 12 and 24 lags are insignificant, signifying no residual autocorrelation.
- Exogenous variables are all standardised, lagged by 1 month

Findings

1. **Accelerating demand** – Demand for Ringgit-denominated sukuk is projected to triple to RM42 billion by 2035, with highest estimate to go beyond RM100 billion. In contrast, demand for bonds is expected to moderate during the same period.
2. **Widening demand-supply gap** – Demand growth will further outpace supply, with bid-to-cover ratio (BTC) forecasted to rise to 2.89x by 2035 (2025: 2.10x). This signals increasing competition among investors for limited Shariah-compliant sukuk issuances.
3. **Forecast incorporates exogenous variables** such as OPR, GDP growth, benchmark 10Y MGS yield, conventional bonds demand & supply, 12M fixed deposits rate by commercial banks, USD/MYR exchange rate. The exogenous variables are adding genuine predictive signal to the differenced mean.
4. **Accuracy metric**: MASE value for Supply and Demand are 0.896, 0.885. Reflecting model's average error to be smaller than naïve baseline.

Supportive anecdotal evidence

Growing appetite from sizeable domestic institutional investors with Shariah-compliant investment mandate. For example, Malaysia's Employee Provident Fund (EPF) – ranked as the 13th largest pension fund globally and 5th in Asia – recorded an 11% increase in total contribution driven by wage growth, among others.

Analysis: Coefficients of the exogenous variables

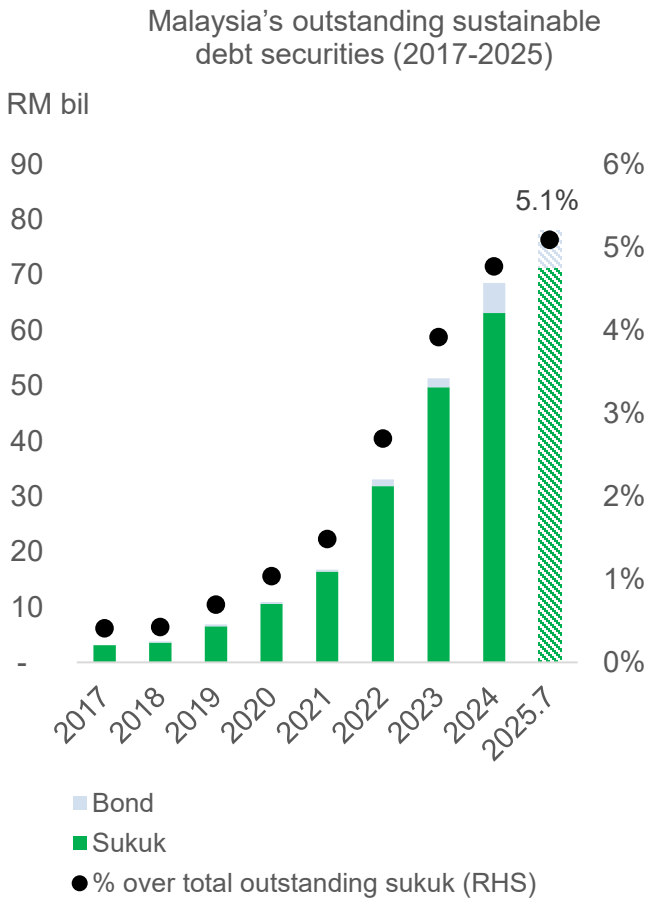
Dependent Variable	Scenario-Unit Impact	Exogenous Variable	Scenario-Unit Impact	Dependent Variable
Sukuk supply	+ RM2.18 bn	**Bond supply (+RM10 bn)**	+ RM4.95 bn	**Sukuk Demand**
	+ RM0.25 bn	**Bond demand (+RM10 bn)**	+ RM0.33 bn	
	+ RM0.77 bn	**OPR (+25 bps)**	+ RM1.10 bn	
	- RM2.68 bn	**12M FD rate (+25 bps)**	- RM5.17 bn	
	+ RM0.36 bn	**USD/MYR rate (+0.10 USD appreciates)**	+ RM0.89 bn	
	+ RM0.12 bn	**GDP growth (+ 1.0 pps)**	+ RM0.30 bn	
	- RM0.82 bn	**MGS 10Y yield (+ 50 bps)**	- RM1.33 bn	

Observations:

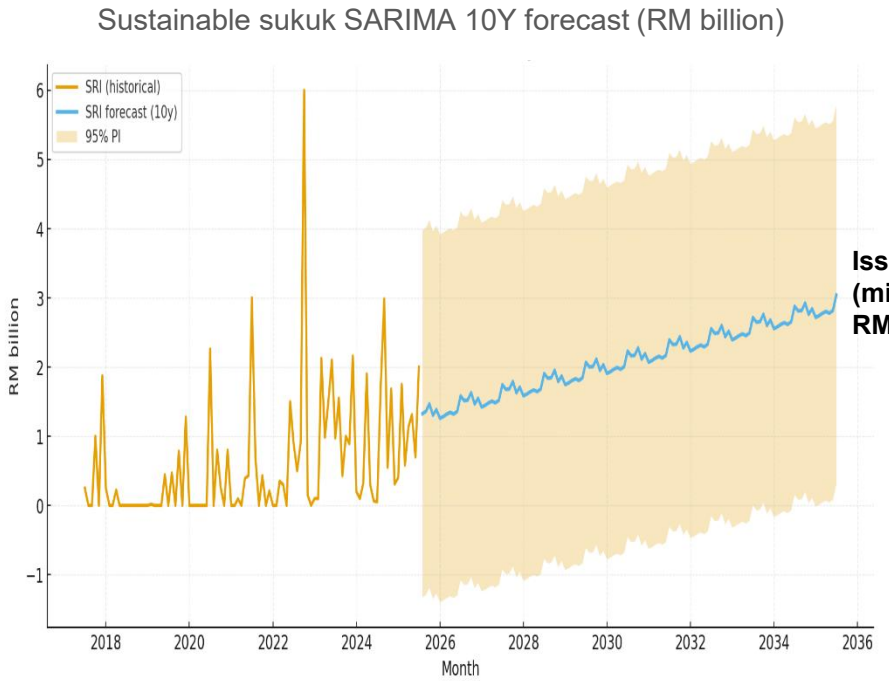
1. **Increasing rates in 12 Month Fixed Deposit rate and MGS 10-year yield** would **impact negatively** on sukuk demand and sukuk supply.
    a) When yields rise, existing bonds with lower coupons become less attractive causing their price to fall. Investors may hold off buying sukuk, expecting better yields (and lower prices) in the near future.
    b) Increase in 12M Fixed Deposit rate offers investors alternatives with higher returns, hence reducing sukuk demand as well as supply
2. **Higher GDP growth** reflects a robust and expanding economy, which boosts business confidence. This economic optimism encourages both companies to issue sukuk for expansion and infrastructure financing (increasing supply) and investors to seek such instruments as a stable, Shariah-compliant investment option (increasing demand).
3. **An increasing OPR** typically indicates a tightening monetary policy environment in response to inflationary concerns. This can lead to higher benchmark yields, making sukuk relatively more attractive as they may offer competitive returns in line with overall market expectations. Consequently, investors will be more inclined to invest, driving both supply and demand upward.
4. **Weaker MYR against USD** may expose companies to higher foreign exchange risks and increased costs in international transactions, prompting them to seek alternative financing options like sukuk to better manage their funding needs.

Analysis: Sustainable sukuk could bridge the expected demand-supply gap

Rapid growth of sustainable sukuk[1] (5Y CAGR: 57%)



Forecasted issuance of sustainable sukuk in 10 years is sufficient to plug the projected demand-supply gap[2] (RM2.95 bil)



Issuance size (mid-2035): RM3.04b

Multiple drivers are expected to maintain momentum in sustainable sukuk growth

Alignment with national agenda (e.g. National Energy Transition Roadmap, New Industrial Master Plan 2030)

Facilitative regulatory landscape (e.g. tax incentives, issuance of industry guidance)

Enhanced integration of ESG into investors' strategy & mandate

Broader range of issuers

[1] Sustainable sukuk include Sustainable and Responsible Investment (SRI) and SRI-linked sukuk as outlined by Securities Commission Malaysia and ASEAN Green, Social, Sustainability and Sustainability-linked Bond as outlined by ASEAN Capital Market Forum (ACMF)
[2] Demand-supply gap refers to difference in forecasted BTC (2.89x) and 20-year average BTC (2.41x)

Challenges and limitations: Considerations for other future studies

Limitations	Description
A **Inconsistency in sukuk issuance data frequency**	Inconsistent monthly sukuk issuance, where there were zero issuance in several months, which can impact the robustness of forecasts. Forecasting models rely on consistent data patterns to make accurate predictions.
B **Severely limited time horizon for sustainable sukuk**	Sustainable sukuk was only first issued in 2017, compared to the overall sukuk dataset that are available from early 21st century. Its limited data timeline renders it incompatible with the overall SARIMAX model.
C **Sustainable sukuk is on private placement only**	Sustainable sukuk is currently offered exclusively through private placement, which renders its exclusion from the overall sukuk forecast.
D **Limited benchmarking on sukuk issuance forecasting**	There are limited studies conducted on forecasting of sukuk in both industry and academia. This gap underscores the need for more rigorous research and data-driven analysis to establish benchmarks and improve predictive methodologies in the sukuk market.

Conclusion

1. Sukuk demand in Malaysia is forecasted to triple within the next decade, expected to widen the demand-supply gap and increase competition among investors seeking for the Shariah-compliant investment instrument.

    - Seasonal Autoregressive Integrated Moving Average (SARIMA) is inadequate to project the forecast accurately, hence necessitating exogenous variables in the said projection (SARIMAX).
    - Incorporated exogenous variables include conventional bonds supply and demand, Overnight Policy Rate, 12-month fixed deposit rate by commercial banks, USD-MYR exchange rate, quarterly GDP growth and Malaysian Government Securities (MGS) 10-year yield.
    - Anecdotal evidences are also supportive, with expectation of growing appetite from major institutional investors with Shariah-compliant mandate e.g. Malaysia's Employee Provident Fund (EPF) recorded 11% increase in contribution size.

2. Sustainable sukuk growth is rapid in Malaysia. The segment could bridge the demand-supply gap within the same period, if growth continues.

    - Supported by multiple drivers such as facilitative regulatory support and alignment with national agenda such as Malaysia's National Energy Transition Roadmap and New Industrial Master Plan 2030. Malaysia commits to achieving net zero by 2050.

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Thank you!

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Appendices

Literature review

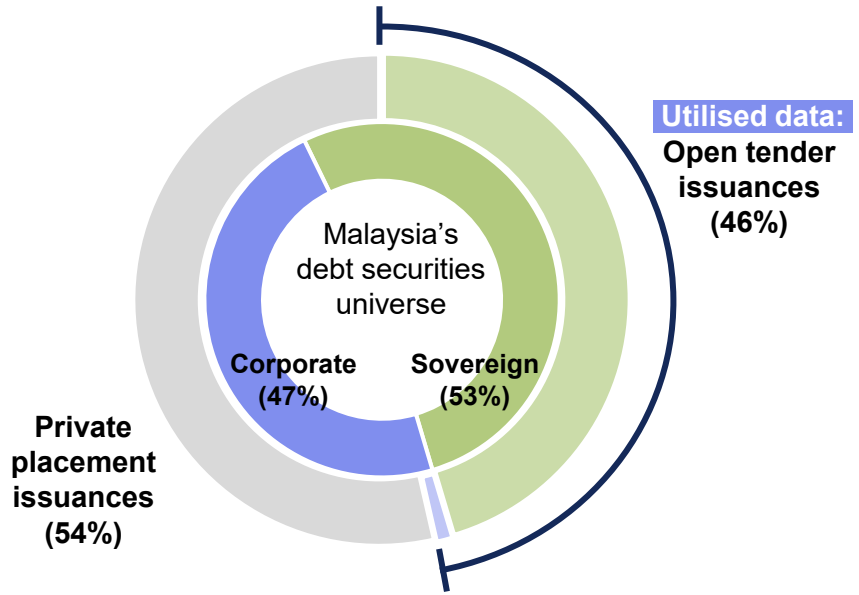
A. Sukuk industry in Malaysia

- **Foundational insights:** Sukuk is the Arabic term for Islamic securities, it simply means certificate. Sukuk is documented as a tool for resource mobilisation (Jobst, Kunzel, Mills & Sy, 2008). Sukuk tend to be structured so the end economic result mimic fixed income instrument such as bond with similar risk-reward structures and features, since bond market plays pivotal roles in the economy and financial markets (Bahari et al., 2016, Sairally et al., 2017).
- **Development and evolution of sukuk**: Early experiences in Malaysia was initiated by the Government of Malaysia by issuing Government Investment Certificate (GIC) in 1983 to provide avenue for short-term liquidity management and long-term investment for Islamic financial institutions during the period. First corporate sukuk was later issued in Malaysia in 1990 by Shell MDS Malaysia Sdn Bhd (Sairally et al., 2017). Malaysia's sukuk is known to finance its domestic infrastructure projects, though the market has structured sukuk to suit variety of specific funding needs of various economic activities for example sale-based sukuk (based on the concept of *Murabahah, Salam, Istisna*), lease-based sukuk (based on the concept of *Ijarah*), partnership-based and agency (based on the concept of *Mudarabah/Musharakah* and *Wakalah*), or any combination thereof. Further innovation introduces capacity sukuk, utilising 'business capacity' of respective companies (such as airtime by telcos, right to travel by airlines) as intangible underlying assets (Djafri et al., 2023).
- **Malaysia's sukuk market:** Malaysia's sukuk market has grown exponentially and even demonstrating positive impact to the Malaysia's economic growth (Abrorov, 2020). Malaysia provides as an ideal dataset for this study, hosting a matured sukuk market under the dual financial system alongside the conventional bond market, enabling fair comparison against between the two vibrant, deep markets.

B. Forecast model

- **ARIMA as a baseline:** Many studies start with ARIMA to establish a benchmark forecast for sukuk or related financial series [Rosadhillah & Ülev, 2024]. It captures autoregressive structure but is limited in scope. Our use of ARIMA as an initial step aligns with common practice and provides a yardstick for improvements.
- **ARIMAX with Causality-based Inputs in Sukuk:** Incorporating exogenous macro drivers is advised by numerous researchers. Empirical results show that including relevant variables (e.g. interest rates, inflation) can enhance forecast accuracy for sukuk, such as the case in Malaysia and Turkiye [Humaida, Nur Atikah and Dini Naziha, 2016; Baykut, 2024]. By using the Toda-Yamamoto causality test (as in Baykut, 2024) to guide variable selection, we ensure our ARIMAX model only includes factors that have proven predictive content for sukuk. This evidence-driven ARIMAX is likely to outperform a pure ARIMA, as supported by findings in other domains where ARIMAX was preferred for greater accuracy [Paul & Sinha, 2016]. Essentially, our approach combined ARIMA forecasting with Toda-Yamamoto Modified Wald Test for sukuk and macroeconomic variables.
- **Machine Learning to Rival Econometric Models: I**ntegration of machine learning techniques with time-series models. Zainuddin et al. (2019) and Çetin & Metlek (2024) examined sukuk investment forecasts using a hybrid of classical moving-average and artificial neural network (ANN) algorithms; they found that a purely statistical moving average (MA) model produced biased estimates for sukuk prices/indices, whereas the proposed ANN-enhanced approach significantly reduced forecast errors. This result underlines a broader point: while linear models like ARIMA/ARDL capture baseline patterns, non-linear or complex patterns might be better handled by machine learning. Other studies in Islamic finance have likewise started comparing traditional models to newer methods (e.g. comparing ARIMA/ARIMAX to deep learning or recurrent networks for financial series) [Elbatal et al., 2025]. In general, these studies show that baseline ARIMA or regression models often benefit from either including exogenous inputs or combining with non-linear learners to capture all dynamics.

Dataset and assumptions



Why open tender issuance data?

Market-driven indicator | **Market benchmark** | **Significant size**

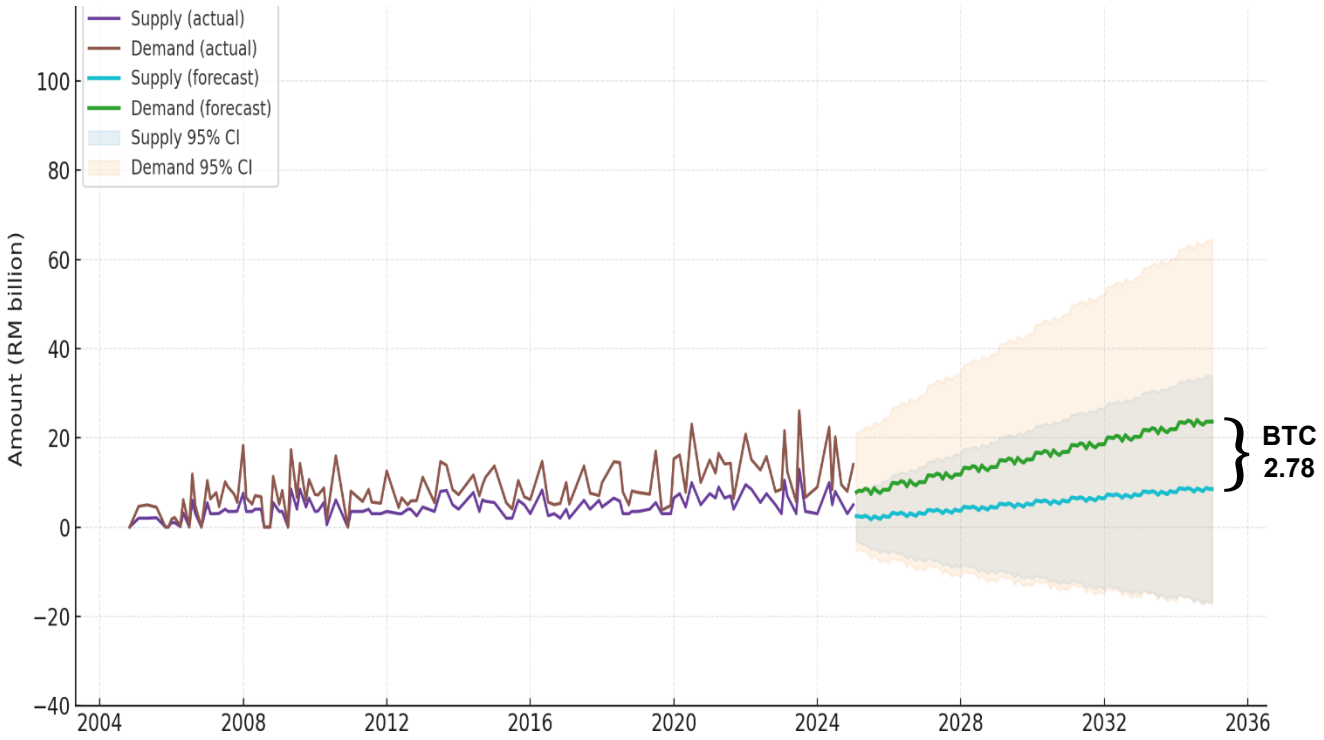
Dataset comprises of 869 issuances from Jan 2000-July 2025, offering a balanced representation across categories

- 655 sovereign issuances (by BNM, GOM) and 214 corporate issuances (from entities such as Khazanah, Cagamas, TNB, Telekom)
- 491 conventional bonds, 378 Shariah-compliant sukuk

General forecast assumptions

Stable political and policy environment	No policy reversal or regulatory changes that could drastically shock the financial market. This includes Shariah regulations.
No black swan events	No major unforeseen disruptions such as global financial crisis or geopolitical conflicts
Continued growth, stable monetary policy	Economic growth and policy rate follows a historically predictable path; OPR are within range of 1.75%-3.50%
Consistent non-resident	Non-resident holdings remains low (average 3.6% over outstanding), following historical trajectory. Forecast excludes potential upside from increased non-resident interest arising from latest efforts to attract foreign investors
Data aggregation	Issuances are aggregated into monthly data, irrespective of tenor, to ensure analytical viability

Conventional bond forecast: Bond demand is expected to moderate amid accelerating demand for sukuk



Model diagnostics

- The same model is applied for forecasting bond $(0, 1, 2)(0,1,1)_{12}$
- Exogenous variables: OPR, 12-month FD rate, FX rate, Quarterly GDP growth, MGS 10-year yield, Islamic demand and supply
- MASE value for Conventional Supply and Demand are 0.68, 0.71 respectively. In terms of accuracy metrics, the model's error are smaller than the naïve benchmark.
- The exogenous variables are adding **genuine predictive signal** to the differenced mean.

Findings

- Islamic demand outpacing conventional demand – beyond 1.70x
- Closing demand-supply gap – Demand growth will decline towards meeting supply, with bid-to-cover ratio (BTC) forecasted to drop to 2.78x by 2035 (2025: 3.19x). This might entail possible shift to Islamic bonds in the long-term.

Irving Fisher Committee on Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Improving the timeliness of the ESCB carbon indicators with nowcasting techniques

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This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

Predicting the Present with the Python Package Oraculo

Imagine you're analyzing portfolio climate risk and need current-year company emissions data, but annual reports won't arrive for another 6-12 months. Or you're tracking unemployment trends and need this month's figures, but the official statistics won't be published for weeks. These data lags can severely hamper the timeliness of your analytics and decision-making.

The solution? **Nowcasting** - using proxy variables that are available in real-time to predict data that exists but hasn't been published yet. Essentially, you're predicting the present (Giannone et al., 2008).

In this blog post, we present **Oraculo**, a Python package, developed to make nowcasting straightforward and accessible. Whether you're forecasting economic indicators, emissions data, or any time-lagged series, Oraculo provides a unified framework for configuration, modeling, and evaluation.

- Note: Since a nowcast is technically a type of forecast, these terms are used interchangeably throughout.

What You'll Learn

In this post, we'll walk through:

1. **Configuration-driven modeling** - How YAML files define your entire nowcasting pipeline, making it easy to experiment with different model specifications
2. **Rapid experimentation** - How Oraculo's design facilitates exploratory modeling by providing instant feedback through error metrics and diagnostic visualizations
3. **Model evaluation** - Using RMAE and RME metrics to assess forecast accuracy
4. **Visual diagnostics** - Identifying error patterns through histograms and plots
5. **Feature importance** - Understanding which proxy variables drive predictions
6. **Benchmark comparison** - Why LOCF is the key baseline to beat
7. **Advanced techniques** - Normalization, lagged features, and hybrid modeling strategies

By the end, you'll see how Oraculo's exploratory framework enables systematic iteration - taking a basic model with 153% error and improving it to 37% through rapid experimentation.

Background: Climate Indicators at the ECB

Since 2020, the European Central Bank has been developing climate and nature-related statistical indicators to support its climate-related financial stability monitoring and monetary policy assessment (ECB, 2021; ECB, 2024). These experimental indicators track the carbon footprint of euro area financial institutions' portfolios, the climate transition risks in the banking sector, and the environmental impact of corporate bond holdings. The ECB publishes these indicators regularly - with recent releases in 2024 providing comprehensive data on greenhouse gas emissions associated with euro area financial sector exposures.

However, a critical challenge undermines the timeliness of these indicators: **company-level emissions data suffers from publication lags of often more than 12 months** (Busch et al., 2022). When the ECB publishes climate indicators in Q1 2026, the underlying emissions data typically reflects 2024 or even 2023 activity. This lag creates a significant blind spot for policymakers and financial supervisors who need to assess current climate risks, not historical ones. For monetary policy decisions and financial stability assessments that require real-time insights, year-old emissions data can miss emerging trends, sudden transitions, or the impact of recent policy interventions.

Oraculo addresses this timeliness gap by combining lagged emissions data with more timely proxy variables - economic indicators, energy consumption patterns, and sector trends - to generate nowcasts that fill the gap until official data becomes available. This approach enables the ECB to maintain more current climate risk assessments and respond more quickly to evolving environmental challenges in the financial system.

A Practical Example: Nowcasting Scope 2 Emissions

To illustrate Oraculo's capabilities, let's nowcast company-level Scope 2 emissions (indirect emissions from purchased electricity). We'll use:

- **Target variable**: Scope 2 emissions from ISS (a data provider that collects emissions from annual reports)
- **Proxy features**:
  - Aggregate GDP data from the World Bank (World Bank, 2024)
  - Oil consumption data from the U.S. Energy Information Administration (EIA, 2024)
  - Historical emissions patterns (lagged values)

The intuition is straightforward: emissions correlate with economic activity and energy consumption, both of which are available with shorter lags than company-reported emissions data.

Configuration-Driven Modeling

Oraculo uses YAML configuration files to define your entire nowcasting pipeline. This design philosophy makes experiments reproducible and facilitates rapid iteration - you can test different model specifications, feature combinations, and data transformations simply by editing a configuration file. No need to rewrite code or manage complex parameter dictionaries.

- *Key advantage for exploratory modeling*: Change your model type, add features, or adjust transformations in seconds, then immediately see the impact on forecast accuracy through Oraculo's built-in evaluation metrics and visualizations.

Let's start with a basic example.

```
name: "Oraculo crystal ball"
series_keys:
```

```
  - "issuerid"
date_key: "date"
forecast_interval:
  years: 1

model_configs:
  - name: "XGBoost Model Scope 2"
    model: "LGBM"  # LightGBM gradient boosting
    target: "scope2"
    train_start: 2018-01-01
    features:
      - oil_consumption
      - gdp

data_config:
  repository: "ISSRepository"
  path: path/to/repositories/iss_repository.py
  refresh: false
  merge:
    repository: "WorldbankRepository"
    path: path/to/repositories/worldbank_repository.py
    refresh: false
    join_keys: ["country", "date"]
    merge:
      repository: "EIARepository"
      path: path/to/repositories/eia_repository.py
      refresh: false
      join_keys: ["country", "date"]
```

Key components:

- **General settings**: Define the series identifier (`issuerid`), date column, and forecast horizon (1 year ahead)
- **Model configuration**: Specify the model type (LightGBM), target variable, training start date, and features
- **Data configuration**: Oraculo's unified data framework handles importing and merging from multiple sources. Each repository is a Python class that knows how to fetch and format data from a specific source (ISS, World Bank, EIA). The nested `merge` structure works sequentially: *start with ISS emissions data → merge in World Bank GDP by country/date → merge in EIA oil consumption by country/date*. This creates a single unified dataset with all features aligned. Note: you need to create repository classes for your data sources.

Running Your First Nowcast

With the configuration in place, running a model is straightforward. For training and evaluation, we'll create a forecast for a historical date (2023-01-01) where we have actual observations to compare against:

```
import datetime as dt
from oraculo.services.model_run_service import ModelRunService
from oraculo.config import config

# Load configuration
fc_basic = config.ForecastConfig.from_yaml(
    "./configs/blog_post_config_basic.yaml",
    "./repositories/template_credentials.yaml"
)

# Create model instance
mrs = ModelRunService()
fd = dt.date(2023, 1, 1)

# # Run model using forecast date and configuration
mrs.run_model(fd, fc_basic)
```

Evaluating Model Performance

Oraculo provides **instant feedback** on model performance to facilitate rapid iteration - a core feature for exploratory modeling. As soon as your model runs, you get immediate diagnostic information without writing additional evaluation code. This tight feedback loop enables you to quickly test hypotheses, identify issues, and refine your approach.

Let's check our basic model's accuracy using two key metrics:

- **Relative Mean Absolute Error (RMAE)**: Average absolute error as a percentage of actual values
- **Relative Mean Error (RME)**: Average error as a percentage (reveals bias)

```
# Create evaluation instance
evr_basic = mrs.return_evaluation_results()
evr_basic.summarise('scope2')
```

The results suggest our basic model isn't performing well:

- **RMAE = 153%**: On average, predictions are off by 153% of actual values
- **RME = +126%**: Indicates severe systematic overestimation

These metrics tell us we need to dig deeper to understand what's going wrong.

Visual Diagnostics: Understanding the Errors

For visual inspection of forecast error distributions, Oraculo provides built-in plotting functions:

```
evr_basic.plot_histogram()
```

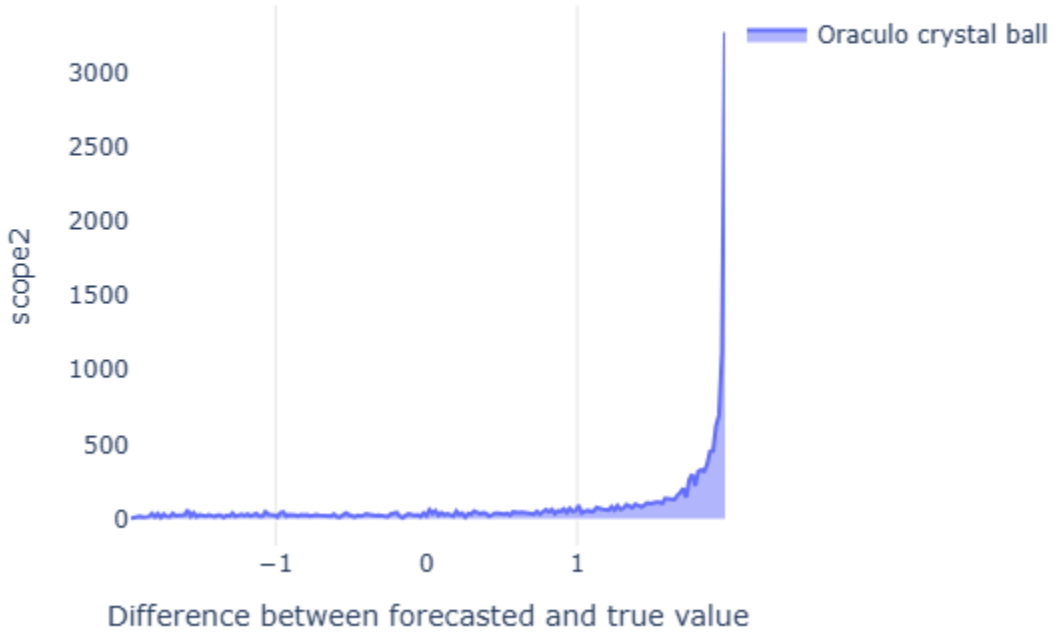


Figure 1: histogram of forecasting errors

The histogram visualization helps reveal the source of our positive bias: errors are concentrated in firms with large Scope 2 emissions. The model struggles with high-emitting companies, likely because:

1. These firms are outliers in the distribution
2. The relationship between features and emissions may be non-linear at high values
3. We haven't normalized the data to handle scale differences

This diagnostic insight will guide our improvements in the next section.

Feature Importance Analysis

For tree-based models, Oraculo can calculate permutation importance scores to understand which features drive predictions:

```
# Check feature importance
mdl = fc_basic.model_configs[0].name
evr_basic.model_permutation_importance(mdl)
```

The permutation importance results reveal interesting insights:

- **Oil consumption** (1.62) and **GDP** (1.58) have nearly equal importance
- Both scores > 1.0 indicate that permuting these features degrades model performance - they're genuinely contributing to predictions
- The similar importance suggests both economic activity and energy consumption are valuable signals for emissions nowcasting
- However, with only two features and no historical emissions data, the model lacks the persistence information that LOCF captures naturally

This analysis suggests we need to add lagged emissions as features to capture temporal patterns.

The LOCF Benchmark: A Reality Check

Last Observation Carried Forward (LOCF) is the most relevant — and often hardest to beat — benchmark for nowcasting. LOCF simply uses the most recent observed value as the prediction. It's naïve but surprisingly effective, especially for slowly changing series.

However, LOCF has important limitations that make it an imperfect solution (Makridakis et al., 2018):

- **Unrealistic assumption**: It assumes values remain exactly constant - emissions are identical to last year's, unemployment is unchanged from last month. This rarely reflects reality.
- **Trend bias**: When data exhibits trends (e.g., declining emissions due to decarbonization efforts, or rising unemployment during recessions), LOCF systematically lags behind, producing biased forecasts.
- **No forward-looking information**: LOCF ignores all available proxy variables that might signal changes (economic indicators, policy shifts, sector trends).
- **Poor performance during transitions**: During periods of structural change or volatility, LOCF fails to anticipate shifts that more sophisticated models might detect.

For these reasons, **while LOCF provides a crucial benchmark, the goal is to develop models that outperform it** by incorporating forward-looking information and capturing dynamics that simple persistence misses. This is especially important for policy and risk assessment applications where understanding current trends matters more than historical values.

Oraculo makes it easy to compare your model against LOCF:

```
mrs.compare_to_LOCF('scope2', fd, fc_basic)
```

The comparison reveals a stark difference in performance:

- **Basic model**: RMAE = 153%, RME = +126%

- **LOCF benchmark**: RMAE = 33%, RME = +8%
- *LOCF dramatically outperforms our basic model** by nearly 5x on RMAE. This is disappointing but informative - it tells us that our current feature set (just GDP and oil consumption) isn't capturing enough signal to beat the simple persistence baseline.

This is a common challenge in nowcasting: you need to add genuine predictive value beyond simple persistence. The key insight is that emissions tend to be sticky - last year's value is often a strong predictor of this year's value. Let's see if we can do better by incorporating this persistence information.

Leveraging Advanced Features of Oraculo

Our basic model underperforms LOCF, but this is where Oraculo's exploratory modeling capabilities shine. The framework makes it easy to systematically test improvements:

Improvements to try:

- **Switch model type**: Try OLS (Ordinary Least Squares) for better interpretability
- **Normalize variables**: Handle scale differences between features and target
- **Add lagged target values**: Include historical emissions as features (captures persistence)
- **Create first-differences**: Model changes rather than levels
- **Split the sample**: Use the model for stable companies (±50% year-over-year change), LOCF for volatile ones

With Oraculo's configuration-driven approach, each of these experiments requires only minor YAML edits - no code changes needed. You can rapidly iterate through different specifications and immediately see the impact on forecast accuracy.

This hybrid approach recognizes that different prediction strategies work better for different types of companies.

Advanced Configuration

Here's how to implement these improvements in the configuration file. **Save this as `blog_post_config.yaml`:**

```
name: "Oraculo improved model"
series_keys:
  - "issuerid"
date_key: "date"
forecast_interval:
  years: 1

model_configs:
  - name: "OLS Model Scope 2"
    model: "OLS"
    target: "scope2"
    train_start: 2018-01-01
    features:
```

```
      - oil_consumption
      - scope2_lag1
      - gdp
    split_filter:
      column: ["scope2_lag1", "scope2_lag1"]
      value: [0.5, 1.5]
      operator: [">", "<"]

  - name: "LOCF Model Scope 2"
    model: "LOCF"
    target: "scope2"
    train_start: 2021-01-01
    split_filter:
      column: [""]
      value: [null]
      operator: ["otherwise"]

data_config:
  repository: "ISSRepository"
  path: path/to/repositories/iss_repository.py
  refresh: false
  merge:
    repository: "WorldbankRepository"
    path: path/to/repositories/worldbank_repository.py
    refresh: false
    join_keys: ["country", "date"]
    merge:
      repository: "EIARepository"
      path: path/to/repositories/eia_repository.py
      refresh: false
      join_keys: ["country", "date"]

data_transformations:
  normalize_dict:
    scope2: "max"
    gdp: "first"
    oil_consumption: "mean"
  target_diff:
    - "scope2"
  simple_lags:
    scope2: [1, 2]
  differences:
    scope2: [[1, 2]]
```

What's new:

- **Two models**: OLS for stable companies, LOCF for volatile ones
- **Split filter**: Routes companies to different models based on year-over-year stability
- **Data transformations**: Normalizes variables, creates lags and differences
- **Lagged features**: `scope2_lag1` captures historical patterns

```
# Load improved configuration
fc = config.ForecastConfig.from_yaml(
    "./configs/blog_post_config.yaml",
    "./repositories/template_credentials.yaml"
)

# Run model using forecast date and configuration
mrs.run_model(fd, fc)

# Create evaluation instance
evr = mrs.return_evaluation_results()

# Plot mean prediction
evr.plot_mean_results('scope2', normalise=False)
```

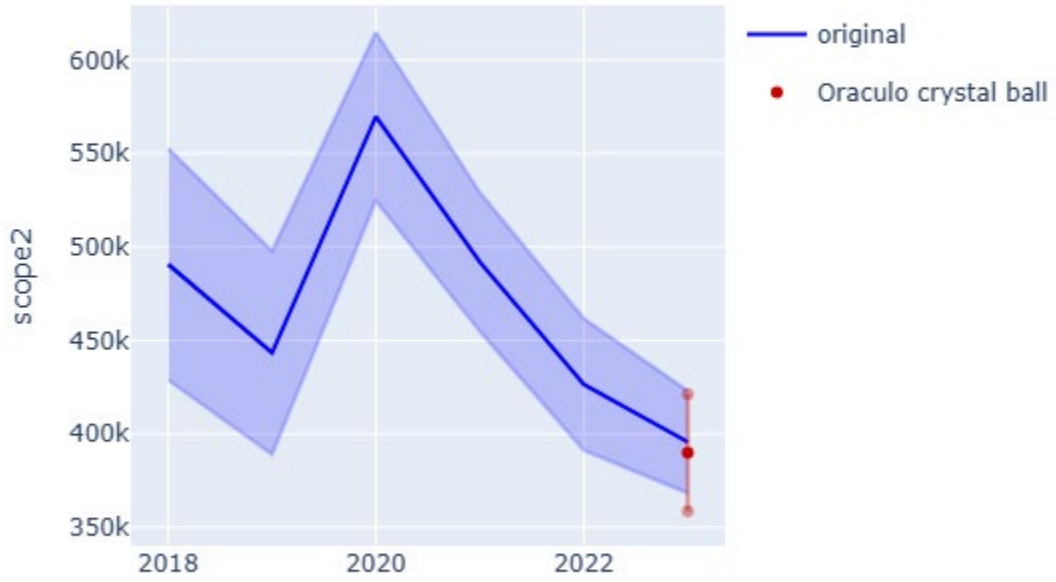


Figure 2: predicted and actual mean emissions +/- 2 standard errors

Results: Significant Improvement

The improvements made a substantial difference! Let's compare the metrics:

Metric	Basic Model	LOCF Baseline	Improved Model	Improvement vs Basic
RMAE	153%	33%	**37%**	**76% reduction**
RME	+126%	+8%	**-2%**	Nearly unbiased
Coverage	37,146 rows	17,589 rows	17,381 rows	Focused on stable firms

Key takeaways:

- The improved model achieves **37% RMAE** - slightly better than LOCF's 33% and dramatically better than the basic model's 153%
- **Bias nearly eliminated**: RME went from +126% overestimation to just -2% (slight underestimation)
- The hybrid approach works: by routing volatile companies to LOCF and stable companies to the OLS model, we leverage each method's strengths
- Normalization handled the scale issues with large emitters
- Adding lagged emissions captured the crucial persistence patterns that the basic model missed

The plot shows that predicted mean emissions closely track actual values, with the model capturing both the overall trend and year-over-year variations.

Conclusion

Oraculo demonstrates how configuration-driven nowcasting can transform lagged data into timely insights. The package's design philosophy centers on facilitating exploratory modeling through rapid experimentation:

Key features for exploratory modeling:

- **Configuration-driven**: Test different models, features, and transformations by editing YAML files - no code changes required
- **Instant feedback**: Immediate error metrics (RMAE, RME) and diagnostic plots after each model run
- **Visual diagnostics**: Built-in histograms, time series plots, and feature importance analysis
- **Easy iteration**: Tight feedback loops enable systematic hypothesis testing and refinement
- **Unified data framework**: Seamlessly merge multiple data sources
- **Flexible modeling**: Support for multiple model types (LGBM, OLS, LOCF, etc.)
- **Built-in transformations**: Normalization, lags, differences, and more
- **Hybrid strategies**: Route different subsets to different models

When to use Oraculo:

- You have time-lagged target variables
- Proxy variables are available with shorter lags
- You need to experiment with multiple modeling approaches
- You want reproducible, configuration-driven workflows
- You value rapid iteration and immediate feedback

Oraculo is not yet published as an open source package. If you are interested in using it, please get in touch with one of the authors.

While most forecasting focuses on predicting the future, nowcasting reminds us that sometimes the most valuable predictions are about the present we can't yet observe.

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ECB Climate Indicators:

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- World Bank (2024). *World Development Indicators*. https://databank.worldbank.org/source/world-development-indicators

Improving the timeliness of the ESCB carbon indicators with nowcasting techniques

DeNederlandscheBank
EUROSYSTEEM

Husby, T.G. (Trond) (STAT_EDB)

ESCB context

- In line with Governing Council action plan and new roadmap, ECB, DNB and ESCB (all other Eurosystem NCBs) committed to produce **euro area statistical indicators**
- **DNB** co-chair of Expert Group on Climate Change and Statistics (EG CCS)
- Where possible, data is sourced from **public/ESCB data collections**
- The new experimental and analytical (= 'more experimental') indicators, like all similar data, come with **significant limitations**, to be used and analyzed with care!
- The second release has been **published April 2024** on the ECB and DNB website and is **expected to be updated in 2025Q4**



Green bonds



Carbon indicators



Physical risk

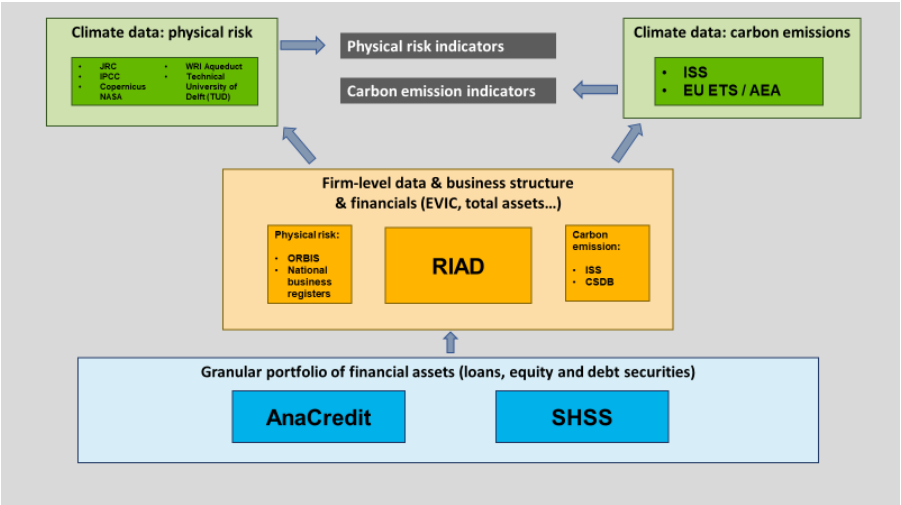
Four carbon indicators and their underlying data sources

Financed emissions | Carbon intensity | Weighted average carbon intensity | Carbon footprint

These four indicators show the amount (and share) of carbon emissions that can be attributed to financial institutions via their securities and loan portfolios.

→ Provide insights into the financial sector's monetary contribution to high-emitting economic activities, either as a ratio of carbon over revenue or the associated exposure to transition risks/financed absolute carbon emissions.

In words:
"If your portfolio holds 10% of a company's total value, you are responsible for 10% of its total (financed) emissions. This is summed for all companies in a portfolio to obtain the Financed Emissions indicator."



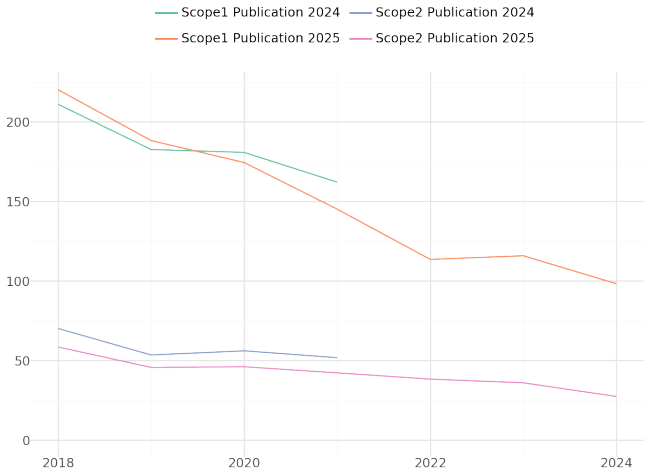
- **Carbon emission indicators** combine corporate securities and loan portfolios of financial institutions with firm-level data and climate data to calculate indicators at the aggregate level. Micro data are also provided to ESCB internal users for carbon and PR.
- **Physical risk (PR) indicators** 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).

Notes: AnaCredit: Analytical credit datasets. SHSS: Securities Holdings Statistics by Sector. RIAD: Register of Institutions and Affiliates Data. ISS is a commercial data provider offering carbon emission information at company level. CSDB: Centralised Securities Database. 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. EVIC: Enterprise value including cash

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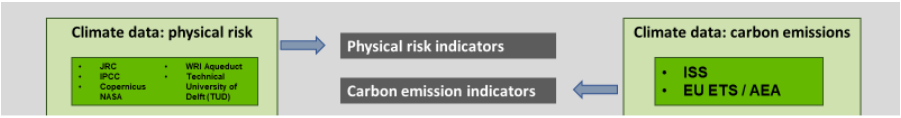
Timeliness of 2024 publication was hampered by availability of counterparty data

Weighted average carbon intensity



Source: ECB/EG CCS. The results of the 2025 publication are preliminary and only used to indicate the improvement in timeliness

Zooming in on data on emission and carbon intensity (emissions/revenue) of counterparties from ISS



- At the time of the 2024 publication of the indicators the most recent counterparty data covered the bookkeeping year 2021
- However, timely data from other sources, such as those on the portfolios of financial assets, were available
- **Improving timeliness a strong user request!**
- For the current (2025) publication, EG CCS members teamed up with the DNB Data Science Hub to develop a python package for **nowcasting**: *predicting the present or the very near future of a variable or system, typically using real-time data*.
- The package was used to predict granular level *emissions* and *financial information* of ISS counterparties, allowing the inclusion of preliminary data points of the year 2024 the 2025 publication of the indicators

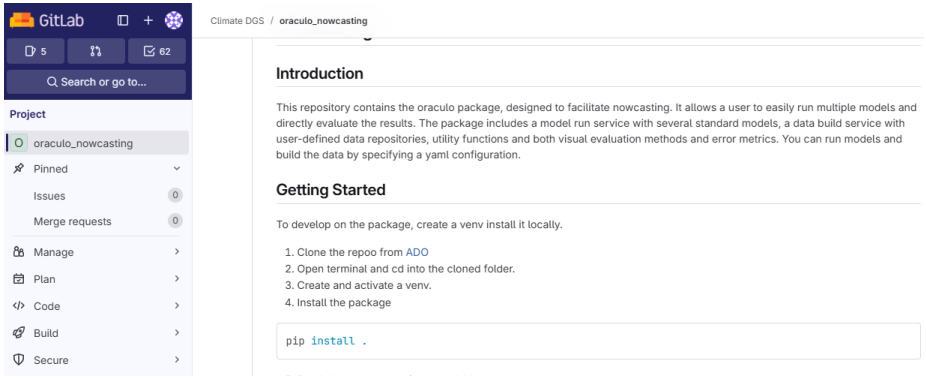
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ORACULO: a python Package for nowcasting

ORACULO:

Package for nowcasting & forecasting of short timeseries

- Application of various models; from simple heuristics to machine learning
- Unified method of importing data
- Plotting and evaluation of forecast results
- Logging of model runs



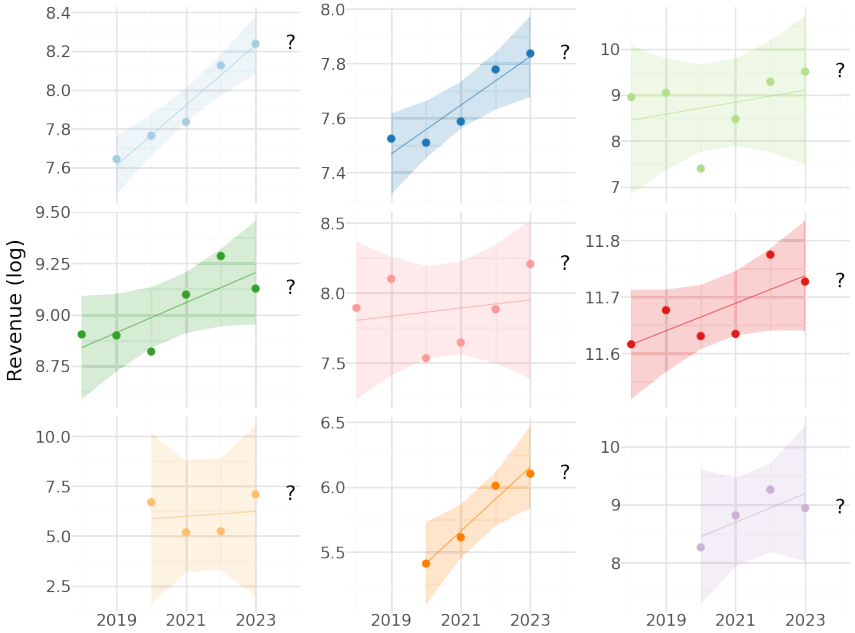
DataScience Hub

DeNederlandscheBank
EUROSYSTEEM

BANCO DE ESPAÑA
Eurosistema

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Producing a better prediction than last observation carried forward



- Last observation carried forward (LOCF) give very accurate, but potentially biased, predictions
- General strategy: use LOCF as benchmark but also main method for entities with short time series or missing values

- The LHS figure shows log revenue (log) along with a trend line for 9 randomly selected issuerids from the ISS dataset
- In many cases there is an upwards trend in revenue, for example due to inflation
- For some entities we can improve predictions using additional features
- Credit rating agencies publish ratings using the latest available information. Ratings from several agencies have recently been added to CSDB
- The credit ratings can help us nudge the predictions in the right direction

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Nowcast of revenue

Prediction model:

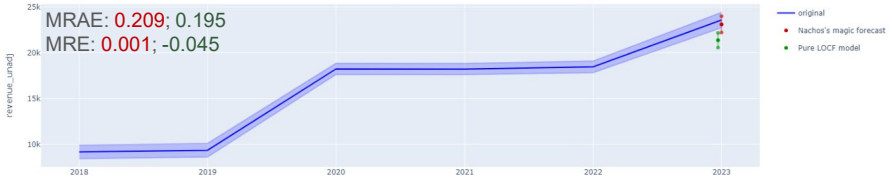
$$\widehat{\text{revenue}}_{i,t} = f\left(\text{revenue}_{i,t-1}, \Delta\text{credit rating}_{i,t}\right)$$

- Features: lag of revenue and change in credit rating
- Credit ratings are average of 5 ratings agencies, and average over a year. Rationale: agencies may have early information about the development of revenue
- Model fitted with XGBoost, results with random forest are similar
- Predictions for companies with credit ratings (about 1/3), LOCF used for companies without credit ratings data

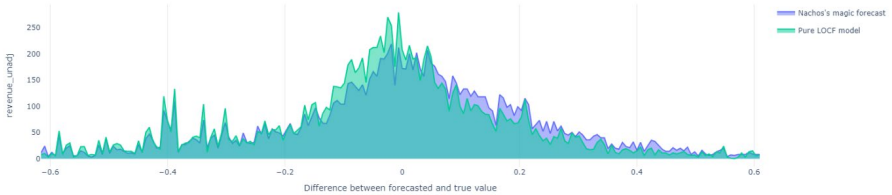
- Results show
  - Model with credit ratings reduces bias: LOCF of revenue ignores upwards trend due to inflation
  - The reduction of bias impacts the trajectory of the indicators
  - Predicted trend in scope1 WACI is more in line with expected values than that of LOCF

Main take away: Credit ratings improve the nowcast of revenue by reducing bias.

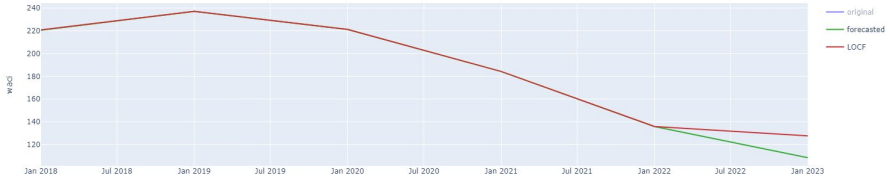
Forecast year 2023



Distribution of prediction errors



Scope1 WACI EA S122



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Nowcast of scope1 and scope2 emissions

Prediction model:

$$\Delta\widehat{\text{emissions}}_{i,t}^{scope} = f\left(\text{emissions}_{i,t-1}^{scope}, \text{oil consumption}_{country,t}, \text{EVIC}_{i,t}\right)$$

- Predict *change* in emissions (scope1/2) for company *i*
- Features: lag emissions; oil consumption in country of HQ; EVIC
- Estimated using OLS, using data from 2020 with filter for extreme (50%) year-on-year changes, LOCF for the rest

- Results show
  - Predictions in 2023 are in general more accurate than those in 2022
  - The prediction model and LOCF perform similar in terms of formal error metrics (relative mean absolute error, relative mean error)
  - The figures show that model predicts the mean(s) of scope1/2 better than LOCF

Main take-away: Prediction accuracy of scope1 are comparable to LOCF, predictions of scope2 are more accurate than LOCF.



*Figures show mean of predictions plus/minus 2*SE of the mean*

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Questions?

Thank you for listening!

Feedback? Interested in using, or contributing to, the package? Please contact t.g.husby@dnb.nl

Oraculo team: Trond Husby, Milan Karsten, Michiel Nijhuis (DNB), Ignacio Felez de Torres (BdE)

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IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Payment systems as carbon proxies a novel big data analytics approach to measure the carbon content of economic activities

Renardi Ardiya Bimantoro, Charvin Lim, Mohammad Khoyrul Hidayat, Muhamad Reza Ramadhan and Azhar Ramadhan, Bank Indonesia

This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

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Payment Systems as Carbon Proxies A Novel Big Data Analytics Approach to Measure the Carbon Content of Economic Activities

4 October 2025

Renardi Ardiya Bimantoro, Muhamad Reza Ramadhan; Charvin Lim; Mohammad Khoyrul Hidayat; Azhar Ramadhan

Department of Data Innovation and Digitalization; Department of Macroprudential Policy, Department of Statistics, Department of Payment System Management – Bank Indonesia

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BACKGROUND

STRATEGIC ENVIRONMENT

- The global financial landscape is undergoing a fundamental transformation, driven by the recognition that climate change poses a systemic risk to financial stability. (Juhro et. al, 2024)
- The legal and institutional foundation for Bank Indonesia's role in sustainable finance has been decisively strengthened by the landmark 2023 Financial Sector Omnibus Law (P2SK Law). This legislation has fundamentally expanded BI's mandate, explicitly empowering it to develop and regulate sustainable finance.
- Climate-related data serves as a fundamental prerequisite for effective policy formulation and informed decision-making. Governments rely on climate data to develop and implement mitigation and adaptation measures, set emissions reduction targets, and track progress towards climate goals, such as those outlined in the Paris Agreement (UNFCCC, 2015).
- Current official carbon emission data, such as that provided by the Badan Pusat Statistik (Indonesia Central Bureau of Statistics), extends only to 2023, with sectoral breakdowns lagging further to 2019. This scarcity impedes comprehensive measurement of the "*carbon content*" of economic activities and hinders timely assessments.

RESEARCH QUESTIONS

- How can central banks leverage high-frequency payment system data to create timely indicators for monitoring climate-related economic activity and transition risks?
- How can a transaction-based carbon indicator complement current official carbon emission data to provide a more dynamic and comprehensive view of climate-related financial risks?

PAYMENTS SYSTEM AS CARBON PROXY

Data Exploration

Wholesale Payment System

RTGS transfer to carbon-intensive sectors

Retail Payment System

Credit Card Trx, QR-payment

Focus Sectors

- **Coal Mining**
- **Logistics**
- **Waste Management**
- **Fuel Consumptions**

Proxy and/or complement for carbon emission data, with:

- higher data frequency (e.g. monthly);
- firm-/household group- level, more granular analysis

LITERATURE REVIEW

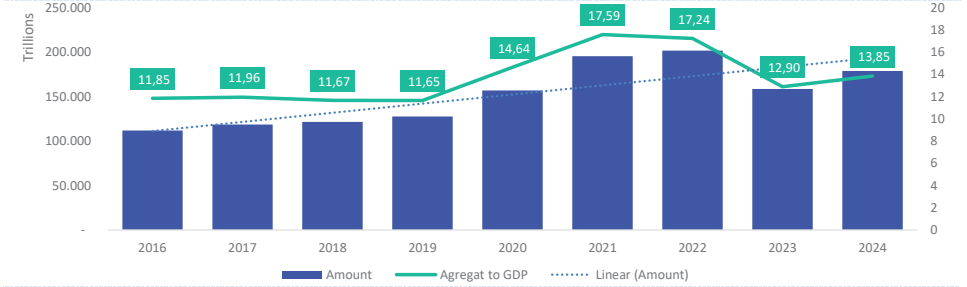
The Evolving Mandate: Central Banks and Climate-Related Financial Stability	• Physical and transition risks can alter credit, market, and liquidity conditions, thereby threatening the resilience of the financial system. Central banks cannot ignore climate risks because climate change acts as an amplifier of systemic financial vulnerabilities (Wiedmann, 2021; Hansen, 2022). • Dikau & Volz (2021) convey that 70 out of 135 central banks have a 'direct' or 'indirect' sustainability mandate, with more CB engaging in incorporating climate risk into financial stability or macro-prudential assessments, joining networks, etc. D'Orazio and Popoyan (2022) find that central banks in G20 countries are increasingly operationalizing climate goals through financial stability mandates.
Carbon Emission: Importance, Concept & Measurement	• Carbon emissions are a critical indicator of environmental and financial sustainability, increasingly integrated into the frameworks of investment risk, regulatory compliance, and economic performance. Measuring carbon emissions is central to designing effective decarbonization strategies. • Wijerathna and Dharmarathna (2023) emphasize the role of financial institutions in either mitigating or exacerbating emissions through their lending patterns, highlighting the importance of integrating carbon footprint metrics into financial product development
AI and Big Data to Support Economic and Financial Analysis	• By processing large volumes of structured and unstructured data (eg emissions disclosures, satellite imagery) AI enables more dynamic and real-time evaluation of corporate sustainability performance. • Adewale et al. (2023) emphasize that AI-powered financial analysis tools are supporting economic and financial analysis by enabling predictive sustainability analytics, real-time monitoring of risks, and enhanced impact measurement. This approach can be leveraged in sustainable finance file.
Prioritizing Sectoral Transition	• Achieving a net-zero future requires green finance to strategically prioritize transitions in both hard-to-abate sectors (eg coal-based power, logistics, and waste management) and in household energy consumption. • Adebayo et al. (2024) emphasize that tailored financing mechanisms such as carbon credits and green bonds are critical to incentivizing emissions reductions and technological upgrades in carbon-intensive industries. On the Household side, Sule et al. (2024) highlight the role of green mortgages, solar panel loans, and climate-focused digital banking tools in enabling sustainable home energy use

Current State of RTGS and NPG in Indonesia

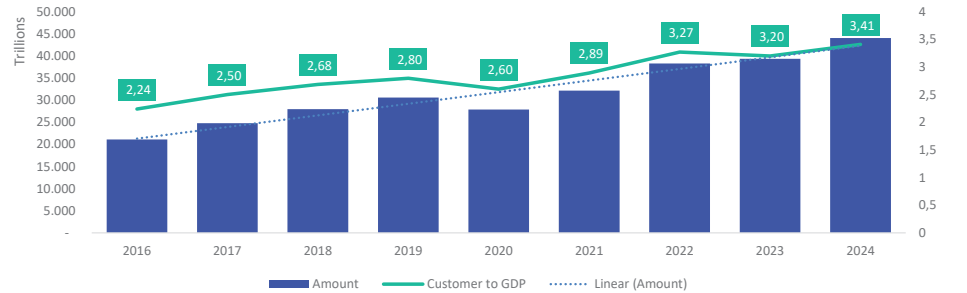
STATE OF RTGS TRANSACTION IN INDONESIA

BI-RTGS is Indonesia's **sole large-value and urgent payment system**, designated as **systemically important**. Since its launch in **2000**, it has become the **backbone** of the **High Value Payment System (HVPS)**, handling transactions above **IDR 100 million**. In **2022**, it processed settlement volumes equal to **17 times national GDP** in aggregate and **3 times GDP** in customer transactions, representing about **90% of total payment value**. As the main channel for interbank settlements in money, FX, securities, and monetary policy operations, BI-RTGS is a cornerstone of financial stability and digital payment infrastructure.

RTGS's Transaction Outlook



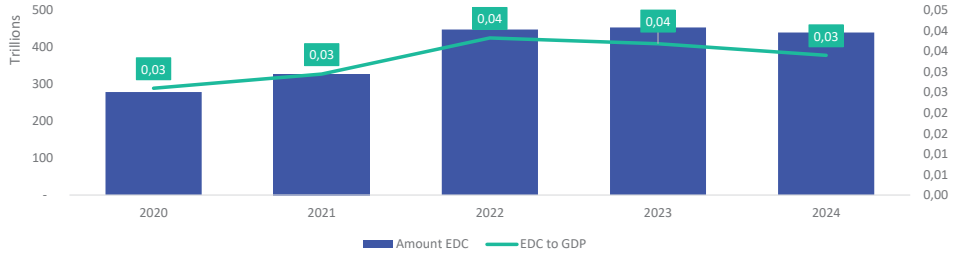
RTGS's Customer Fund Transfer Transaction



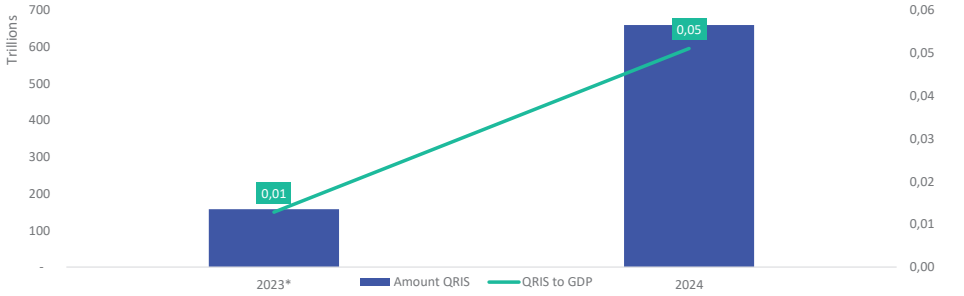
STATE OF NPG TRANSACTION IN INDONESIA

The **National Payment Gateway (GPN)** was launched by Bank Indonesia in 2017 to unify domestic retail payment transactions. Debit transactions through GPN now reach **0.04 times GDP**, while **QRIS**, introduced more recently, has grown rapidly to **0.05 times GDP**. QRIS has become the main retail payment instrument, used from **MSMEs to large merchants**, with a limit of **around IDR 10 million per transaction**, driving digitalization and financial inclusion nationwide.

Electronic Data Capture (EDC) Transaction for Purchasing



Quick Response Code Indonesian Standard (QRIS) Transaction



DATA SOURCES & METHODOLOGY

DATA SOURCE

Wholesale Payment

RTGS

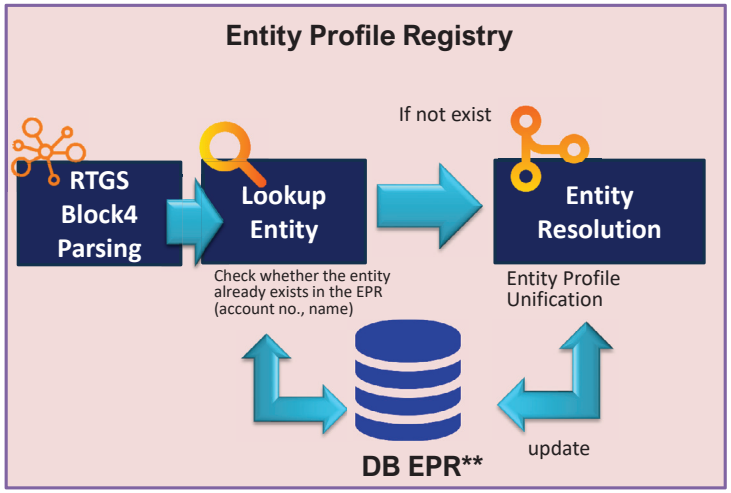
Monetary Operation
Interbank Money Market
Capital Market
Foreign Exchange Transaction
Customer Fund Transfer

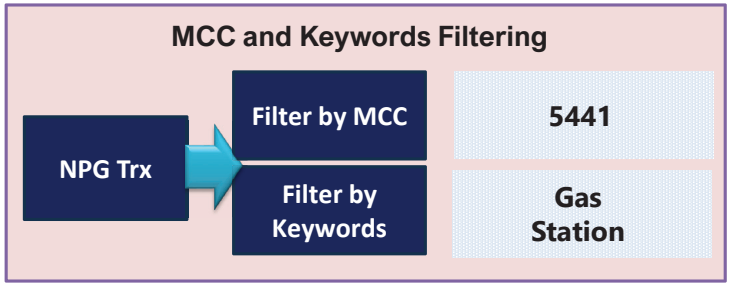
Retail Payment

SKNBI
NPG
BI-FAST

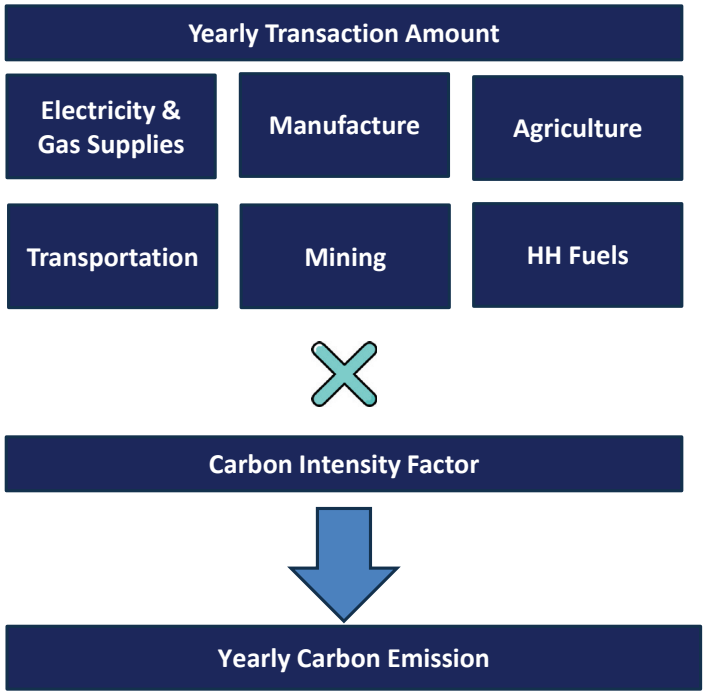
ATM Transfer
EDC Machine
QRIS

DATA PROCESSING





CALCULATE CARBON INTENSITY FACTOR



$$CO_2e = \beta \; x \; Transaction_in_Billions_IDR \; x \; intercept$$

CO_2e : *Carbon dioxide equivalent* β: *Carbon intensity factor*

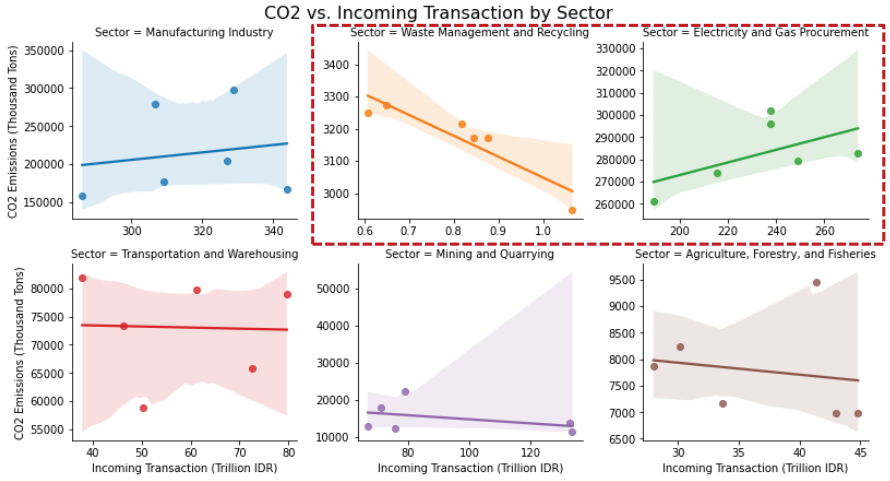
RESULT AND ANALYSIS

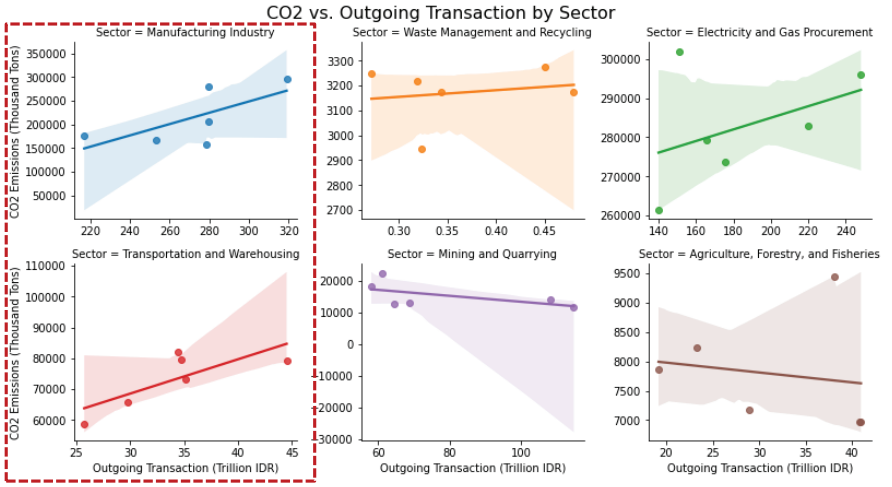
Statistical Testing for Incoming Transaction

Sektor	Observations	Correlation	R-squared	MAPE (%)	Intercept	Factor (Slope)	P-value (Slope)
Manufacturing Industry	6.00	0.17	0.03	22.97	58,859.07	489.63	0.75
Waste Management and Recycling	**6.00**	**(0.91)**	**0.84**	**1.22**	**3,695.36**	**(646.74)**	**0.01**
Electricity and Gas Procurement	**6.00**	**0.56**	**0.31**	**3.57**	**216,103.57**	**284.02**	**0.25**
Transportation and Warehousing	6.00	(0.03)	0.00	10.36	74,209.02	(19.18)	0.95
Mining and Quarrying	6.00	(0.41)	0.17	19.04	20,346.63	(54.95)	0.42
Agriculture, Forestry, and Fisheries	6.00	(0.17)	0.03	8.63	8,613.03	(22.61)	0.75

Statistical Testing for Outgoing Transaction

Sektor	Observations	Correlation	R-squared	MAPE (%)	Intercept	Factor (Slope)	P-value (Slope)
Manufacturing Industry	**6**	**0.68**	**0.46**	**18.22**	**(111,096.10)**	**1,198.55**	**0.14**
Waste Management and Recycling	6	0.19	0.03	2.62	3,073.77	268.39	0.72
Electricity and Gas Procurement	6	0.42	0.18	3.29	255,333.43	148.15	0.40
Transportation and Warehousing	**6**	**0.77**	**0.59**	**6.45**	**35,064.07**	**1,115.90**	**0.07**
Mining and Quarrying	6	(0.57)	0.32	16.67	22,679.69	(94.18)	0.24
Agriculture, Forestry, and Fisheries	6	(0.16)	0.03	8.67	8,316.20	(16.81)	0.76

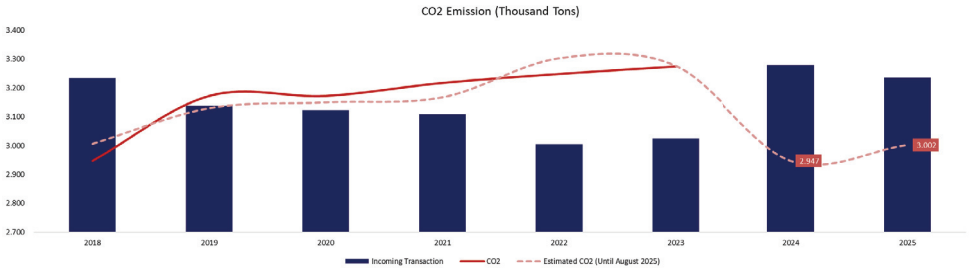




RESULT AND ANALYSIS

Waste Management and Recycling

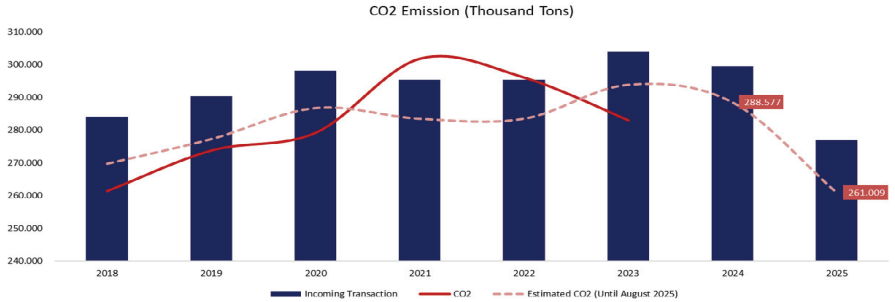
CO2 Emissions = (−646.74 × Incoming Transaction Amount) + 3,695.36



This model suggests a negative relationship for this sector; as incoming transaction amounts increase, CO2 emissions are predicted to decrease.

Electricity and Gas Procurement

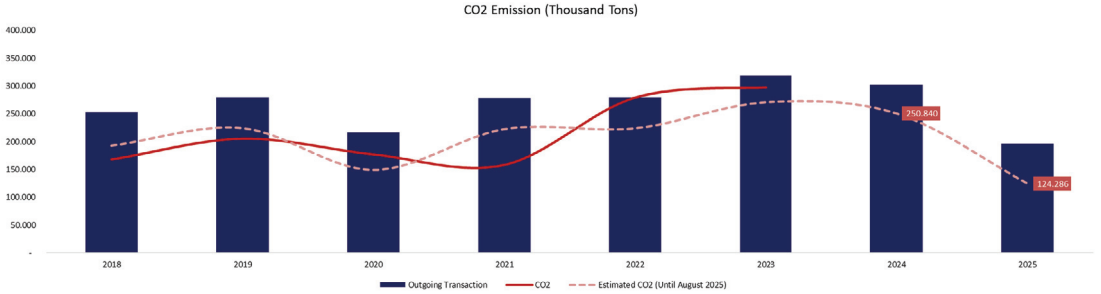
CO2 Emissions = (284.02 × Incoming Transaction Amount) + 216,103.57



This model suggests a positive relationship; as incoming transaction amounts increase, CO2 emissions are also predicted to increase.

Manufacturing Industry

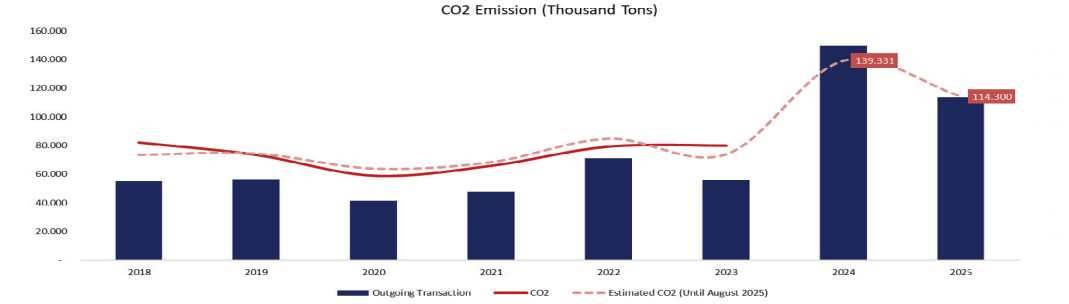
CO2 Emissions = (1,198.55 × Outgoing Transaction Amount) − 111,096.10



This model suggests a positive relationship for this sector; as outgoing transaction amounts increase, CO2 emissions are predicted to increase.

Transportation and Warehousing

CO2 Emissions = (1,115.90 × Outgoing Transaction Amount) + 35,064.07



This model suggests a positive relationship for this sector; as outgoing transaction amounts increase, CO2 emissions are predicted to increase.

RESULT AND ANALYSIS

Estimation of CO2 emission per fuel type.
Average price of 1L of gasoline since 2020 per Fuel Type

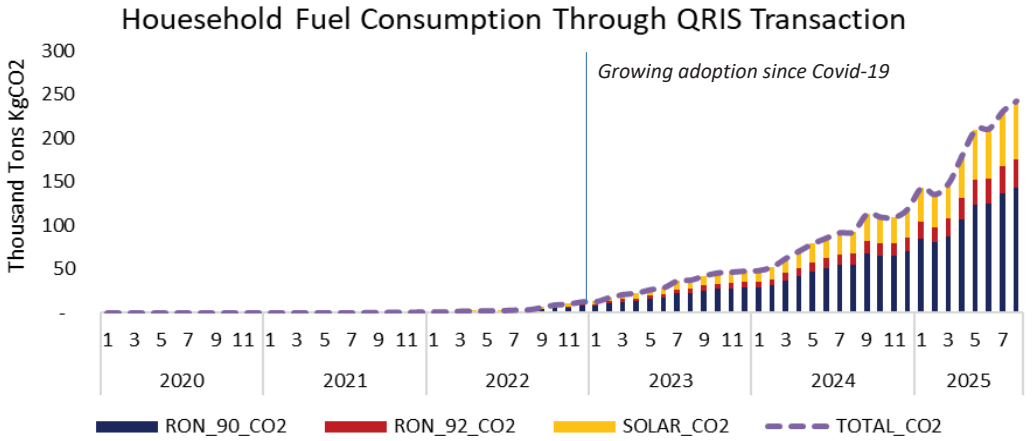
Fuel type	CO_2 tailpipe emissions (kg/L)
Gasoline	2.29
E10 (10% ethanol + 90% gasoline)	2.21
E85 (85% ethanol + 15% gasoline)	1.61
Diesel	2.66
B5 (5% biodiesel + 95% diesel)	2.65
B20 (20% biodiesel + 80% diesel)	2.62

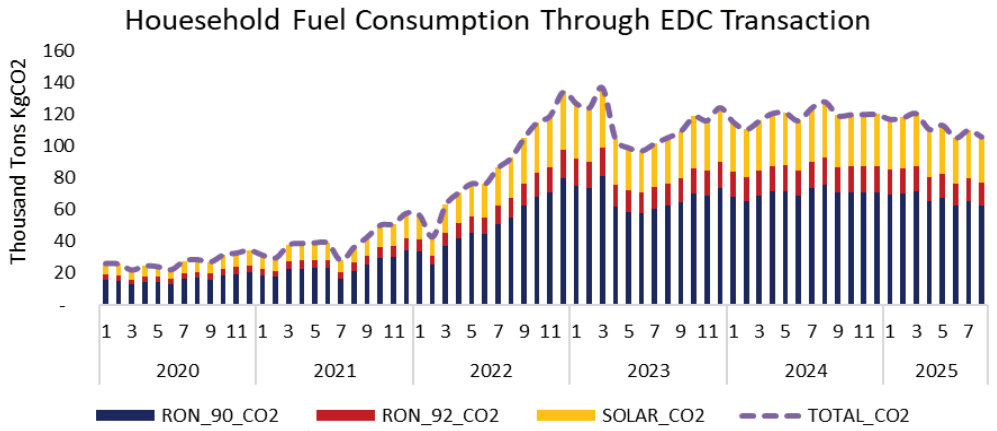
Source: Natural Resources Canda

Fuel Type	Average Price (Rp/L)	Weight Sales
RON 90	9050	50
RON 92	12000	15
SOLAR	6800	35

Source: Author's synthesis from Pertamina & Ministry of Natural Resources Report

CO2 Emissions = Total Sales x Weight Sales x Average Price per Litre x CO2 Emission/L





KEY FINDINGS & FUTURE WORKS

KEY FINDINGS:

1. For sectors such as Transportation, Manufacturing, and Electricity, the transaction amount shows a correlation with operational activity. Higher spending on inputs (such as fuel and materials) or higher income (for electricity) is linked to increased energy use, which in turn leads to higher CO2 emissions.

2. In the waste management case, increased economic activity reflects an environmental service that causes a net reduction in emissions.

3. While emissions tracked through traditional card payments appear stable, the growth in QRIS transactions still shows an uptrend in the carbon footprint of household transportation

FUTURE WORK:

1. Conduct a qualitative analysis to understand why higher incoming and outgoing transactions correlate with lower and higher emissions.
2. Confirm the interpretations by differentiating transaction purposes within each sector by breaking down sectoral interconnections, for example, the manufacturing industry and electricity supply.

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THANK YOU

15 September 2025

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A comparative analysis of machine learning and classical statistical techniques for the imputation of corporate green house gas emissions

Susanne Walter,
Deutsche Bundesbank

This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

A Comparative Analysis of Machine Learning and Classical Statistical Techniques for the Imputation of Corporate Green House Gas Emissions

Susanne Walter

Abstract

The recognition that climate change has significant implications for the health of the financial system has elevated the necessity for improved access to reliable sustainability data among data producers and central banks. To capture the heterogeneity of firms within the financial system, micro-level data—specifically at the company level—are of particular importance. Despite extensive efforts to enhance corporate reporting, significant data gaps persist, particularly in the reporting of greenhouse gas (GHG) emissions. A high proportion of missing values poses a risk of sample bias in analyses. This paper addresses this issue by testing and evaluating various imputation approaches for corporate carbon emissions to mitigate these data gaps. In addition to individual balance sheet data, we utilize novel geospatial data, including characteristics of company real estate and its usage. We compare classical statistical methods with modern machine learning techniques. Approaches that account for the missing data generation process demonstrate superiority over simpler methods, yet they are outperformed by machine learning methods.

Keywords: data gaps, climate data, GHG emission, carbon footprint, EU ETS, missing data, imputation, machine learning, balance sheet data, Heckman correction, sample selection, LOD1, building data, digital twin

JEL classification: C38, C53, Q54

This contribution was prepared for the conference. The views expressed are those of the authors and do not necessarily reflect the views of the BIS, the IFC, Deutsche Bundesbank or the other central banks and institutions represented at the event.

Usage of AI: Ai assistants were used to correct grammar, for vocabulary check and code debugging.

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1. Introduction

The awareness that the stability of the financial system is also affected by risks stemming from climate change was a fertile soil for several initiatives of central banks and other public institutions (NGFS 2019, European Commission 2024). Monitoring, evaluation and mitigation of these risks require sound reporting and reliable data (NGFS 2019, TCFD 2016). Since 2021 the IMF[1] and since 2023 the ECB[2] publish aggregated indicators on sustainable finance. Despite the intensive efforts to introduce harmonized and mandatory reporting frameworks, the data landscape on climate related information is still highly fragmented and inconsistent, especially in the field of corporate carbon emission data (NGFS 2024, European Commission 2024). While there exists a plethora of commercial data, reliable official data is rather scarce and characterized by low coverage (ECB 2024, NGFS 2024). Furthermore, a high proportion of commercial data is estimated based on black box of estimation methods (Kalesnik et al. 2022).

One solution to address these pressing data gaps is the imputation of missing data. Imputation of missing data is a standard technique in statistical production. Many approaches have been tested and evaluated in view of their suitability (Preising et al. 2021, Thurow et al. 2021, Schnetzer et al. 2015). Multivariate imputation with chained equations (MICE), predictive mean matching, nearest neighbor method and single regression-based techniques are among the most commonly employed and studied. More recent advances focus on the application of machine learning algorithms to fill missing data (Niederhametner at al. 2025, Jerez et al. 2010). Random forest-based methods have shown promising results (Stekhoven & Buehlmann 2012).

In the concrete case of corporate green house gas (GHG) emission data, imputation approaches can be conceptually differentiated regarding the starting point of the procedure: top down or bottom-up approaches. While top-down approaches break down sector emission aggregates to the individual company level using corporate employment shares (Hirvonen et al. 2021), bottom-up approaches predict emissions on the company level by using other company variables (for instance key financial performance figures) (see for instance Kalesnik et al. 2022, Olesiewicz et al. 2023). The ECB for instance uses the top-down approach to impute the GHG emission for constructing their carbon footprint indicators[3]. Whilst their simplicity of implementation clearly speaks in favor of top-down approaches, they base on strong assumptions about proportionality (e.g. between emissions and employment) and neglect production and business model related heterogeneity of firms. However, microlevel analyses with company data require incorporating firm heterogeneity, especially when emission data is linked and set into relation to other firm variables (such as financial obligations and credit volumes). Therefore, more detailed bottom-up approaches can be more suitable in these cases. Machine learning methods have also demonstrated high accuracy in this particular use case of forecasting GHG emissions at the country level (Begum and Mobin 2025).

Another approach is based on using the production and consumption-oriented interrelations between sectors as depicted in Input-Output-Tables from the National Accounts (Liu&Fan 2017, Matthews et al. 2008, v. Kalckreuth 2022).

One important determinant for selecting a suitable approach is understanding the nature of the underlying data. Especially for the problem of imputation, it is crucial to understand the data generation mechanisms that resulted in the inherent missing pattern (Rubin 1976). Most of the approaches required the data to be missing at random (MAR) (Buczak et al. 2023), i.e. missing in emission data can be

[1] https://www.imf.org/external/pubs/ft/ar/2022/in-focus/climate-change/

[2] https://www.ecb.europa.eu/press/pr/date/2023/html/ecb.pr230124~c83dbef220.en.html

[3] Technical Annex to the Report on Climate change-related statistical indicators, November 2025, https://www.ecb.europa.eu/stats/all-key-statistics/horizontal-indicators/sustainability-indicators/data/shared/files/Technical_annex.en.pdf

completely explained by observable factors. However, in the case of GHG emission data, the missing data generation process is assumed to be missing not at random (MNAR) due to the legal frameworks. In addition to observable company characteristics, the level of emissions itself determines whether a company reports its emissions. If the non-random nature of the missing data process is not considered during imputation, the estimates may be distorted due to sample selection bias (Heckman 1976, Heckman 1979).

To our knowledge, there is no study that compares several imputation approaches with respect to their accuracy when imputing individual corporate GHG emissions and also addresses the missing mechanism explicitly when predicting emission data.

Thus, the aim of this study is to compare different bottom-up approaches for imputing GHG emissions on the individual company level. As training data, we use official emission data from the EU emission trading system (EU ETS), as it is deemed most reliable (exhibit the least measurement error) and has the same observational unit as the company data (single entity). Another reason for using EU ETS is that it only covers emissions originating directly from companies' operative activity (as the channel is clearer as compared to estimating scope 2 or 3 emissions)[4].

This study represents the methodological extension of the works of Walter (2025). Walter used a Heckman correction to explicitly model the sample selection of the missing data stemming from the MNAR process in official emission data. We found that when considering a rich set of data sources and covariates, the process can be assumed to be MAR which allows for other approaches to be tested. In this study we use the same rich set of variables (including novel geospatial data) and introduce novel machine learning approaches (based on random forests) to impute missing values and compare their performance to classical imputation techniques (MICE, KNN, Heckmann correction and single regression methods) and top-down approaches.

We find that bottom-up approaches outperform simpler top-down methods. Furthermore, consistently with prior studies (Stekhoven & Buehlmann 2012), random forests outperform all other approaches. The remainder of the paper is structured as follows: in **section 2** we provide a short overview of data sources used in this study. Subsequently, in the methodological **section 3**, the applied imputation techniques are briefly introduced. In **Section 4,** the main results are presented. **Section 5** concludes and presents some avenues for further research.

2. Data

For this study we combine several data from various sources. The panel of balance sheet data is taken from the Individual financial statements of non-financial firms (JANIS)[5] from the Deutsche Bundesbank. The corresponding panel on GHG emissions is taken from the publicly available dataset on traded emissions from the EU Emission Trading System (EU ETS[6]). Companies are required to report their emissions that fall under the EU certificate trading. The obligation to report as a foundation for carbon pricing makes them the most reliable in the range of corporate emission data. Furthermore, as compared to data from corporate sustainable reports and commercial data providers, the observational units equal the one in the balance sheet data (single installation/ enterprise). The emissions on the installation level were aggregated to the operator/ company-level.

[4] Scope 2 emissions cover all indirect emissions originating from energy consumption. Scope 3 cover all indirect emissions from upstream and downstream value chain activities (GHG 2024)

[5] Here we use the internal, non-anonymized version of the JANIS dataset, which only contains individual financial reports from commercial data providers. DOI: 10.12757/Bbk.JANIS.9723.14.14, https://www.bundesbank.de/resource/blob/862454/016baaec31b6eefc6e47fc899e9a4b99/mL/2024-18-janis-data.pdf (Becker et al. 2024)

[6] https://climate.ec.europa.eu/eu-action/carbon-markets/eu-emissions-trading-system-eu-ets_en

The data is enriched with information about the corporate building type and its usage from the 3D building model data from the Federal Agency for Cartography and Geodesy[7]. The combined dataset comprises 4,855 complete observations across all variables for 822 unique companies (forming an unbalanced company panel) over the period from 2012 to 2020.

To break down sector aggregates as the benchmark analysis, we also include the aggregate GHG emissions for Germany from the Air Emission Accounts on the NACE Rev2 1-digit level[8].

3. Methodology

To compare several imputation approaches, from standard methods in medical research and official statistics to more modern machine learning techniques, we first split our sample randomly into 70% training and 30% test data. For the test data, the emission values were set to missing. This is necessary to calculate the accuracy metrics and to compare the prediction against the true values.

We chose the simplest approach as our benchmark approach which is the allocation of **sector specific emission aggregates** from the **Air emission accounts based on employment shares (I.)** as used by Hirvonen et al. 2021 and ECB 2024. A company's employment is divided by the total employment in the sector in which the company is active. Those employment shares are then multiplied with the total emissions of the sector to yield individual corporate emissions. Its simplicity and consistency at the aggregate level speak in favor for this approach. However, firm heterogeneity with respect to production technology and technical equipment is neglected. Furthermore, the assumption about proportionality between employees and emission output might not hold, particularly for service sectors.

As a second approach, we explicitly want to address the underlying selection mechanism that results in the missing pattern to correct for potential bias (we assume emission data to be MNAR). Furthermore, we use multivariate regression to model the relationship between a company's production process and their emission intensity. We use the widely accepted and used **Heckman correction (II.)** (Heckman 1976, Heckman 1979). The idea of this two-step approach is to explicitly model the selection (the missingness in the target variable, here emissions) and then run the imputation of emissions including a correction factor from the first step. The selection is modeled using a binary probit model, the outcome regression uses an OLS estimation. To analyse the value added of geospatial data for imputation accuracy, we first run the output model solely on the **balance sheet data and employment (IIa)** and then extend the model by also including the **building type from the geodata (IIb)** to predict emissions. Detailed descriptions and results can be found in Walter 2025.

Third, we also aim to compare a standard method used in statistics from various domains: **Multivariate Imputation by chained equations (MICE) (III.) (**van Buuren & Groothuis-Oudshoorn 2011**).** Usually, MICE is used to account for the uncertainty in the imputation process as it produces multiple imputed datasets (Azur et al. 2011). However, as our use case focuses on the prediction of individual emission values and not inferential analyses, we do not use this feature of multiple imputation here. We impute only one dataset (m=1) using **predictive mean matching** for 5 donors. Out of the 5 potential candidates, whose predicted values are closest to the prediction of the missing value, one is randomly chosen whose emission value replaces the missing value (Morris et al. 2014). One advantage of this method is that predicted values range within the plausible boundaries of the original values. [Morris et al. 2014] The analyses were implemented using the mice package in R.

[7] We use here Level-of-Detail 1 data because it contains the building function. https://gdz.bkg.bund.de/index.php/default/3d-gebaudemodelle-lod1-deutschland-lod1-de.html

[8] https://ec.europa.eu/eurostat/databrowser/view/env_ac_aigg_q/default/table?lang=en&category=env.env_air.env_air_aa

As a fourth approach, we impute emissions by the **k-nearest neighbour algorithm (IV.).** In this very popular approach, the mean of the k-most similar neighbours of the target variable is used to impute the missing value. We set the number of neighbours that are used to calculate the mean to 5 (k=5).

Recent evidence (e.g. Stekhoven & Buehlmann 2012, Tan and Ishwaran 2017) has shown that modern machine learning methods might outperform these widely applied, classical imputation approaches. For this reason, we also include modern imputation techniques that are based on **random forests (V.)** These Machine Learning approaches have the advantages that they require less assumptions about distributions and parameters as compared to single regression-based methods (Stekhoven & Buehlmann 2012). Random forests are estimated to predict missing emission values. We test the most common implementations of the random forest-based approaches in R: the **MissForest (Va)** packages by Stekhoven & Buehlmann (2012). This package is very flexible with regards of data types and distributional assumptions (Stekhoven & Buehlmann 2012). We then compare it to the **Ranger Random Forest (Vb)** and the **XGBoost (Gradient Boosting) method (Vc)** from the VIM package (Kowarik & Templ 2016), developed by Statistics Austria. Like MissForest, these two imputation methods focus on random forests, while XGBoost is based on Gradient Boosting.

To compare the accuracy of the predictions the deviation between the predicted values from the true values was calculated. Here we use the standard metric from the machine learning literature as a diagnostic tool (Hodson 2022): the root mean squared error (RMSE). It calculates the average deviation of the actual values from the predicted ones. As we want to come closest to the real values, when imputing them, RMSE is deemed an appropriate measure.

To compare all the approaches, only one column was set to missing (emissions as the target variable to impute) while all other variables did not contain any missings.

Table 1 provides an overview of the covariates used in each approach to impute the missing emissions. The continuous variables were transformed to correct for outliers and skewed distributions (censoring to 99% percentile, normalized, logarithmic values).

Variables used in the models **Table 1**

Variables	Approaches					
Dependent: GHG-Emissions	**I. Employment shares**	**IIa. Heckman balance sheet data**	**IIb. Heckman balance sheet data and building data**	**III. MICE**	**IV. KNN**	**V. Random Forest**
Employment	X	X				
Intangibles		X	X	X	X	X
Land and buildings		X	X	X	X	X
Technical equipment and machinery		X	X	X	X	X
Raw materials and consumables		X	X	X	X	X
Building type			X	X	X	X
NACE (2-digit)	X (1-digit)	X	X	X	X	X

4. Results

Table 2 provides an overview over the imputation accuracy of the implemented approaches. The simple top-down approach allocating sector aggregates by employment shares (I.) is outperformed by all bottom-up approaches, as firm heterogeneity seems to drive companies' emission intensities. The explicit consideration of the selection process with the Heckman correction yields more accurate estimates (IIa&IIb.). Including building function into the model besides sector dummies and balance sheet items improve accuracy even more (IIb). Walter 2025 has additionally shown that the missingness in emissions can be treated as MAR process when a rich set of firm variables is included and the selection and outcome can sufficiently be explained the relevant covariates. This is the foundation for the usage of further imputation methods as most approaches require the process to be MAR to yield unbiased estimates (Tan & Ishwaran 2017, Buczak et al. 2023). The single value imputation with the Heckman correction even outperforms the predictive mean matching in mice and the KNN-method. However, all approaches were outperformed by random forest-based methods (especially MissForest Va). This is in line with other findings from other domains (see for instance Jerez et al. 2010 and Tan & Ishwaran 2017 for the medical domain, Stekhoven & Buehlmann 2012 for bioinformatics and Niederhametner at al. 2025).

Predictive mean matching in MICE, when accounting for firm heterogeneity, yields values that are almost as accurate as those produced by the very simple approach based on employment shares.

Accuracy of imputation approaches **Table 2**

Approach	Top down	Bottom-Up approaches						
	(I)	**(IIa)**	**(IIb)**	**III**	**(IV)**	**(Va)**	**(Vb)**	**(Vc)**
	Traditional: Using employment shares per industry	Heckman correction Including balance sheets	Heckman correction Including balance sheets Including building information	MICE (m=1, pmm)	KNN (k=5)	MissForest	Ranger Random Forest (VIM)	XGBoost (VIM)
Root Mean Squared Error (Deviation imputed from actual values)	2.525187	1.8865	1.7070	2.399804	2.1356	**1.0009**	1.1167	1.13713

5. Conclusion

Our analyses for the German case have shown, that modern machine learning technique (especially random forest imputations) can benefit and improve the accuracy of imputing corporate GHG emissions. Even simpler bottom-up approaches, that account for firm heterogeneity at the microlevel, outperform top-down approaches based on employment weights. The higher accuracy at the microlevel emphasizes the superiority of bottom-up approaches when conducting analyses with microdata. Moreover, we have seen that novel data sources such as building data can help to overcome potential selection bias, add more explanatory power and increase the accuracy of the imputations.

Given that machine learning methods require bigger training data sets, our analyses could be further improved by multiple dimensions. First with respect to coverage, as individual emission data from the federal statistical offices might be integrated. In doing so, the proportions of missing in the data could be reduced and the robustness of our results could be evaluated. One approach could be to run the analysis for all countries covered by EU ETS and proof the generalizability of our results.

Second, as we only assume the data to be MAR, a combination of explicitly addressing an MNAR process and machine learning techniques could shed more light on the latent selection bias. Furthermore, other novel data sources (such as satellite or overflight images from the company property) can be combined to add more relevant information for the variation in corporate emission intensities.

Furthermore, our analyses could be complemented by the equally popular approach using input-output-tables (Liu&Fan 2017, Matthews et al. 2008, v. Kalckreuth 2022).

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DEUTSCHE BUNDESBANK EUROSYSTEM

Estimating companies' GHG emissions using information from individual financial accounts and building data

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All views expressed in this presentation are personal views of the authors and do not necessarily reflect the views of Deutsche Bundesbank or the Eurosystem.

Data Service Centre

Outline

1. Motivation
2. Challenges
3. Data Overview
4. Results
5. Conclusion and extensions

Motivation
Data gaps in the sustainable finance landscape

- Measuring potential **risk exposure** imposed by **climate change** for financial systems
- **Publication** of climate related **indicators** to substantiate policy making:
  - Central banks (ECB and national banks) started to publish climate related indicators to depict physical and transitory risks (such as emerging from CO2 emissions)
  - An international working has developed indicators for carbon footprint
- **Data gaps** in GHG emission data
  - Low **coverage**: Plethora of commercial data on GHG but reliable official data is rather scarce and low coverage (due to existing framework)
  - Lack of **transparency**: black box of estimation methods
  - Reported data by companies voluntary, not properly audited and not harmonised



Motivation
Goal

Can we use other official data to close the data gaps

- Propose **bottom-up approach** to close data gaps (beyond employment and sector information)
- Combine financial data and novel geospatial data with emission data
- Model the **data generation process** explicitely for missing emission data
- Evaluate **official data** on company GHG emissions
- Compare **performance** of different approaches

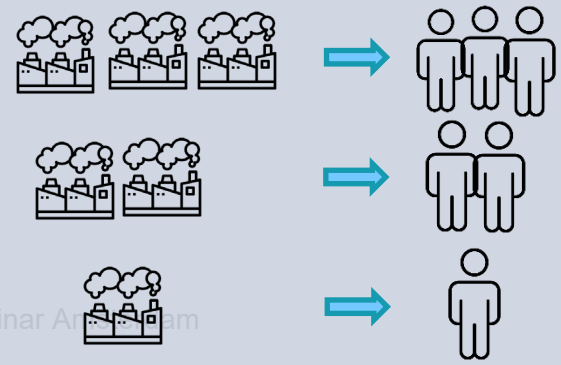
Challenges
Data characteristics

- **Missing data generation** (Rubin classification 1976)
  - Missing completely at random (MCAR)
  - Missing at random (MAR)
  - Missing not at random (MNAR)
- Emission data are **MNAR** because the amount of emissions would determine whether a company reports emissions or not
- **Only 1,470 German companies** report emission data in the official registry
- Commercial emission data **mostly estimated** (models are blackbox)
- Reported emissions in financial reports comprise the GHG emissions of the **whole enterprise group**

Challenges
Solution approaches

Top down

- **Breakdown** of country/ sector aggregates to company level proportional to employment
- Easy to implement
- Proportionality assumption



Input Output Tables

- Company emissions are estimated based on **Input-Output-Tables**
- e.g. Liu & Fan (2017) or Matthews et al. (2008)

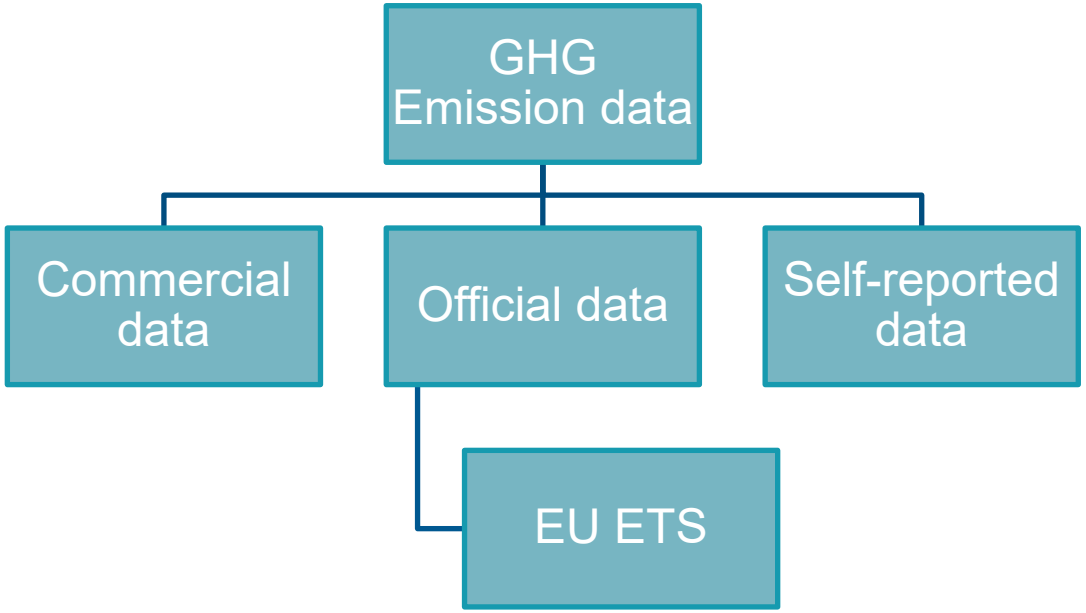
Bottom up

- Impute/ Predict emissions by means of **other company variables**
- Kalesnik et al. (2020): evluate voluntary reporting and commercial data for listed companies in UK
- Olesiewicz et al. (2023) advanced imputation approach, but restricted set of variables



Data Overview
Official Emission data

- Emission data from the EU Emisson Trading Systems (EU ETS) starting from 2008
  - ✓ **Reliable**
  - ✓ **Standardised:** multiple countries engaged in emission trading
  - ✓ **Granular:** Information on plant level (not like commercial data or data from financial reports)
  - ✓ **Linkable:** to financial data or other company data (identifiers, entity concepts)
- Cover **Scope 1** emissions (directly produced during production process)

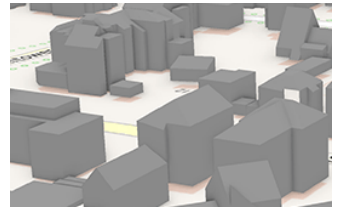


Data Overview
Bundesbank data

- Individual **financial statements** of German non-financial firms from public sources (provided by commercial providers) (JANIKA)
- Financial figures from financial reporting (balance sheets and income statements) of German companies from 1997-2023
- Anonymous version is **accessible** for researchers (Annual financial statements of non-financial firms (JANIS and Ustan) | Deutsche Bundesbank)
- Balance sheet items as **depictions of production factors** and value added → approximation of production process
- Gather information on **nexus** between emissions and production factors
- More **exact distribution** of emissions

Data Overview
Geospatial Data

- Digital Twin Data from the Federal Agency for Cartography and Geodesy
- LoD1 Data: Level of Detail (3D-Gebäudemodelle LoD2 Deutschland (bund.de)
- Detailed information on buildings in the German jurisdiction, including the building type and function as well as 3D model with geocoordinates (CityGML) and other characteristics (# floors, volume, height, rooftypes)
- Can the function of a company building predict emissions?



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Fig. 1. The five LODs of CityGML 2.0. The geometric detail and the semantic complexity increase, ending with the LOD4 containing indoor features

Data Overview
Model to account for sample selection

Heckman‘s two step procedure (Heckman 1976) :

I. Model the **Selection** (the „missingness“)

$$M_{it} = Size_{it} + NACE_{it} \rightarrow IMR_{it}$$

II. Model the **Outcome** (GHG emissions values)

Inverse Mills Ratio as correction factor for selection

$$E_{it} = \beta_0 + \beta_1 build_{it} + \beta_2 NACE_{it} + \beta_3 Intang_{it} + \beta_4 Land_{it} + \beta_5 Tech_{it} + \beta_6 Raw_{it} + \beta_7 IMR_{it} + \sum_{j=8}^{n} \beta_j X_{itj}$$

Data cleaning

- Censoring (outlier correction)
- Normalisation (in relation to total assets, emissions relative and log transformation)
- Clustered standard errors (company level)
- Industry fixed effects (unobserved heterogeneity)

Variables

- *M* – Missing in emissions (yes=0, no=1)
- *E* - Emissions
- *Build* – Building function
- *Intang* –Intangible Assets
- *Size* – Company size class (XS-L), employment
- *Land* – Land and buildings
- *IMR* – Inverse Mills Ratio
- *Tech* – Technical equipment and machinery
- *Raw* – Raw materials and consumables
- *NACE* – Industry Fixed Effects

Results
Selection model

- Size mainly drives Reporting of Emissions
- Due to nature of data opposite to Olesiewicz et al. (2023)
- Larger companies are more likely to report emissions (largest companies as reference category here)

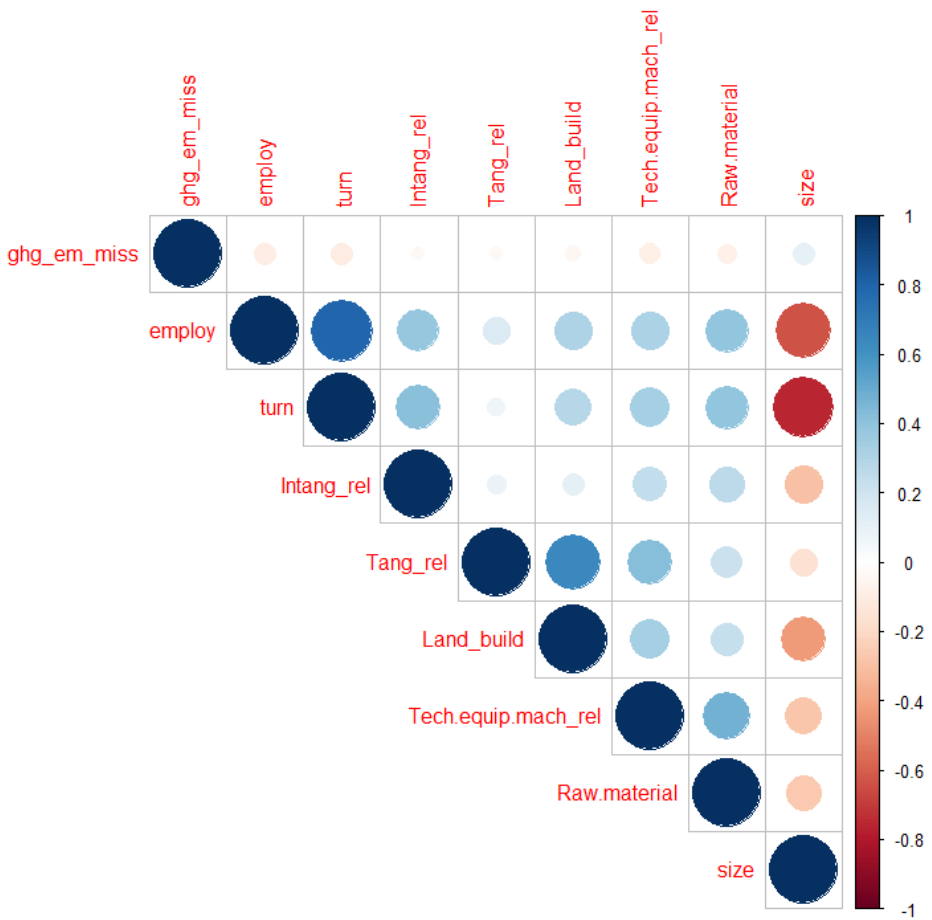
	Probit				
	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-5.53	130.20	-0.042	0.966	
sizeM	-0.75	0.02	-43.788	<2e-16	***
sizeS	-1.25	0.03	-42.486	<2e-16	***
sizeXS	-1.89	0.08	-24.614	<2e-16	***
Industry FE			Yes		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 57,619 on 573,663 degrees of freedom

Residual deviance: 35,583 on 573,575 degrees of freedom



Results
Outcome model

Bottom up approach: Step Two Estimation of Outcome Model (Estimating GHG based on balance sheet items)

	Dependent Variable: GHG emissions (rel_log)		
Independent Variables	(1)	(2)	(3)
Constant	4.79*** (0.425)		
log(employ)	-0.121* (0.052)	-0.075 (0.254)	-0.243 (0.241)
IMR	-0.743*** (0.135)	0.244 (0.269)	0.101 (0.279)
log(empl)^2		0.012 (0.024)	0.029 (0.023)
Intangibles_rel			-0.420*** (0.092)
Land_rel			0.155* (0.069)
Tech_and_mach_rel			0.025 (0.069)
Raw_materials_and_consum_rel			0.439*** (0.094)
Fixed-Effects:			
Industry	No	Yes	Yes
S.E.: Clustered	by: Company ID	by: Company ID	by: Company ID
Observations	5,025	5,025	5,025
R^2	0.040	0.156	0.198
Within R^2	--	0.002	0.051

Results
Outcome model

Bottom up approach: Outcome model incorporating building data

Dependent Variable: GHG emissions (rel_log)		
Independent Variables	(4)	(5)
Constant	4.79*** (0.425)	
log(employ)	-0.340 (0.243)	
IMR	0.160 (0.242)	0.156 (0.209)
log(empl)^2	0.033 (0.023)	
Intangibles_rel	-0.386*** (0.088)	-0.387*** (0.088)
Land_rel	0.178* (0.072)	0.169* (0.071)
Tech_and_mach_rel	0.002 (0.065)	-0.007 (0.065)
Raw_materials_and_consum_rel	0.333*** (0.080)	0.321*** (0.079)
Controls: Building type	Yes	Yes
Fixed-Effects:		
Industry	Yes	Yes
S.E.: Clustered	by: Company ID	by: Company ID
Observations	4,855	4,855
R^2	0.378	0.376
Within R^2	0.260	0.258

Results Evaluation

Performance of different approaches (Top down, bottom up)

Approach	**Top down**	**Bottom up**				
	(I)	(II)	(III)	(IV)	(V)	(VI)
	Using employment shares per industry	Heckman correction Including balance sheets	Heckman correction Including balance sheets Including building information	KNN (k=5)	MissForest	Ranger Random Forest (VIM)
Root Mean Squared Error (Deviation imputed from actual values)	2.4624	1.8865	**1.7070**	2.1356	**1.0009**	**1.1167**

Conclusion
Potential extensions and further research avenues

Summary

- **Bottom up** approaches that incorporate further data **outperform** top down approach based on employment weights alone
- Machine Learning approaches (especially **random forests imputations**) **outperform** classical statistical approaches
- **Building** data adds significant **explanatory power**
- Emissions are more closely related to production processes and input intensities—such as **tangible fixed assets, land** and **buildings, and raw materials**—than to firm size, even after controlling for industry-specific effects.
- Top- down methods based only on industry and employment data may overlook **firm-level variation**
- Firms with a higher share of **intangible assets**—often associated with innovation and R&D—appear to have a lower **emissions footprint**, hinting at a potential link between innovative capacity and carbon efficiency.

Possible extensions

- **Linkage:** Integrate **Energy consumption** from structural business statistics X **emission factors** (from UBA)
- **Generalisability:** Include other countries (ETS covers EU-countries and linktables are available)
- **Novel approaches:** Test further ML approaches such as **XGBoost** or **Transfomer Models** (VIM will be extended)

Thank you for your attention

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BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

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A data driven approach for portfolio decarbonization

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A data driven approach for portfolio decarbonization

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Abstract

An increasing number of institutional investors are integrating ESG and climate-related considerations into investment process. In this context, prevailing frameworks use backward-looking and forward-looking climate metrics, each with specific advantages and limitations. In addition, current practices often fail to capture the materiality of firms' activities for the transition.

Such approaches may result in paper decarbonization, in methodological complexity, and in a significant distortion in portfolio allocations across sectors and companies. To address these pitfalls, we propose a data-driven approach based on a commitment indicator and a classification of transition-relevant activities, integrating backward- and forward-looking information from multiple data sources. An empirical analysis shows that it is possible to decarbonize portfolio and simultaneously favour committed companies without deviating excessively from the benchmark. Compared with an unconstrained case, portfolios constructed using this approach exhibit higher exposure to "brown but committed" securities.

Keywords: Sustainable finance, Portfolio decarbonization, Climate transition commitments

JEL classification: G11, G12, Q56

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The views expressed herein are those of the authors and do not necessarily reflect those of the Bank of Italy.

Introduction

An increasing number of institutional investors are integrating environmental, social and governance (ESG) and climate-related considerations into investment and risk-management strategies. Sustainability criteria are typically introduced alongside traditional financial objectives in the risk–return space. In line with emerging practices, investors may also seek alignment with carbon-neutrality goals by leveraging available climate-transition data while preserving the portfolio's risk–return profile.

In this context, current frameworks increasingly rely on both backward-looking and forward-looking climate metrics. Each offers strengths and limitations. Backward-looking indicators are widely available and methodologically transparent, but they present a key shortcoming: reducing exposure to high emitters and reallocating it to low emitters helps achieve portfolio-level decarbonization targets yet does not necessarily contribute to real-economy emissions reductions. These naïve decarbonization strategies have been described as forms of *paper decarbonization* (GFANZ, 2023; Angelini, 2024).

An emerging paradigm, instead, promotes supporting high emitters that are genuinely engaged in transition efforts. From this perspective, a truly green company is not necessarily a low emitter, but rather a "virtuous" high emitter that effectively and transparently works to reduce its carbon footprint. Investors are therefore encouraged to channel capital toward transition leaders, underweight exposures to laggards, and reward ambitious and credible decarbonization plans. Forward-looking metrics offer a potentially powerful framework to assess transition alignment, yet their implementation remains hindered by methodological complexity and limited transparency.

Moreover, most investment strategies overlook the material relevance of firms' activities in driving or hindering the low-carbon transition. In such cases, applying forward-looking metrics broadly and under carbon constraints may generate adverse effects on portfolio construction. Without distinguishing between activities that are genuinely material for the transition and those with limited impact, investors risk overweighting companies or sectors with strong formal commitments but limited real influence on aggregate emissions.

To address these challenges, the paper proposes a two-pillar approach:

(i) a forward-looking indicator based on firms' decarbonisation commitments, to be used alongside the backward-looking carbon-intensity metric;

(ii) a classification of transition-relevant activities.

The commitment indicator combines multiple data sources and captures three key dimensions: the level of carbon-neutrality ambition; the presence of time-bound commitments to reduce material emissions over at least a three-year horizon; and the alignment of medium- and long-term decarbonisation trajectories with a 1.5°C scenario.

Transition-relevant activities are identified within the NACE sector classification by isolating those associated with the highest direct emissions in the European Union, along with activities whose products or services generate high indirect (scope 3) emissions.

As an illustration, we present the results of an optimization that combines the *commitment indicator* with the *classification based on material activities*. We simulate portfolios managed against a traditional benchmark, which are progressively tilted towards increasingly ambitious levels of the commitment indicator. The optimisation shows that, compared to the case of a more traditional tilting, that does not rely on the proposed methodological innovations:

a) the overall exposure to high-emitting firms increases as the constraint on the indicator becomes more ambitious; at the same time, within such exposure, the share of firms with stronger commitments increases as well, at the expense of those with weaker commitments;

b) introducing a constraint on the indicator does not significantly increase the financial deviation from the benchmark (tracking-error volatility, TEV), except in the case of very ambitious constraints, where the reduced portfolio breadth leads to higher TEV.

The paper is structured as follows. Section 1 reviews current practices; Section 2 presents the proposed framework; Section 3 discusses the results of the portfolio-optimisation exercise.

1. Current practices

Current portfolio decarbonization practices rely on two main building blocks: climate-related metrics and the relevance of economic activities for the transition. The first concerns how investors assess firms' past and prospective contributions to decarbonization, typically combining backward-looking and forward-looking indicators. The second refers to how sectors and activities are classified according to their materiality for achieving the transition, which shapes the interpretation and application of metrics in portfolio construction. The following paragraphs consider key pitfalls associated with climate-metric use, as well as sectoral and firm-level allocation effects emerging in common portfolio decarbonization practices.

1.1 Carbon Metrics

Most transition strategies rely heavily on backward-looking indicators, such as carbon emissions and related metrics (e.g. footprints and intensities). These metrics are easily available and require limited input from firms' financial data, but their informational value is constrained by several limitations.

First, portfolio carbon metrics can be improved simply by underweighting or excluding high emitters — even when these firms have credible transition plans (Angelini, 2022a). Divesting may reduce exposure to transition risks but does not necessarily translate into real-economy emissions reductions. Making finance more expensive for high emitters may even induce them to retain polluting technologies that require less capital (Hartzmark and Shue, 2023).

Second, if many investors simultaneously stop financing high emitters before substitutes are available, the prices of carbon-intensive products may surge — an instance of the *fallacy of composition* (Angelini, 2022b). What is feasible for a single investor may not be feasible collectively unless major technological breakthroughs or rapid shifts in consumption occur.

Third, backward-looking metrics offer limited insights into a firm's ability to follow a net-zero pathway. Since they exclude information on corporate transition plans, they can identify alignment only ex post.

Recent approaches increasingly incorporate forward-looking metrics, such as carbon transition scores, climate value-at-risk and implied temperature rise measures. These indicators take two main forms: (i) complex, model-based metrics and (ii) commitment-based metrics reflecting firms' decarbonization targets, notably those validated by the Science Based Targets initiative (SBTi).

Both approaches face limitations. Model-based metrics depend on heterogeneous assumptions and methodologies regarding emissions pathways, carbon-budget allocations across sectors and countries, the relationship between carbon-budget overshoots and long-term temperature outcomes, and the evolution of carbon prices. These modelling choices can yield inconsistent results across datasets and are often only partially disclosed, undermining transparency and replicability. Commitment-based metrics depend on SBTi coverage, which remains partial and concentrated in large, listed firms and specific sectors. Several high-emission or hard-to-abate sectors, including parts of the energy industry, still lack complete methodological guidance.

1.2 Activities

Most strategies overlook the material relevance of firms' activities in driving or hindering the transition. The EU Climate Benchmark Regulation (Regulation (EU) 2019/2089) distinguishes between high-climate-impact sectors (HCIS) and low-climate-impact sectors (LCIS) based on their contribution to total greenhouse gas emissions. HCIS include energy, utilities, transport, materials (e.g. steel and cement) and agriculture — sectors responsible for a large share of global emissions. These industries are expected to deliver substantial emission reductions. LCIS include finance, health care, information technology and communications, where alignment is assessed through indirect channels such as financing or supply-chain decisions.

Within EU Climate Transition Benchmarks (CTB) and Paris-aligned Benchmarks (PAB), exposure to HCIS must at least match their weight in the investable universe. The Technical Expert Group (TEG, 2020) mapped NACE classes to several sector classification systems, including BICS (Bloomberg), GICS (MSCI and S&P), ICB (FTSE) and TRBC (Refinitiv). Under GICS, 129 out of 185 sub-industries — around 70% — are classified as HCIS. This breadth has attracted criticism (Le Guenedal and Roncalli, 2022): nearly all economic activities are deemed critical for the transition. Only communication services and financials are classified exclusively as LCIS, while over half of health care and information technology sub-industries fall under HCIS.

The original rationale for the HCIS constraint was to ensure adequate financing for sectors essential to the transition, such as energy and utilities. With such a broad classification, however, the constraint becomes weak and may encourage substitutions *between* sectors or industries rather than *within* them (ESMA, 2022). This can lead to misalignments — for example, shifts from electricity generation to health-care equipment, rather than between green and brown electricity producers — a concern also highlighted in supervisory discussions (NGFS, 2023).

2. The proposed approach

To address these limitations, we propose an approach that integrates both backward-looking (carbon intensity) and forward-looking (commitment-based) information. The framework combines data from multiple sources and focuses on relevant activities for the transition. The following sections present a *commitment indicator* and a *classification of material activities*.

2.1 The commitment indicator

The *Commitment Indicator* (CI) measures the extent to which companies align with a net-zero pathway. It evaluates four key features drawn from leading frameworks on corporate transition plans (Climate Action, 2023; GFANZ, 2022; TPT, 2023). Each feature receives a binary score — 0 if the verification criteria are not met, 1 if they are — yielding an overall CI that ranges from 0 (no feature verified) to 4 (all features verified).

The features are as follows:

- an ambition to achieve carbon neutrality within a timeframe within a science-based timeframe
- a commitment to reduce material emissions over at least three years;
- the alignment of the decarbonisation trajectory with a 1.5°C scenario in the medium term;
- the alignment of the decarbonisation trajectory with a 1.5°C scenario in the long term.

Commitment indicator — Table 1

Feature	Description	Score
Net zero ambition	Net-zero targets expected to be achieved by 2050 (2040)	0/1
Commitment on material emission	Commitment to reduce material emissions over a time horizon of at least 3y	0/1
Medium term NZ alignment	Decarbonization trajectory in line with a 1.5°C scenario by 2030	0/1
Long term NZ alignment	Decarbonization trajectory in line with a 1.5°C scenario by 2050	0/1

Source: SBTi, TPI, ESG providers

Multiple data sources can be used, combining public information — such as SBTi, the Transition Pathway Initiative (TPI), and company reports or other disclosures — with private data from ESG providers. These sources provide complementary views of firms' climate performance: SBTi validates emission-reduction targets, TPI evaluates management quality and transition alignment, and ESG providers supply carbon and ESG datasets across companies. We describe each feature below.

Net-zero ambition. This feature refers to the formal statement of a company's strategic intention to achieve carbon neutrality within a timeframe consistent with climate-science recommendations. A key source of information is the SBTi Target Dashboard which lists companies have already set net-zero targets expected to be achieved by 2050, or by 2040 for firms in the power sector. The *net-zero ambition* feature is verified if the company has a "Target Set" status (SBTi, 2021).[1]

Alternatively, the ambition is also verified if the firm has publicly announced at least one comprehensive, self-declared net-zero target. This latter information can be sourced from company reports, press releases, other public disclosures, or from ESG data providers that collect and standardise such information.

$$\boldsymbol{NZ\ Ambition} = SBTi(NZ\ Target\ ) \vee self - declared\ NZ$$

[1] The *SBTi Target Dashboard* lists companies and financial institutions that have either set science-based targets or committed to doing so. The "Net-zero SBTi" status indicates whether a company has already set net-zero targets ("Target Set" status) or has committed to setting such targets in accordance with the SBTi *Commitment Compliance Policy* ("Committed" status) (SBTi, 2021).

Commitment on material emissions. This feature captures whether a company has committed to reducing emissions that are material to its activities over a horizon of at least three years. The commitment is identified through the SBTi Target Dashboard, based on the presence of one or more "Active Targets" — near-term or long-term — aligned with a meaningful temperature ambition ("1.5°C", "Well-below 2°C", or "2°C") under the SBTi classification (SBTi, 2021). To cover firms outside the SBTi scope, the feature also considers whether a company has announced at least one comprehensive, firm-wide commitment to reduce material emissions, with full coverage and a target year of 2030 or later. In line with TPI's focus on relevant emissions — including sector-relevant Scope 3 where applicable — material emissions are defined as the set of scopes that, when ranked by size, cumulatively represent a significant share (e.g. 75%) of total emissions (TPI, 2024). This threshold is broadly consistent with leading transition frameworks (SBTi, 2021; TPI, 2024; Climate Bonds Initiative, 2023). Details are provided in Annex 1.

Estimated emissions are preferred in defining material emissions to ensure comparability across firms and sectors. Reported emissions often differ due to differences in accounting boundaries, reporting standards, and data quality — particularly for Scope 3. Using estimated emissions derived from harmonized models mitigates these divergences, providing a consistent basis for assessing commitments across companies and industries.

$$\boldsymbol{Commitment\ on\ material\ emissions} = SBTi(Active\ target\ \ 1.5, \mathrm{WB2}, 2) \vee (Mat.Emiss. \wedge Target_{cov} \wedge Target_{Year} \geq 2030)$$

Medium-term net-zero alignment. This feature captures whether a company's decarbonisation trajectory aligns with a 1.5°C pathway over the medium term, drawing on three data sources.

Firstly, the feature is verified when the company has an "Active" near-term target classified as 1.5°C-aligned by the SBTi (SBTi, 2021). Secondly, for firms outside the SBTi scope, the feature is verified leveraging the TPI carbon-performance assessment. It evaluates whether current and projected emissions are consistent with sector-specific 1.5°C pathways (TPI, 2024). We require alignment both today and by 2035. Thirdly, a further option relies on medium-term net-zero assessments from ESG data providers. For example, MSCI deems a company aligned if it plans at least a 95% cut in aggregate Scope 1–2 absolute emissions by 2030, and a 67% cut in estimated Scope 3 emissions by the same year (MSCI, 2024). These thresholds reflect SBTi definitions of required emissions coverage for different net-zero target years (SBTi, 2021).

$$\boldsymbol{Medium\ Term\ Alignment} = SBTi(Active\ near\ term\ target\ \ 1.5) \vee$$
$$\vee \left[\mathrm{TPI}_{\mathrm{Align}}(2025) \wedge \mathrm{TPI}_{\mathrm{Align}}(2035)\right] \vee \mathrm{Provider}_{\mathrm{Align}}(2030)$$

Long-term net-zero alignment. This feature reflects the alignment of a company's decarbonisation trajectory with a 1.5°C scenario by 2050 or earlier. As for the medium-term alignment, the same data sources are considered. Firstly, the commitment is identified through the *SBTi Target Dashboard*, where it is inferred from the presence of an "Active" long-term target aligned with a 1.5°C scenario (SBTi, 2021). Secondly, for companies outside the scope of the SBTi, the feature is verified based on the carbon performance TPI assessment for the 2025, 2035 and 2050 aligned with a "1.5°C" scenario. Thirdly, data points coming from ESG data providers could be used to assess a long-term net zero alignment based on any ESG provider assessment for the 2030 and the 2050 (e.g. MSCI).

$$\boldsymbol{Long\ Term\ Alignment} = SBTi(Active\ long\ term\ target\ \ 1.5) \vee$$
$$\vee \left[\mathrm{TPI}_{\mathrm{Align}}(2025) \wedge \mathrm{TPI}_{\mathrm{Align}}(2035) \wedge \mathrm{TPI}_{\mathrm{Align}}(2050)\right] \vee \left[\mathrm{Provider}(2030) \wedge \mathrm{Provider}_{\mathrm{Align}}(2050)\right]$$

2.2 A classification focused on material activities

Commitment metrics can generate adverse effects on portfolio construction when applied broadly and in the presence of carbon constraints. Without distinguishing between activities that are truly material for the low-carbon transition and those that are not, investors may end up favouring companies or sectors with strong formal commitments but limited real impact on aggregate emissions.

We illustrate these effects by considering an investment strategy subject to portfolio-level constraints. In this setting, security and sector allocations are driven by the distribution of commitment scores. However, these allocations — both within sectors (favouring one security over another) and across sectors (favouring one sector over another) — do not account for the actual relevance of firms' commitments to the energy transition.[2] This can distort portfolio construction through both selection and allocation effects.[3] These effects are illustrated below.

Potential selection and allocation effects

Table 2

Case	Company (C) / Sector(S)	Materiality	Commitment indicator	Carbon intensity	Preference
1	Alpha (C)	Y	3	High	-
	Beta (C)	N	3	Low	+
2	Gamma (S)	Y	4	High	-
	Delta (S)	Y	4	High	-
3	Epsilon (S)	N	3.5	Low	+
	Zeta (S)	N	2.5	Low	-

The distorted **selection effect** arises when two companies (e.g., Alfa and Beta) within the same sector carry out activities with differing relevance to the energy transition (high for Alfa and low for Beta), yet both obtain the same score on the commitment indicator. Since activities that are less relevant to the transition (such as Beta's) typically exhibit lower carbon intensity, it follows that, all else being equal, the

[2] For certain activities, in fact, setting an emission reduction target requires a significant effort. Consider, for example, a long-term net zero target validated by SBTi for a company operating in electricity generation. Achieving such a target entails substantial investments needed to replace fossil-fuel based production plants with renewable energy facilities. In contrast, a long-term net zero target validated by SBTi for a pharmaceutical company could be achieved with considerably less effort. Despite the differing relevance of these targets, the current framework does not differentiate between the objectives of the two companies. The same issue arises even among companies within the same sector that are involved in activities with varying degrees of relevance to the energy transition.

[3] The inclusion of companies engaged in activities with differing relevance to the transition within the same sector is possible because the sector classifications used in the financial industry (e.g., the Industrial Classification Benchmark – ICB, or the Global Industry Classification Standard – GICS) group companies based on their core business and commercial operations. This classification logic differs from one based on relevance to the energy transition or on companies' emissions. Moreover, the level of sector aggregation used in ICB or GICS classifications can also result in grouping together companies with very different core businesses within the same sector. For example, under the highest level of sector aggregation in the ICB, the "Consumer Discretionary" sector includes both car manufacturers and media companies. This is also the case in the Bank's investment activity, which uses the ICB classification with a breakdown into 10 sectors (referred to as Industries).

company (Beta) engaged in the less transition-relevant activity and displaying lower carbon intensity (another portfolio constraint) would be preferred over the other (Alfa) (Table 2, Case 1).

The distorted **allocation effect** can emerge in two cases. In the first, two sectors (e.g., Gamma and Delta) have the same weighted average commitment score but differ in transition relevance — high for Gamma, low for Delta. Since Delta typically shows lower carbon intensity, the portfolio would tend to favour it (Table 2, Case 2). In the second, two sectors (e.g., Epsilon and Zeta) both exhibit low transition relevance but differ in commitment scores. The portfolio would then favour the higher-scoring sector (Epsilon), even though commitments in both cases have negligible importance for the transition (Table 2, Case 3).

To address these distortions, we identified the material activities within the NACE sector classification, considering:

a) activities with the highest direct emissions in the European Union;
b) activities related to the production of goods and services whose use entails high emissions.

For the first criterion, the included activities account for approximately 90% of the total direct emissions in the European Union, based on Eurostat data. The second criterion allows for the inclusion of activities with a significant share of scope 3 emissions, that is, the indirect emissions generated by end users, such as the production of automobiles or semiconductors. These activities are identified within the industry sectors of companies included in a broad euro-area equity market index that exhibit the highest total carbon intensities (scope 1, 2 and 3). This approach therefore captures additional activities that do not emerge under the first criterion because they exhibit low direct emissions but high scope 3 emissions.

Based on these criteria, the selection covers NACE macro-sectors A, B, D, E, and H, eleven activities falling under macro-sector C, and two activities belonging to macro-sectors F and G (Table 3).

Material NACE sectors

Table 3

NACE		Sectors	Contribution to EU Emissions*	Intensity**
A		Agriculture, forestry and fishing	17.0%	1.62
B		Mining and quarrying	1.9%	0.88
C		Manufacturing	25.9%	0.27
	17	-paper and paper products	1.0%	
	19	-coke and refined petroleum products	4.3%	
	20	-chemicals and chemical products	4.7%	
	22	-rubber and plastic products	**0.3%**	
	23	-other non-metallic mineral products	6.1%	
	24	-basic metals	5.2%	
	25	-fabricated metal products, except machinery and equipment	**0.4%**	
	27	-electrical equipment	**0.1%**	
	28	-machinery and equipment n.	**0.3%**	
	29	-motor vehicles, trailers and semi-trailers	**0.4%**	
	30	-other transport equipment	**0.1%**	
D		Electricity, gas, steam and air cond. supply	22.2%	1.5
E		Water supply; sewerage, waste management and remediation activities	5.5%	1.01
F		Construction	2.0%	0.06
	42	-Civil engineering	**0.0%**	
G	46	Wholesale and retail trade; repair of motor vehicles and motorcycles	2.8%	0.04
		-Wholesale trade, except of motor vehicles and motorcycles	**1.4%**	
H		Transportation and storage	17.5%	0.63
Total			2,674.80*	0.17**

* Tonnes of Greenhouse gases (GHG; CO2 and CO2 equivalent (N2O, CH4, HFC, PFC, SF6 and NF3)) and ** Kilograms of GHG per euro of gross value added. Scope 1 and 2 emissions; Bold for Scope 3.

Source: internal elaborations on the Eurostat dataset “Air emissions accounts by NACE” and “Air emissions intensities by NACE”. European Union - 27 countries. Year 2023Absolute emissions (MtonnCO2e)

3. Empirical application of the approach

We present the results of an optimization that combines the *commitment indicator* with the *classification based on material activities*. We simulate portfolios managed against a traditional benchmark, which are progressively tilted towards increasingly ambitious levels of the commitment indicator. The benchmark used is the MSCI EMU ex-financials (excluding banks, insurance companies and financial services).[4]

The exercise is a standard constrained quadratic optimization problem. The objective function is the tracking error volatility ex-ante (TEV), given by the variance–covariance matrix pre-multiplied and post-multiplied the active weights. The variance-covariance matrix is estimated using the well-known macroeconomic multifactor Burmeister-Roll-Ross model (BIRR model, Burmeister et al., 1997).

To reflect a sustainable investor profile, the optimization includes the following constraints: an ESG score at least 5% higher than that of the benchmark, a weighted average carbon intensity (WACI) at least 50% lower than the benchmark, and sectoral and issuer concentration limits of 1% and 2%, respectively. The formal representation of the optimization is provided in the Annex 2.[5]

We show how portfolio allocation evolves across simulations (Table 4), from the unconstrained case to scenarios with progressively higher average commitment score levels. The portfolio allocation is analysed by grouping companies. Specifically, we first distinguish between those for which the indicator does not apply ("No material" column) and those for which it does ("Material" column). Within the latter group, companies are further classified according to their commitment score (from 0 to 4). The analysis considers both the number of securities included in each simulated portfolio - to assess the diversification effect - and their overall percentage exposure.

The overall percentage exposure to material companies remains broadly independent of the commitment score level imposed by the constraint (*blue panel*, Table 4). As the commitment score constraint becomes more ambitious, the portfolio's exposure to low-commitment securities decreases, while the exposure to high-commitment securities increases (*red and green arrows*, respectively).

Under the extreme solutions, portfolio cardinality falls (*dark-grey arrows*), and score-3 holdings decline in favour of score-4 securities, which remain fully included (*amber and green arrows*).

Table 4

Holdings and Weights by Commitment Score

	No material		Material		Material - Committment score breakdown									
					0		1		2		3		4	
Optimizations	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**
Benchmark (3,07)	78	46,0%	81	54,0%	4	1,5%	1	0,1%	22	9,2%	34	25,4%	20	17,7%
Unconstrained (3,07)	66	46,7%	70	53,3%	4	1,6%	1	0,1%	17	9,7%	29	23,5%	19	18,4%
3,15	67	46,8%	68	53,2%	4	1,0%	0	0,0%	16	8,8%	29	23,7%	19	19,7%
3,25	66	47,3%	65	52,7%	2	0,5%	0	0,0%	15	7,0%	29	23,4%	19	21,9%
3,37	66	48,3%	55	51,7%	1	0,2%	0	0,0%	8	4,6%	26	22,2%	20	24,7%
3,49	65	49,2%	43	50,8%	0	0,0%	0	0,0%	4	3,6%	19	18,6%	20	28,7%
3,61	58	49,3%	33	50,7%	0	0,0%	0	0,0%	2	2,9%	11	13,8%	20	34,0%
3,73	36	44,4%	28	55,6%	0	0,0%	0	0,0%	2	1,4%	9	12,2%	17	42,0%

As the constraint on the commitment indicator becomes more ambitious (Figure 1):

[4] This index is described in terms of the number of constituents (cardinality), sector composition, ESG score, and weighted average carbon intensity.

[5] All constraints are linear, except for the one related to the commitment indicator, as the active weights considered apply only to the subset of stocks classified under the material activities.

• the tracking error volatility (TEV) increases more than proportionally; however, it remains possible to favour committed companies without deviating excessively from the benchmark (TEV < 1%);

• the exposure across carbon-intensity quintiles remains largely stable.

Compared with the unconstrained case, portfolios constructed using the commitment indicator display higher exposure to brown securities (Q1; Figure 2) — and in particular to brown committed ones — while brown non-committed companies are further penalized.

Figure 1.
Ex-ante TEV (left axis) and exposure to carbon intensity quantiles (right axis)

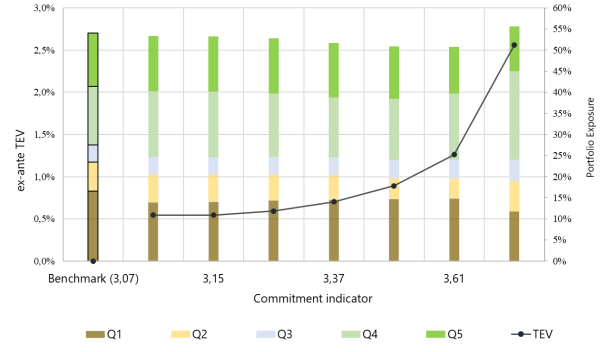
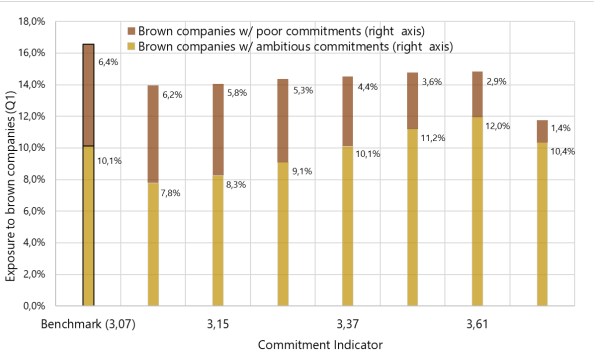


Figure 2.
Brown companies (Q1): overall exposure and breakdown on commitments



Conclusions

This paper proposes a data-driven approach to assessing portfolio decarbonization that combines forward- and backward-looking information while accounting for the materiality of firms' activities. By integrating commitment indicators with a classification of transition-relevant sectors, the framework mitigates the risk of paper decarbonization, thereby enabling a more credible alignment with real-economy transition pathways.

The empirical results show that it is possible to favour committed companies — including those in high-emission sectors — without materially deviating from the benchmark. This suggests that sustainable portfolio construction can be consistent with both financial and climate objectives, provided that commitments are credible and targeted toward material sources of emissions.

In line with recent reflections, effective decarbonization strategies should not rely solely on portfolio reallocation, but on approaches that strengthen the link between investment decisions and the real economy's transition dynamics. This calls for continued efforts to improve data quality, transparency, and methodological consistency in assessing transition alignment.

Annexes

Annex 1. Material Emissions

Let's consider a company with the following estimated GHG emissions by scope (in metric tons of CO_2 equivalent):

- Scope 1 (direct emissions): 100,000 tCO_2e
- Scope 2 (indirect emissions from purchased electricity): 250,000 tCO_2e
- Scope 3 (all other indirect emissions): 650,000 tCO_2e

Step 1: Total emissions
Total = 100,000 (S1) + 250,000 (S2) + 650,000 (S3) = 1,000,000 tCO_2e

Step 2: Order scopes by size (descending)

2. **Scope 3** = 650,000 → 65%
3. **Scope 2** = 250,000 → 25%
4. **Scope 1** = 100,000 → 10%

Step 3: Identify scopes covering at least 75% of total emissions
We add the scopes cumulatively until the 75% threshold is reached:

- Scope 3 (65%)
- Scope 2 (25%) → cumulative **= 90%** > 75%

Thus, Scope 3 and Scope 2 together are identified as material emissions, while Scope 1 is not considered material under this definition.

Annex 2. Optimisation problem

$$\min_x x^T \cdot \Sigma_{total} \cdot x$$

sub

$$\sum_{i=1}^{N} x_i = 0$$

$$\left|\sum_{i=1}^{N_s} x_{i|sector=s}\right| \leq \bar{\delta}$$

$$lb \leq x \leq ub$$

$$\sum_{i=1}^{N} x_i \cdot ESG_i \geq \overline{ESG}$$

$$\sum_{i=1}^{N} x_i \cdot WACI_i \leq \overline{WACI}$$

$$\frac{\sum_{i=1}^{Nmat} x_i \cdot CI_i}{\sum_{i=1}^{Nmat} x_i} \leq \overline{CI}$$

with

- $x = w_{port} - w_{bench}$, the $N \times 1$ vector containing the weight differentials of each security (x_i), obtained as the difference between the vector of weights in the replicating portfolio w_{port} and the vector of weights in the benchmark w_{bench};
- Σ_{total} , the N × N variance-covariance matrix of the securities in the benchmark;
- $\bar{\delta}$, the maximum deviation for each sector s, with N_s equal to the number of securities that make up the sector and $x_{i|settore=s}$ equal to the differential weight of each i-th security belonging to sector s;
- lb and ub , the N × 1 vectors containing respectively the lower and upper bounds of the active weights;
- ESG_i, $WACI_i$ and CI_i , denote the ESG scores, the carbon intensities and the commitment indicator of each stock;
- $\overline{ESG}$, $\overline{WACI}$, and $\overline{CI}$, the minimum desired levels of the ESG score, the weighted average carbon intensity, and the commitment indicator at the portfolio level.
- N_{mat} the number of stocks belonging to the material activities.

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EUROSISTEMA

A data-driven approach for portfolio transition

Irving Fisher Committee - De Nederlandsche Bank
Satellite Seminar on Sustainability data issues and central banks' experience

4 October 2025, Amsterdam

Marco Fanari and Francesco Savino
Financial Risk Management Directorate

The views expressed herein are those of the authors and do not necessarily reflect those of the Bank of Italy

Overview

Current practices on portfolio transition

Most practices rely on backward-looking information (carbon footprint)

Recent strategies include forward-looking metrics based on:

- complex metrics → ITR, Climate VaR
- commitment → SBTi targets

Potential pitfalls

Complex metrics suffer from heterogeneity of assumptions and methodologies

Commitments are based only on SBTi

Metrics disregard the materiality of each activity for the transition

Our analysis

blends carbon footprint and commitment data

feeds commitment data from multiple sources

focuses on material activities

} **Commitment indicator**
Material activities

The commitment indicator (1)

The **commitment indicator** (CI) assesses how companies are aligned with a Net zero pathway.
It covers **four features**. Each gets a score of 0 (not verified) or 1 (verified). Therefore, CI ranges from 0 (no feature verified) to 4 (all features verified).
Multiple data sources are used: SBTi, MSCI, TPI.

Features	Description	Scores
Net Zero Ambition	Net-zero targets expected to be achieved by 2050 (2040)	0/1
Commitment on material emissions	Committment to reduce material emissions over a time horizon of at least 3 years.	0/1
Medium term NZ alignment	Decarbonization trajectory in line with a 1.5°C scenario by 2030	0/1
Long term NZ alignment	Decarbonization trajectory in line with a 1.5°C scenario by 2050	0/1

1) Net Zero Ambition

The company has the ambition to achieve net zero emissions by 2050 (2040 power sector)

→ SBTI: "Target set" for Net zero status

→ MSCI: company's net zero emissions ambition statement

2) Commitment on material emissions

The company is committed to reducing its material emissions*

Target criteria: *(i) material emissions, (ii) company-wide scope, (iii) 3-year horizon*

→ SBTi: active "Near-term target" or "Long-term target"

→ MSCI: datapoint on at least one target comply with these criteria

** Material emissions*

Scope 1-3 emissions, ranked in decreasing order, cumulatively account for X% of the company's emissions (e.g. 75%).

The commitment indicator (2)

3) Medium-term Net zero alignment

The decarbonization trajectory is in line with the 1.5°C scenario in the medium-term

→ Comparison of company's vs sector-specific carbon intensity pathway by 2030

- SBTI: "Target set" for Net zero status & "1.5°C" for Near term target classification
- MSCI: "Net zero 2030", science-based absolute emission reduction by 2030
- TPI: "1.5°C" for Carbon performance assessment in 2025 and 2035

4) Long-term Net zero alignment

The decarbonization trajectory is in line with the 1.5°C scenario in the long term

→ Comparison of company's vs sector-specific carbon intensity pathway by 2050

similar to Medium-term Net zero alignment with horizon in 2050 (2040)

Why focusing only on material activities?

A broad portfolio application of CI could generate adverse effects in the presence of carbon constraints

Case	Company/sector	Materialility	Score Commitment	Carbon intensity	Preference
1	Alpha (company)	Y	3	High	-
	Beta (company)	N	3	Low	+
2	Gamma (sector)	Y	4	High	-
	Delta (sector)	N	4	Low	+
3	Epsilon (sector)	N	3,5	Low	+
	Zeta (sector)	N	2,5	Low	-

Adverse selection effect

Case 1 – Company Beta, engaged in a non-material activity and exhibiting lower carbon intensity, is preferred over Company Alpha

Adverse allocation effect

Case 2 – Sector Delta, with non-material activities and a lower carbon intensity, is preferred over Sector Gamma

Case 3 – Sector Epsilon, with a higher score, is preferred over Sector Zeta, even though the commitments made by companies in both sectors are non-material

We propose a **focus on material activities**

How to identify material activities

We employ the **NACE classification** based on the **contribution to total EU's emissions**.

We consider:

- activities with the highest direct emissions in the economy (Scope 1&2)
- activities aimed at the production of goods and services whose use generates high emissions (Scope 3)

The included activities account for
88,4% of the EU's emissions

	Material NACE sectors (1)	Contribution to EU Emissions (2)	Intensity (3)
A	Agriculture, forestry and fishing	17,0%	1,62
B	Mining and quarrying	1,9%	0,88
C	Manufacturing	25,9%	0,27
17	Manufacture of paper and paper products	1,0%	
19	Manufacture of coke and refined petroleum products	4,3%	
20	Manufacture of chemicals and chemical products	4,7%	
22	Manufacture of rubber and plastic products	0,3%	
23	Manufacture of other non-metallic mineral products	6,1%	
24	Manufacture of basic metals	5,2%	
25	Manufacture of fabricated metal products, except machinery and equipment	0,4%	
27	Manufacture of electrical equipment	0,1%	
28	Manufacture of machinery and equipment n.e.c.	0,3%	
29	Manufacture of motor vehicles, trailers and semi-trailers	0,4%	
30	Manufacture of other transport equipment	0,1%	
D	Electricity, gas, steam and air conditioning supply	22,2%	1,50
E	Water supply; sewerage, waste management and remediation activities	5,5%	1,01
F	Construction	2,0%	0,06
42	Civil engineering	0,0%	
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	2,8%	0,04
46	Wholesale trade, except of motor vehicles and motorcycles	1,4%	
H	Transportation and storage	17,5%	0,63
Total **(2) Absolute emissions (MtonnCO2e)** **(3) Intensity (kCO2e/€)**		**2.674,8**	**0,17**

Contribution to Scope 1,2

Contribution to Scope 3

Source: internal elaborations on the Eurostat dataset "Air emissions accounts by NACE" and "Air emissions intensities by NACE".
Tonnes of Greenhouse gases (GHG; CO2 and CO2 equivalent (N2O, CH4, HFC, PFC, SF6 and NF3)) and Kilograms of GHG per euro of gross value added.
European Union - 27 countries. Year 2023

Portfolio construction

By way of example, we present the results of an optimization exercise using the commitment indicator

Assumptions

Portfolio is constructed against a traditional benchmark
(euro area equity, no financials)

Optimization problem

Min ex-ante Tracking Error Volatility (TEV)

Constraints (vs benchmark)

- enhanced ESG score (at least 5%)
- enhanced WACI (at least 50% and 7% decarbonization annually)
- sector (max 1%) and issuer (max 2%)
- composite indicator

Tilting towards increasingly ambitious levels

from the unconstrained case…

…to progressively higher scores

Constrained quadratic optimisation

$$\min_x x^T \cdot \Sigma_{total} \cdot x$$

sub

$$\sum_{i=1}^{N} x_i = 0$$

$$\left|\sum_{i=1}^{N_s} x_{i|sector=s}\right| \leq \bar{\delta}$$

$$lb \leq x \leq ub$$

$$w_{port} \cdot ESG \geq \overline{ESG}$$

$$w_{port} \cdot WACI \leq \overline{WACI}$$

$$\boldsymbol{w_{port} \cdot CI \leq \overline{CI}}$$

Results – exposure to committed companies

The overall exposure to material companies is independent of the commitment score level required by the constraint (*blue panel*)

As the commitment score constraint becomes more ambitious, the overall exposure to low (high-) committed companies decreases (increases) (*red/green arrow*)

In the extreme solutions,

- the cardinality of the portfolio is reduced (*dark grey*),
- a reduction in score 3 securities is also observed, along with an increase in exposure to score 4 securities (always included) (*amber/green arrow*)

	No material		Material		Material - Committment score breakdown									
					0		1		2		3		4	
Optimizations	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**	**N**	**Weight**
Benchmark (3,07)	78	46,0%	81	54,0%	4	1,5%	1	0,1%	22	9,2%	34	25,4%	20	17,7%
Unconstrained (3,07)	66	46,7%	70	53,3%	4	1,6%	1	0,1%	17	9,7%	29	23,5%	19	18,4%
3,15	67	46,8%	68	53,2%	4	1,0%	0	0,0%	16	8,8%	29	23,7%	19	19,7%
3,25	66	47,3%	65	52,7%	2	0,5%	0	0,0%	15	7,0%	29	23,4%	19	21,9%
3,37	66	48,3%	55	51,7%	1	0,2%	0	0,0%	8	4,6%	26	22,2%	20	24,7%
3,49	65	49,2%	43	50,8%	0	0,0%	0	0,0%	4	3,6%	19	18,6%	20	28,7%
3,61	58	49,3%	33	50,7%	0	0,0%	0	0,0%	2	2,9%	11	13,8%	20	34,0%
3,73	36	44,4%	28	55,6%	0	0,0%	0	0,0%	2	1,4%	9	12,2%	17	42,0%

Results - TEV and carbon intensity quintiles

As the CI constraint becomes more ambitious:

- TEV increases more than proportionally (fig. 1); however, it is possible to favour committed companies, without deviating excessively from the benchmark (TEV<1%)
- Exposure to companies across the different carbon intensity quintiles remains largely stable (fig. 1)

Compared to the unconstrained case, portfolios built with the CI show higher exposure to brown companies (Q1; fig. 2) and, in particular, to transition-committed brown ones, while non-committed brown companies are further penalized

Figure 1. *Ex-ante TEV (left axis) and exposure to carbon intensity quantiles (right axis) across simulations*

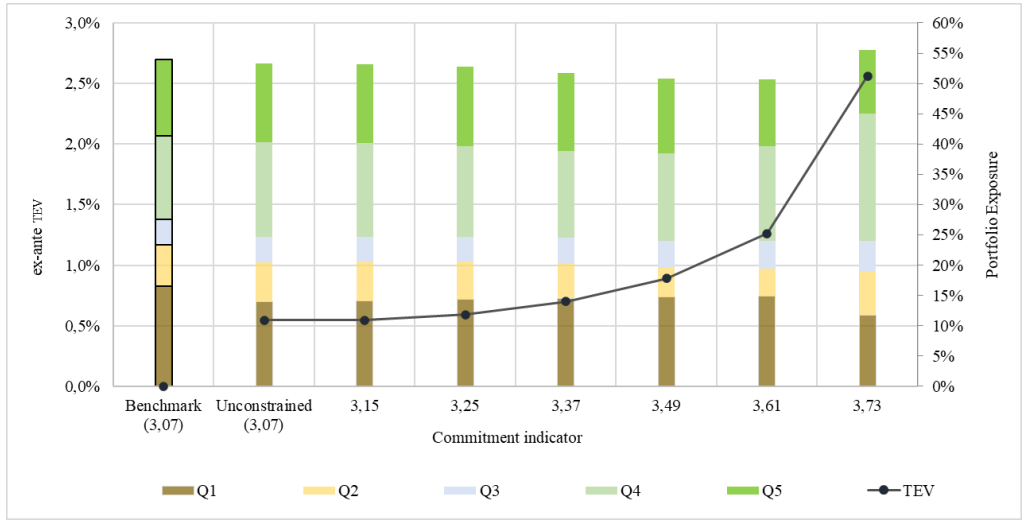
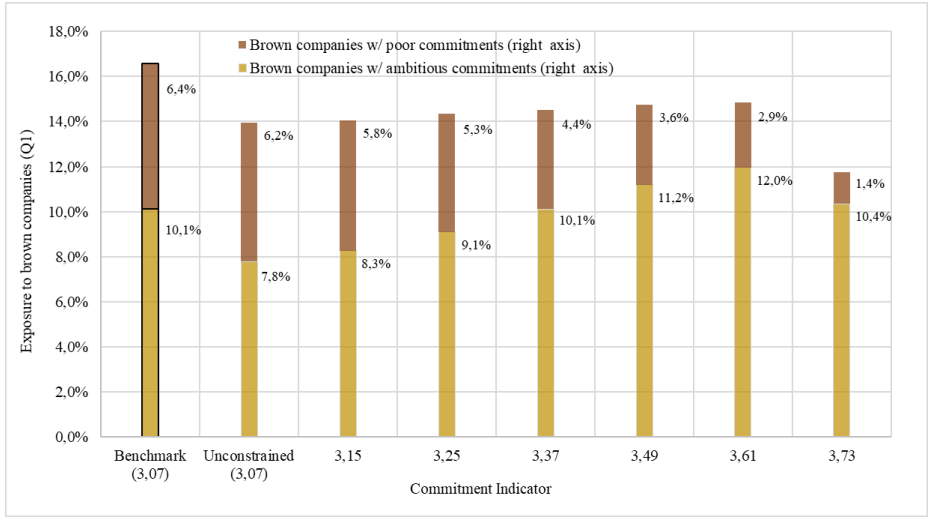


Figure 2. *Brown companies (Q1): overall exposure and breakdown on committments*



Thank you!

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Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

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Marshall Edgeworth: riding the carbon trails of the great investment plains

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Marshall Edgeworth: riding the carbon trails of the great investment plains

Stijn Ferrari

Abstract

This article applies a look-through approach and Marshall-Edgeworth decomposition to trace financed emissions in investment portfolios. By examining both direct and indirect corporate securities holdings of Belgian financial corporations and households, the analysis reveals that indirect investments significantly shape carbon exposure. Between 2018 and 2023, total financed emissions declined, driven by portfolio reallocations and corporate emission reductions. Crucially, the decomposition highlights how revaluation effects can obscure the true impact of investment decisions, underscoring the need for flow-based analysis.

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Concluding remarks 12

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1. Introduction

This article chronicles the endeavours of Marshal Edgeworth. Like the famed lawmen who brought order to frontier towns in the untamed West, he rides the Great Investment Plains. His mission is not to chase outlaws, but to track the elusive carbon trails left by investment portfolios. Some of these trails stretch clearly across the open plains of direct investments, while others remain hidden, concealed within the shadowed canyons of indirect exposures through investment funds.

Just as the marshals of old relied on sharp instincts and unwavering resolve, Marshal Edgeworth depends on his trusted tracker, Luke Through. With an unrivaled ability to peer into the rugged terrain of indirect investments, Luke uncovers concealed carbon trails within investment funds, ensuring no hidden emissions escape detection. Once the trails are revealed, Marshal Edgeworth applies his decomposition expertise to map the intricate paths of financed emissions, bringing clarity to an otherwise obscured frontier.

Behind this stylised narrative lies a pressing financial reality. Climate change presents growing challenges for the financial sector, reshaping investment strategies and risk assessments. As economies transition toward net-zero targets, investors must integrate climate considerations into their decision-making to ensure both financial resilience and sustainable capital allocation. Monitoring the drivers of a portfolio's carbon footprint is essential for aligning investment strategies with climate goals.

To meet these demands, investors and financial supervisors need robust tools that go beyond surface-level metrics. A well-equipped climate finance toolkit helps monitor portfolio carbon profiles, assess transition risks, and evaluate the financial sector's role in the net-zero shift. It also supports data validation and effective sustainability storytelling. These capabilities are strategic imperatives – enhancing transparency, guiding informed decisions, and reinforcing the financial system's contribution to decarbonisation.[1]

In this article, we apply a look-through approach and Marshall-Edgeworth decomposition to the corporate securities portfolios of Belgian financial corporations and households. The analysis reveals that indirect investments represent a substantial share of their exposure to non-financial corporations. When hidden carbon trails are accounted for, financed emissions rise significantly.[2]

Yet between 2018 and 2023, total financed emissions declined for both financial corporations and households. This decrease was primarily driven by emission reductions within the firms in portfolio and by reallocations away from high-emitting firms. Financial corporations achieved this mainly through direct portfolio adjustments, while households benefited largely from changes in Belgian and Luxembourgish investment fund holdings.[3]

Importantly, the decomposition analysis reveals that revaluation effects can obscure the true impact of investment decisions – particularly for households – highlighting the need to examine underlying flows to accurately assess portfolio decarbonisation. In fact, flow-based analysis shows that households

[1] Also see for instance UN-convened Net-Zero Asset Owner Alliance (2023), which encourages investors to establish their own emissions attribution analyses and to share knowledge on how to do so among financial institutions.

[2] For an earlier application of a look-through approach to analyse the carbon footprint of Dutch insurance corporations' and pension funds' securities holdings, see for instance Berkhout et al. (2024).

[3] Alternative decompositions or attribution analyses of changes in carbon indicators for investment portfolios have been performed by for instance Berkhout et al. (2023), Shemfe et al. (2024) and Statistics Committee Expert Group on Climate Change and Statistics and Working Group on Securities (2024a). To our knowledge, we are the first to apply such decomposition on both direct and indirect holdings and analyse financed emissions of households' securities portfolios. For an application of a look-through approach to euro area households' portfolio holdings, see for instance Carvalho and Schmitz (2021).

did actively shift their portfolios away from high-emitting firms, but this effect was offset by positive revaluation effects.

The remainder of the article is structured as follows: Section 2 introduces the methodological framework; Section 3 details the data sources; Section 4 presents the main empirical findings; and Section 5 offers some concluding remarks.

2. Methodology

This section presents the methodological framework, structured around four logical steps. First, we define the investment portfolio. Second, we identify the relevant carbon emissions indicators. Third, we select the sample used to compute these indicators. Fourth, we analyse the drivers behind changes in the computed carbon metrics.[4]

Look-through methodology

Investors can hold an issuer's securities either directly or indirectly. Direct holdings occur when an investor acquires listed shares or bonds issued by the company. Indirect holdings arise when the investor purchases shares in investment funds that, in turn, include the issuer's securities in their portfolios.

Investor h's direct investment $I^d_{h,j}$ in securities issued by company j is equal to the total market value $H_{h,j,s}$ of all securities s (including listed shares and bonds) issued by company j and directly held by investor h:

$$I^d_{h,j} = \sum_s H_{h,j,s}$$

Indirect investment $I^i_{h,j}$ by investor h in issuer j's securities is determined by the total market value $H_{f,j,s}$ of all securities s issued by company j and held by the investment funds f within investor h's portfolio. However, this investment amount is limited by the ownership share of investor h in fund f, which is calculated as the ratio of the market value $H_{h,f}$ of investor h's participation in fund f to the total market value V_f of investment fund shares issued by f:

$$I^i_{h,j} = \sum_f \frac{H_{h,f}}{V_f} \sum_s H_{f,j,s}$$

Total investment $I_{h,j}$ of investor h in issuer j's securities is the sum of direct and indirect investment:

$$I_{h,j} = I^d_{h,j} + I^i_{h,j}$$

Finally, the total securities portfolio I_h of investor h amounts to the total investment in all issuers of which securities are held by investor h:

$$I_h = \sum_j I_{h,j}$$

[4] All measures are time-specific; however, the time subscript t is omitted where possible to simplify notation.

Note that investment funds held by an investor can, in turn, invest in other investment funds, creating a multi-layered structure. In principle, the look-through methodology can be applied iteratively, tracing exposures through successive layers of fund investments. However, in the analysis below, we apply the look-through approach only once, limiting indirect investments to the direct holdings of investment funds within the portfolio. This approach streamlines the analysis while ensuring a comprehensive reflection of the investment structure and underlying holdings within the portfolio.

Carbon emissions indicators

Carbon emissions indicators for investment portfolios incorporate double materiality, by considering both the environmental impact of the portfolio and the financial risks associated with exposure to high-emitting firms. While the methods in this article can be applied to a variety of carbon emissions indicators, the analysis will focus on financed emissions.

Financed emissions quantify the total greenhouse gas emissions tied to an investor's holdings, offering insight into the climate implications of their financial decisions. This metric is crucial for sustainable finance, as it helps investors assess their contribution to global emissions and align their portfolios with climate goals.

The financed emissions $FE_{h,j}$ associated with issuer j reflect the portion of company j's total carbon emissions that can be linked to investor h's financial support. They are obtained by weighting company j's emissions E_j according to investor h's proportional funding share, which is measured as the ratio of investor h's investment in issuer j's securities ($I_{h,j}$) to issuer j's total company value C_j:

$$FE_{h,j} = \frac{I_{h,j}}{C_j} E_j$$

The total financed emissions of investor h are calculated as the sum of the financed emissions of all issuers in their portfolio:

$$FE_h = \sum_j FE_{h,j}$$

Flex balancing

When tracking financed emissions over time, variations may arise due to changes in firms' emissions or financial data, as well as shifts in portfolio composition. These compositional changes occur due to investment or divestment decisions by security holders and to missing emissions or financial data for certain issuers in some time periods. While one would want to account for shifts in holdings, changes in sample composition due to missing data are less desirable.

To address this, a balancing methodology developed in a statistical paper by the ECB[5] ensures consistency in issuer representation across periods. If a firm appears as a security issuer in an investor's portfolio but lacks financial or emissions data in a given period, it is removed entirely from the holder's portfolio (for all periods) to avoid bias. Conversely, if a firm is absent in some periods but has complete financial and emissions data in others, it remains in the dataset for those periods, reflecting investment

[5] Statistics Committee Expert Group on Climate Change and Statistics and Working Group on Securities (2024a)

and divestment decisions of the holder. This approach ensures a consistent portfolio composition over time while maintaining meaningful financial trends.[6]

Marshall-Edgeworth decomposition

Monitoring financed emissions over time is crucial for understanding their evolution and identifying the key drivers behind observed changes. Decomposition methods serve as powerful tools for breaking down complex trends into their underlying components, helping analysts disentangle the effects of individual factors on overall variations. These techniques are widely applied in economics, finance, and environmental research to analyse time-dependent shifts influenced by multiple variables.

The Marshall-Edgeworth (ME) decomposition, named after Alfred Marshall and Francis Edgeworth for their foundational work on index numbers[7], provides a systematic approach for isolating the contributions of different variables to total change. This method has been extensively used in index number theory and price and quantity analysis, facilitating a clearer understanding of fluctuations in financial indicators over time.[8] By applying this method to carbon accounting and sustainability reporting, investors and policymakers can gain deeper insights into the impact of market dynamics and green initiatives on financed emissions and climate-related financial risks.

For $X = xy$, the ME decomposition amounts to

$$\Delta X = (\Delta x)\bar{y} + (\Delta y)\bar{x}$$

where $\Delta x = x_t - x_{t-1}$ and $\bar{x} = \frac{(x_t + x_{t-1})}{2}$.

For $X = xyz$, it can be shown that

$$\Delta X = (\Delta x)\frac{\overline{yz} + 2\bar{y}\bar{z}}{3} + (\Delta y)\frac{\overline{xz} + 2\bar{x}\bar{z}}{3} + (\Delta z)\frac{\overline{xy} + 2\bar{x}\bar{y}}{3}$$

While many other decomposition methods could be applied, the ME decomposition possesses several desirable properties that enhance the interpretability and transparency of portfolio-level carbon analysis for investors. Notably, it ensures additivity, whereby the total change in carbon emissions indicators can be precisely partitioned into distinct, non-overlapping components whose sum equals the overall change. Furthermore, the decomposition exhibits a zero residual property, meaning that the entire variation in the carbon indicator is fully attributable to its underlying drivers, with no unexplained remainder.[9]

[6] However, a limitation is that firms with incomplete data in any period are removed entirely, even if they have complete information in others. This could potentially result in the sample portfolio no longer being representative in the longer run. However, such effects are minimised by estimating missing emissions and financial data. UN-convened Net-Zero Asset Owner Alliance (2023) suggests a dummy variable approach to include data coverage effects in the decomposition.

[7] The ME decomposition is sometimes also referred to as the Bennet decomposition.

[8] For example, Huerga and Steklacova (2008) provide an application focused on interest rates, while Carlino et al. (2017) examine financial ratios among European non-financial listed companies.

[9] For more detail on the mathematical properties of the ME decomposition, see for instance Huerga and Steklacova (2008).

3. Data and scope

This article examines the directly and indirectly financed scope 1 emissions linked to securities portfolios – specifically listed shares and bonds issued by non-financial corporations – held by Belgian deposit-taking corporations except the central bank, insurance corporations, pension funds (collectively referred to as "financial corporations"), and households over the period 2018–2023. By applying a look-through approach, the analysis captures the full carbon footprint associated with both direct holdings and indirect exposures through investment funds.

A comprehensive assessment of financed emissions requires granular, security-level data on the market value of portfolio holdings, combined with firm-level information on company valuations and greenhouse gas emissions. This integrated dataset enables a detailed decomposition of emission trends, offering insights into how investment decisions and portfolio structures influence carbon exposure across different investor types.

Securities information

Security-by-security data used in this analysis is sourced from the European Central Bank's Securities Holdings Statistics by Sector (SHSS), a rich and granular dataset that offers detailed insights into securities held by euro area resident sectors. These holdings are categorised by multiple dimensions, including holder country and sector, instrument type (e.g. listed shares or bonds), and issuer country and sector. This multidimensional structure enables a nuanced understanding of portfolio composition and cross-border investment patterns. While containing security-by-security information, the data are aggregated at the investor sector level, meaning they reflect the holdings of entire investor sectors – such as the Belgian investment fund sector – rather than those of individual funds or investors.

This aggregation introduces a degree of approximation when analysing the securities held by investment funds in which Belgian financial corporations and households are invested. The methodology assumes that the portfolio of investment funds domiciled in a given country is representative of the portfolio of the funds in that country actually held by Belgian investors. While this assumption is necessary due to data limitations, it may obscure fund-level variations in carbon exposure and investment strategy. Nonetheless, the sector-level granularity still provides valuable insights into the broader trends and structural shifts in financed emissions.[10]

We complement the security-by-security holdings data from the SHSS with country-level data from the ECB's Investment Fund Statistics. The Investment Fund Statistics report the total market value of investment fund shares issued by European funds across jurisdictions. By combining these datasets, we determine the ownership shares of Belgian investors in investment funds domiciled in different countries, which are then used to attribute indirect financed emissions accordingly.

Importantly, both SHSS and Investment Fund Statistics distinguish between outstanding stocks and the underlying flows that drive changes in those stocks. These flows are broken down into components such as transactions, price and exchange rate effects, and statistical reclassifications. This distinction is crucial for disentangling the drivers of changes in financed emissions – whether they stem from active investment decisions, market dynamics, or data adjustments – and adds a layer of analytical depth to the decomposition framework.

[10] In future extensions, fund-by-fund data for Belgian investment funds could be used to refine the analysis.

Issuer information

Company-level scope 1 carbon emissions and enterprise value including cash (EVIC) are sourced from the ISS Climate Core dataset, which offers comprehensive coverage of over 25,000 firms worldwide, with annual data available from 2012 onward. The dataset provides absolute emissions and EVIC figures, enabling consistent and comparable carbon metrics across firms and time. Importantly, our analysis relies exclusively on reported emissions, deliberately excluding modelled estimates by the commercial provider to maintain transparency and data integrity. To address gaps in coverage, missing carbon emissions and EVIC values are imputed using standardised methodologies developed by the Statistics Committee Expert Group on Climate Change and Statistics.[11]

Issuer-level information is linked to the securities holdings using matching tables provided by the Expert Group, ensuring accurate alignment between financial instruments and their corresponding corporate entities. This integration of climate and financial data forms the backbone of the financed emissions calculations and supports robust portfolio-level analysis.[12]

4. Results

This section presents the core findings of our analysis of Belgian financial corporations' and households' financed emissions in their corporate securities portfolios. By tracing both direct and indirect holdings, we uncover how investment decisions and portfolio compositions influence carbon exposure over time. The results offer a nuanced view of the drivers behind emission reductions, highlighting the roles of investor behaviour, fund structures, and the evolving carbon footprint of underlying firms.

Directly and indirectly financed emissions

Applying the look-through approach to the corporate securities portfolio of Belgian financial corporations and households shows that for both sectors indirect investments make up a substantial part of the exposure to non-financial corporations (left-hand panel of Graph 1). For financial corporations this mainly occurs through foreign funds, whereas for households the distribution across Belgian and foreign investment funds is more balanced.

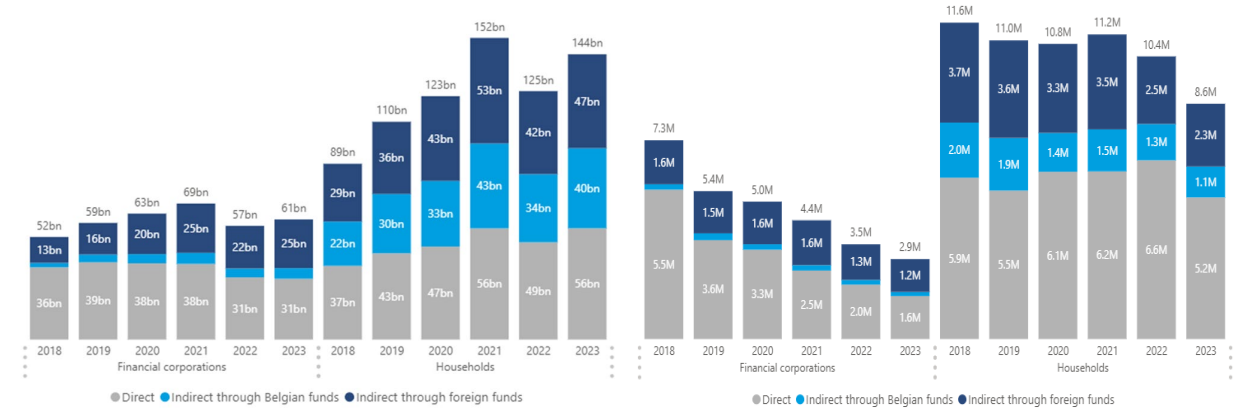
As anticipated, financed emissions increase substantially when indirect investments are included (right-hand panel of Graph 1). Yet, over the sample period, total financed emissions – stemming from both direct and indirect holdings – declined for both financial corporations and households. For financial corporations, this reduction is primarily driven by a decrease in directly financed emissions, which account for 3.9 million of the total 4.4 million ton CO_2e reduction. As a result, the relative share of indirectly financed emissions rose from approximately 25% in 2018 to 45% in 2023. In contrast, households saw a 3 million ton CO2e decline in financed emissions, with indirect investments contributing 2.3 million tons of that

[11] These methods are documented in Statistics Committee Expert Group on Climate Change and Statistics and Working Group on Securities (2024a, 2024b), which outline procedures for estimating missing values while preserving consistency with reported data.

[12] Further technical details and documentation are available in Statistics Committee Expert Group on Climate Change and Statistics and Working Group on Securities (2024a, 2024b).

reduction. This shift led to a decrease in the share of household-financed emissions stemming from indirect holdings, falling from nearly 50% in 2018 to 40% in 2023.

Directly and indirectly financed corporate emissions Graph 1

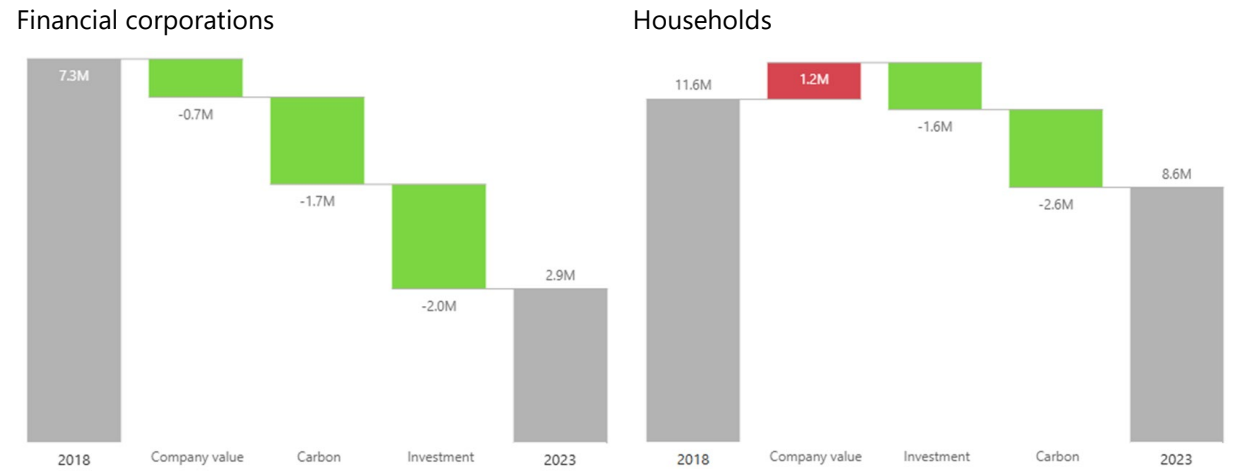


Investment is the market value in EUR at year-end of holdings of listed shares and bonds issued by non-financial corporations after initial data cleaning (e.g. removal of short positions). Financed emissions are scope 1 emissions expressed in tons of carbon dioxide equivalent (CO_2e). Financial corporations include deposit-taking corporations except the central bank, insurance corporations and pension funds.

Source: NBB, ECB, ISS

Delving into the drivers behind this decline (Graph 2), two key factors emerge. First, both financial corporations and households have reduced their exposure to high-emitting firms. This reallocation of investments accounts for a decrease of approximately 2 million tons of CO_2e for financial corporations and 1.6 million tons for households. Second, the non-financial firms held within these portfolios have lowered their greenhouse gas emissions over the sample period, contributing a negative carbon component of –1.7 million tons of CO_2e for financial corporations and –2.6 million tons for households.

Baseline decomposition Graph 2

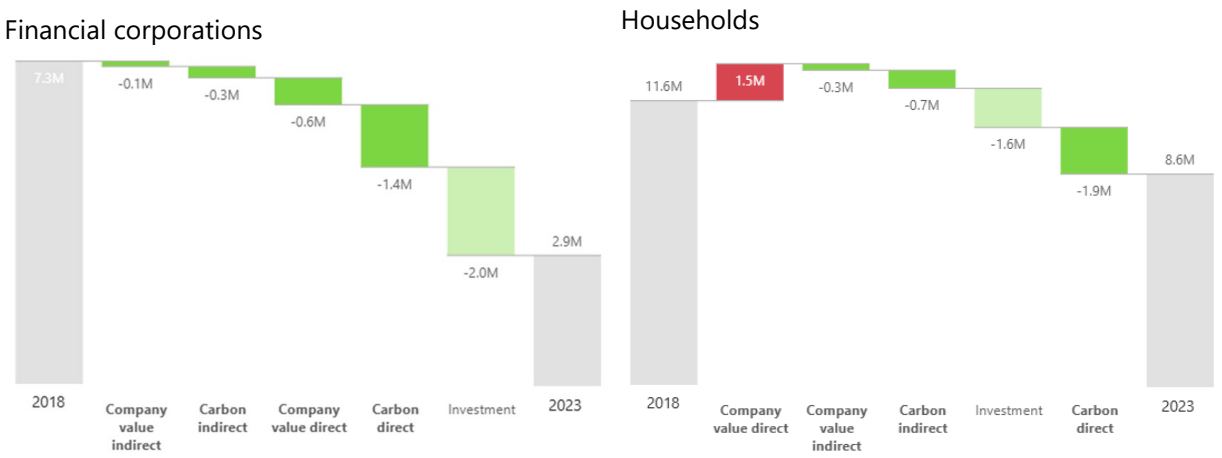


Financed emissions are scope 1 emissions expressed in tons of carbon dioxide equivalent (CO_2e). Financial corporations include deposit-taking corporations except the central bank, insurance corporations and pension funds.

Source: NBB, ECB, ISS

These reductions in financed emissions originate from both direct holdings and indirect investments via funds, though Graph 3 reveals that the bulk of the carbon effect stems from directly held firms. Specifically, over 80% of the 1.7 million ton reduction for financial corporations and nearly 75% of the 2.6 million ton reduction for households are attributable to emission cuts by directly invested companies.

Firm characteristics decomposition — Graph 3

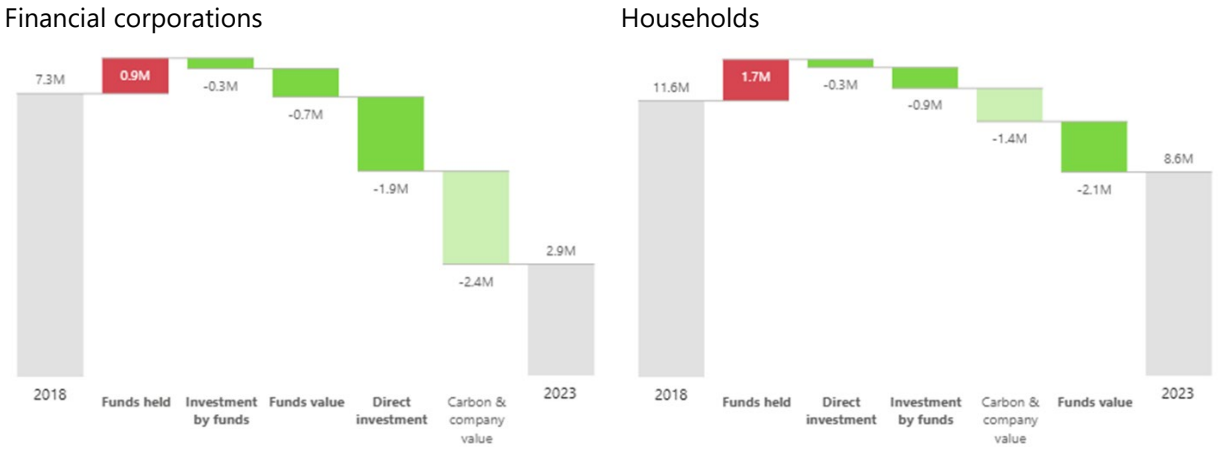


Financed emissions are scope 1 emissions expressed in tons of carbon dioxide equivalent (CO_2e). Financial corporations include deposit-taking corporations except the central bank, insurance corporations and pension funds.

Source: NBB, ECB, ISS

An additional noteworthy observation is that all company value components contributing to changes in financed emissions are negative, except for the one in households' direct portfolios. This may suggest that financial corporations and investment funds actively adjust their portfolios to avoid firms in distress, while households tend to follow a more passive investment strategy.

Investment components decomposition — Graph 4



Financed emissions are scope 1 emissions expressed in tons of carbon dioxide equivalent (CO_2e). Financial corporations include deposit-taking corporations except the central bank, insurance corporations and pension funds.

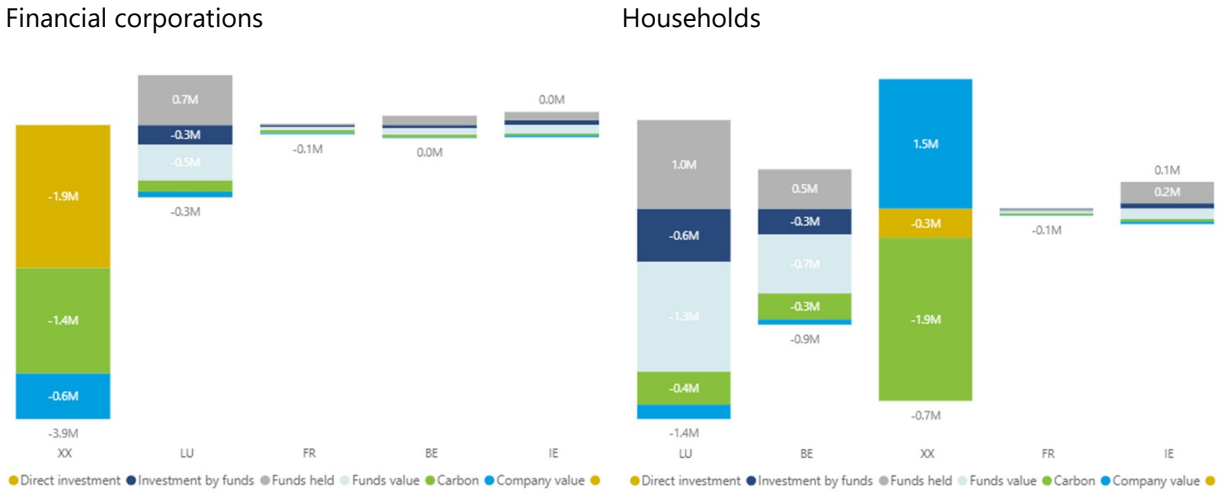
Source: NBB, ECB, ISS

A closer decomposition of the investment component in Graph 2 into direct and indirect effects reveals that the 2 million ton CO_2e reduction in financed emissions by changes in financial corporations' portfolio composition is predominantly driven by adjustments in their direct holdings (left-hand panel of Graph 4). This indicates a reallocation away from high-emitting firms within their directly managed portfolios. In contrast, the decline in household-financed emissions is chiefly attributable to changes in their indirect investments via investment funds (right-hand panel of Graph 4).

Notably, while households have increased their overall investments in funds during the sample period, this has not translated into a proportional rise in financed emissions. This is due to a dilution effect: as the total value of these investment funds has grown, the relative ownership share held by households has diminished. This dynamic results in a net reduction of approximately –0.4 million tons of CO_2e. In addition, the investment funds themselves have shifted their portfolios away from carbon-intensive firms, further reducing household-financed emissions by an estimated –0.9 million tons of CO_2e. Together, these effects underscore the significant role that indirect investment channels can play in shaping the carbon footprint of household portfolios.

Graph 5 provides a detailed summary of our findings by further disaggregating the time series components of financed emissions according to the country of origin of the investment funds held. The right-hand panel reveals that the bulk of the indirect investment effects on households' financed emissions stem from Luxembourgish and Belgian funds, contributing reductions of –1.4 million and –0.9 million tons of CO_2e respectively. This geographic breakdown highlights the pivotal role that cross-border fund allocations play in determining the carbon footprint of household portfolios.

Decomposition by fund country (2018-2023) Graph 5



Financed emissions are scope 1 emissions expressed in tons of carbon dioxide equivalent (CO_2e). Financial corporations include deposit-taking corporations except the central bank, insurance corporations and pension funds. Country "XX" on the x-axis refers to direct holdings.

Source: NBB, ECB, ISS

The granularity of this analysis underscores the analytical precision enabled by the decomposition framework – in combination with a look-through approach – in tracing the evolution of financed emissions. By isolating the impact of specific fund jurisdictions, we gain a clearer understanding of how investment flows across borders contribute to decarbonisation. This level of detail not only enhances transparency but also supports targeted policy interventions and investor strategies aimed at accelerating the transition to a net zero economy.

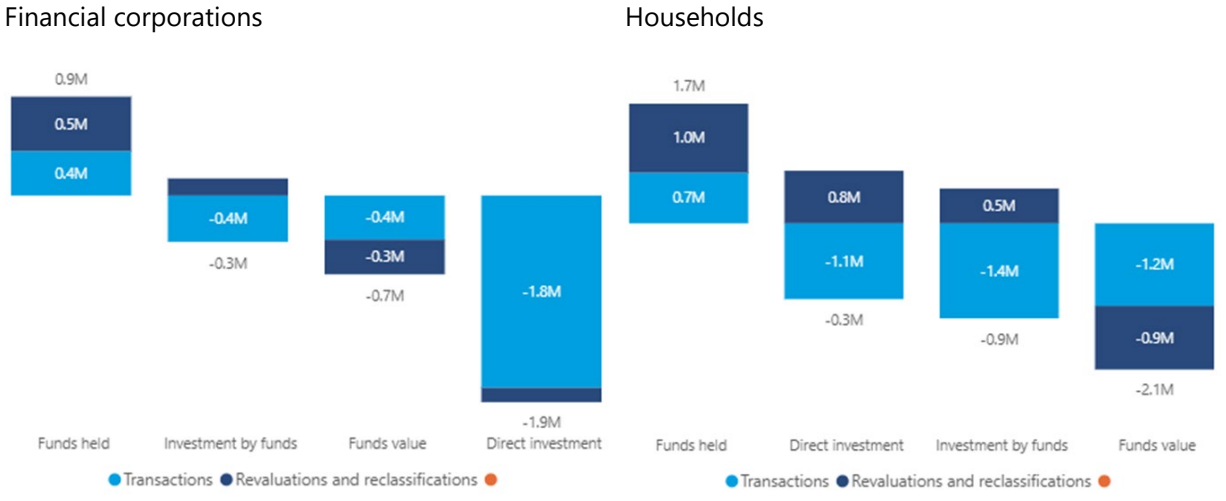
Moreover, the same decomposition logic can be extended to other dimensions of portfolio analysis. For instance, similar breakdowns could be performed by sector or industry of the firms held within the portfolios, revealing which economic activities are most responsive to investor pressure or regulatory shifts. Likewise, country-level emissions effects of the underlying firms could be examined to assess the global reach of domestic investment decisions. These extensions would further enrich the narrative around sustainable finance and provide actionable insights for both policymakers and market participants.

Underlying flows of investment effects

The findings presented in the previous sub-section underscore the influence of investment decisions by financial corporations and households on their financed emissions. Specifically, financial corporations have primarily reduced their exposure to high-emitting firms through adjustments in their direct portfolios. In contrast, households have achieved similar reductions largely through indirect channels, particularly via investment fund holdings.

It is important to recognize, however, that these exposures are measured in market values, which can be influenced not only by actual investment transactions but also by valuation effects. For instance, an investor's exposure may shift due to asset price fluctuations even in the absence of portfolio rebalancing. Additionally, statistical reclassifications – such as correcting a misclassified counterparty from the financial to the non-financial sector – can alter exposure figures without reflecting real-world investment changes. This highlights the need to examine the underlying flows that drive changes in portfolio market values.

Underlying investment flows (2018-2023) Graph 6



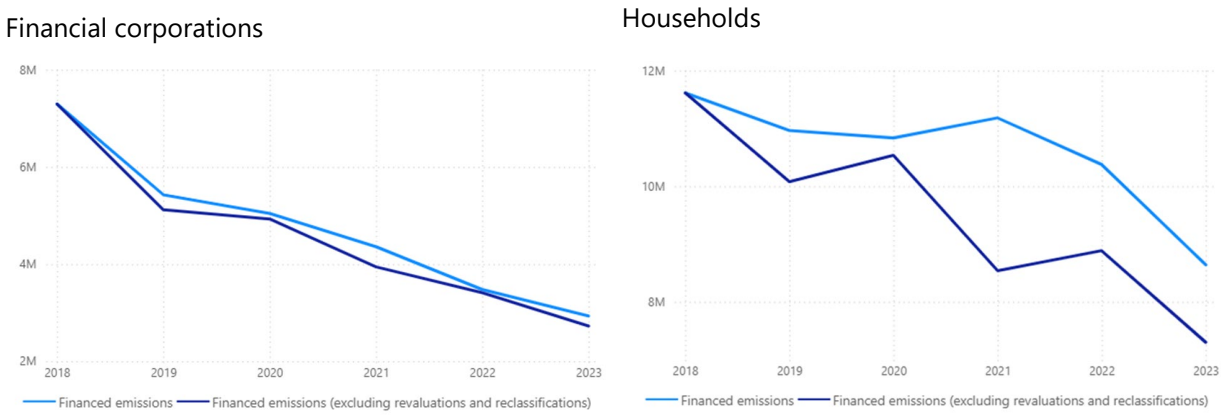
Financed emissions are scope 1 emissions expressed in tons of carbon dioxide equivalent (CO_2e). Financial corporations include deposit-taking corporations except the central bank, insurance corporations and pension funds.

Source: NBB, ECB, ISS

Graph 6 disaggregates the investment components underlying the change in financed emissions shown in Graph 4 into transactions and revaluation and reclassifications. The left-hand panel reveals that nearly the entire reduction in financial corporations' financed emissions stemming from direct investments (1.8 million out of 1.9 million tons of CO_2e) is attributable to investment transactions. This indicates a deliberate shift away from high-emitting firms over the sample period.

For households, a surface-level analysis of market value changes (Graph 4) might suggest little movement away from high-emitting firms in their direct portfolios. However, the right-hand panel of Graph 6 tells a more nuanced story; direct transactions led to a substantial reduction in financed emissions (–1.1 million tons of CO_2e), nearly matching the impact of investment fund reallocations. Yet, this effect was offset by positive valuation changes (+0.8 million tons of CO_2e) in households' direct holdings. These findings reinforce the importance of analysing investment flows alongside stock data to accurately assess portfolio decarbonisation. Based on flow data, households did actively steer their direct investments away from high-emitting firms.

Financed emissions: excluding revaluations and reclassifications — Graph 7



Financed emissions are scope 1 emissions expressed in tons of carbon dioxide equivalent (CO_2e). Financial corporations include deposit-taking corporations except the central bank, insurance corporations and pension funds.

Source: NBB, ECB, ISS

The preceding analysis raises an important question: how would financed emissions appear if we excluded revaluation and reclassification effects from the picture? Graph 7 provides a compelling answer. For financial corporations, these effects have minimal influence over the sample period, suggesting that changes in financed emissions are largely driven by actual investment decisions. In contrast, for households, abstracting from revaluation effects leads to a significantly lower estimate of financed emissions, revealing that valuation changes can obscure the true impact of portfolio shifts.

This distinction underscores a broader methodological challenge in monitoring carbon footprints of investment portfolios, namely the importance of correcting for inflation and exchange rate effects when calculating carbon metrics over time.[13] However, the findings here suggest that inflation correction to firms' financials alone is not sufficient. Revaluation effects – stemming from asset price fluctuations unrelated to investor actions – can similarly distort the interpretation of carbon metrics.

5. Concluding remarks

As the financial sector advances toward a net-zero future, the tools wielded by today's carbon trackers must be as sharp as those of any lawman riding the plains. The decomposition method applied in this article, paired with a look-through approach, offers a powerful framework for tracing the carbon trails left

[13] Inflation and exchange rate adjustments ensure that changes in carbon indicators reflect real economic activity rather than nominal price movements (see e.g. Janssen et al. (2022), Shimfe et al. (2024) and Statistics Committee Expert Group on Climate Change and Statistics and Working Group on Securities (2024a)).

by investment portfolios. By disentangling the effects of firms' financials, their carbon reductions, investment flows and revaluation dynamics, this toolkit enhances transparency and supports more informed investment strategies.

A key methodological insight is the importance of accounting for revaluation effects. While inflation adjustments are increasingly used to refine carbon metrics, they alone may not capture the full picture. Revaluation effects can similarly distort the interpretation of portfolio decarbonisation, highlighting the need for more nuanced approaches in carbon accounting. Adjusting for revaluation effects enables a more accurate attribution of changes in a portfolio's carbon profile to genuine investment decisions, rather than to shifts in asset valuations beyond investor control. By equipping investors and policymakers with sharper tools and clearer metrics, we can ensure that the journey toward a net-zero economy is guided not only by ambition, but by analytical precision.

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Marshall Edgeworth: Riding the carbon trails of the great investment plains

Stijn Ferrari | IFC Satellite Seminar on “Sustainability data issues and central banks”, 4 October 2025, Amsterdam

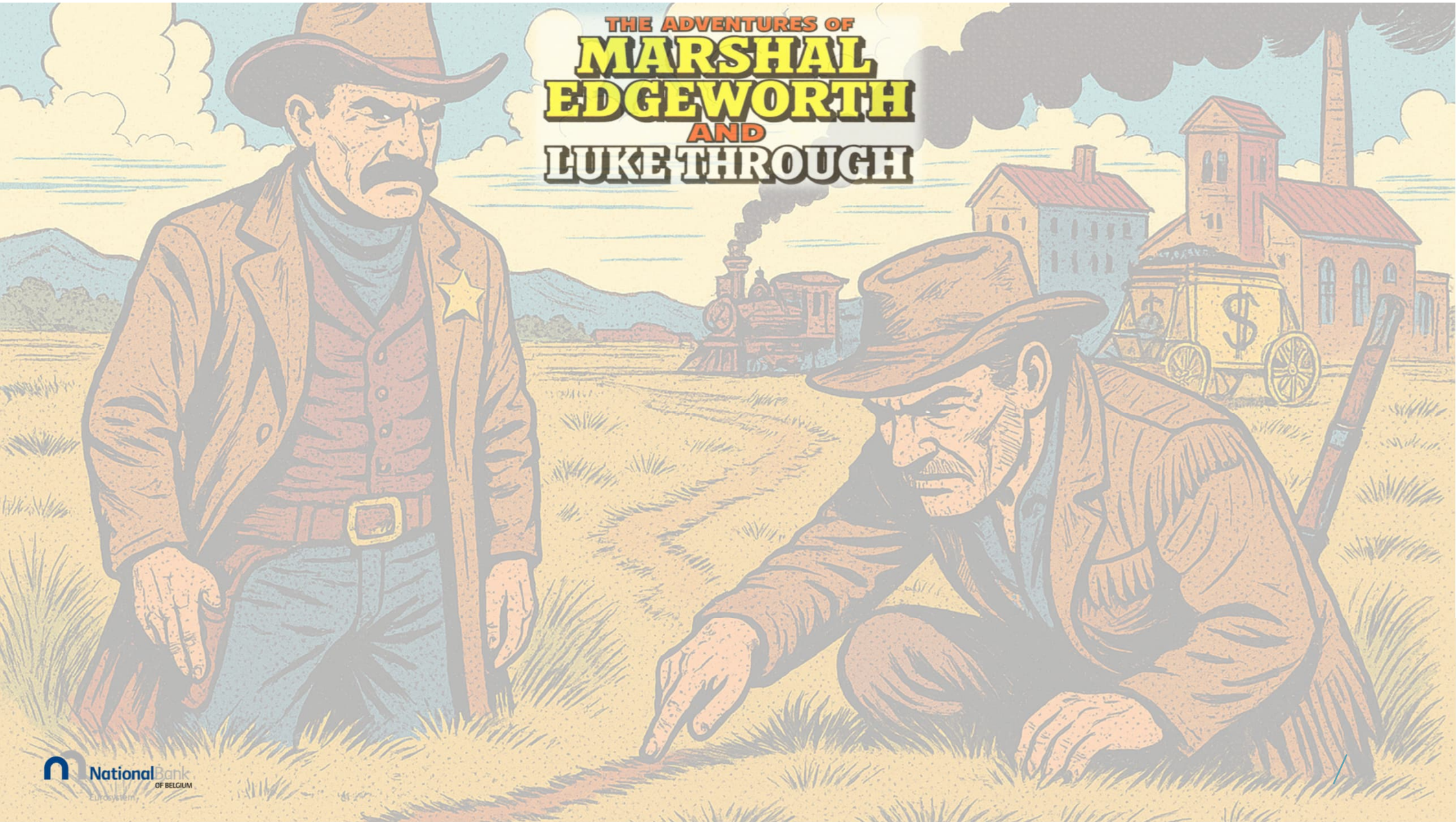
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Eurosystem



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The results in this study may deviate from official statistics published by the National Bank of Belgium and the European Central Bank.



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Eurosystem



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Eurosystem


THE ADVENTURES OF
MARSHAL EDGEWORTH
AND
LUKE THROUGH
Carbon profile of investment portfolios
Marshall-Edgeworth decomposition
Look-through approach



Toolkit for investors and financial supervisors (including central banks) for

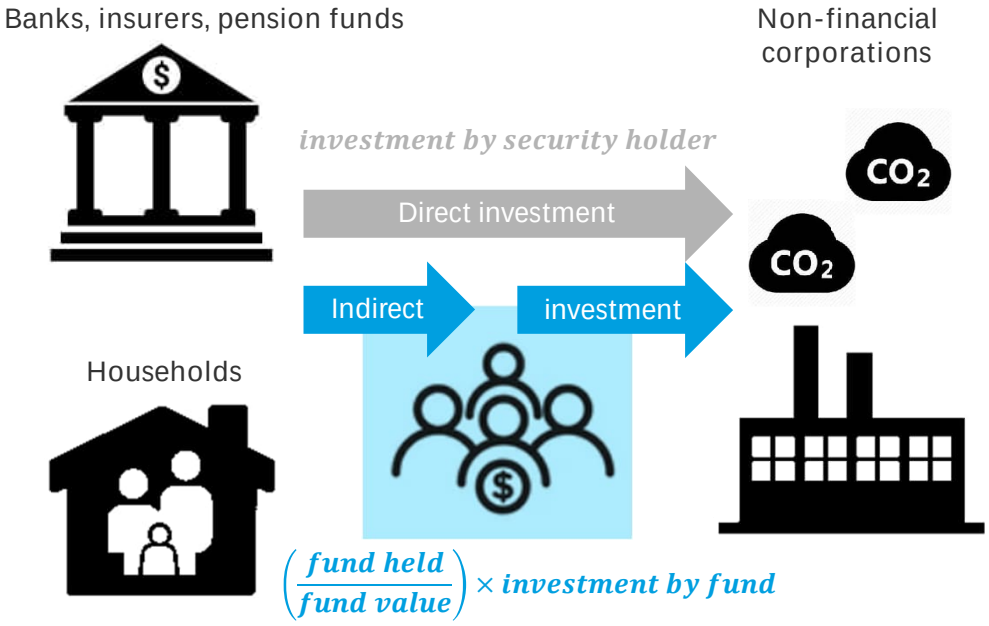
1. Monitoring investment portfolios' carbon profile and exposure to transition risk
2. Evaluating the greening of the financial sector and its contribution to a net zero economy
3. Facilitating data validation and storytelling



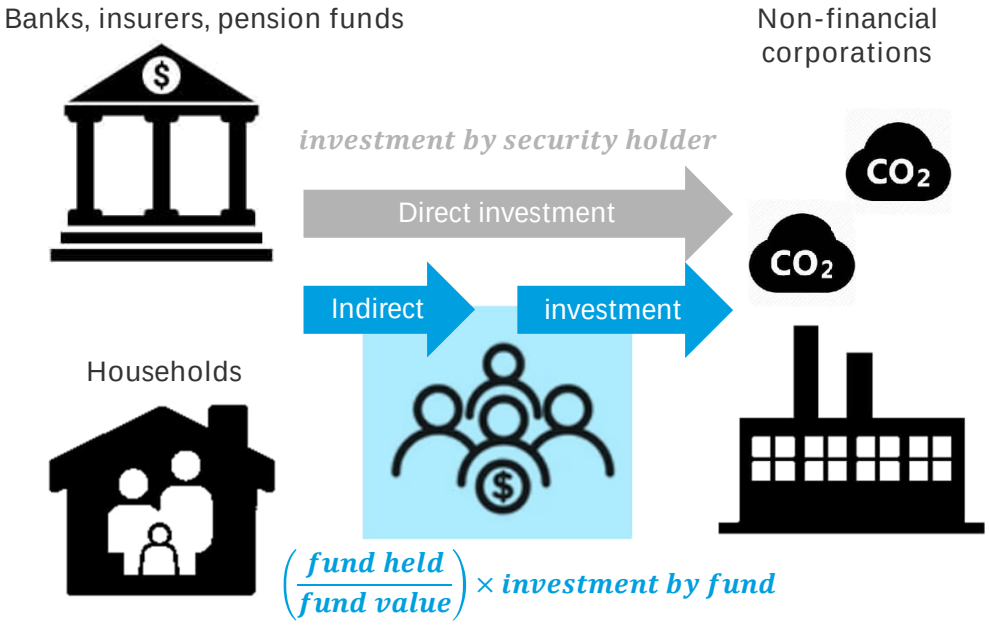
Key insights on corporate emissions financed by Belgian financial corporations' and households

1. Corporate securities portfolios held by Belgian financial corporations and households are showing a decline in financed emissions
2. Including indirect investments significantly increases corporate financed emissions
3. Emission reductions by directly invested firms have beneficial impact on financed emissions
4. Direct investment transactions drive down emissions financed by financial corporations
5. Indirect investments via Luxembourgish and Belgian funds play a key role in reducing household-financed emissions…
6. … though aligned direct transactions highlight the need to examine underlying flows

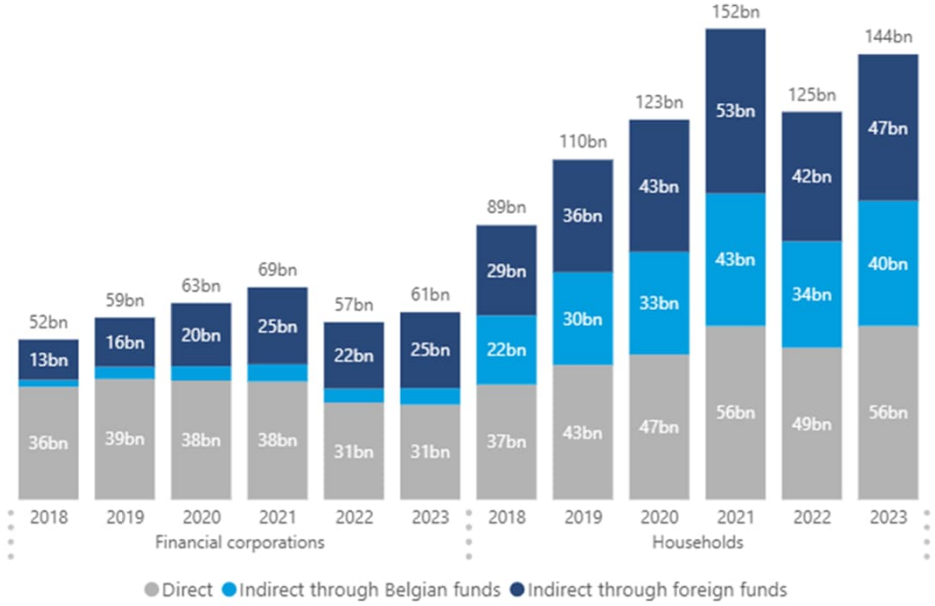
Belgian financial corporations and households hold corporate securities both directly and through funds



Belgian financial corporations and households hold corporate securities both directly and through funds



Direct and indirect investment in non-financial corporations



Source: NBB, ECB, ISS

Including indirect investments significantly increases corporate financed emissions

Financed emissions

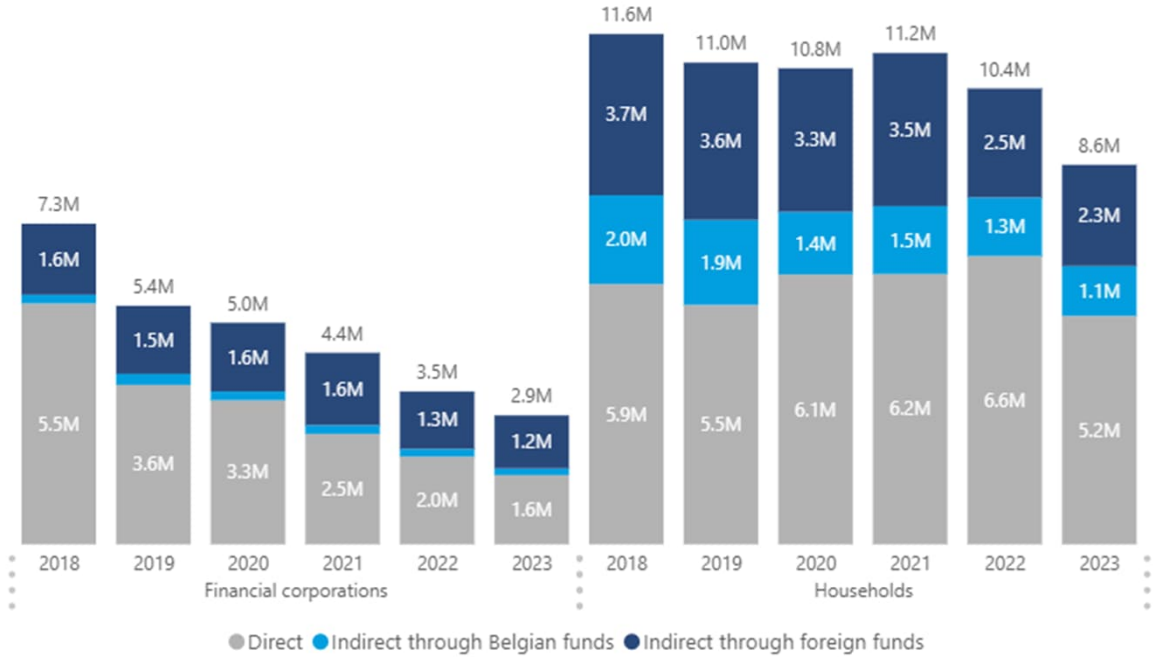
$$= \boldsymbol{carbon\ emissions} \times \left(\frac{\boldsymbol{investment}}{\boldsymbol{company\ value}} \right)$$

Including indirect investments significantly increases corporate financed emissions

Financed emissions

$$= \boldsymbol{carbon\ emissions} \times \left(\frac{\boldsymbol{investment}}{\boldsymbol{company\ value}} \right)$$

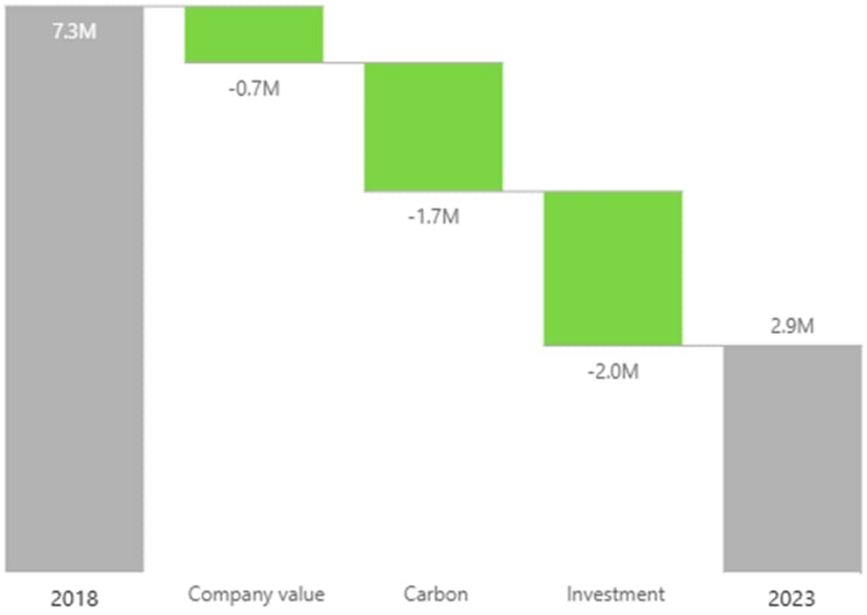
Directly and indirectly financed corporate emissions (scope 1)



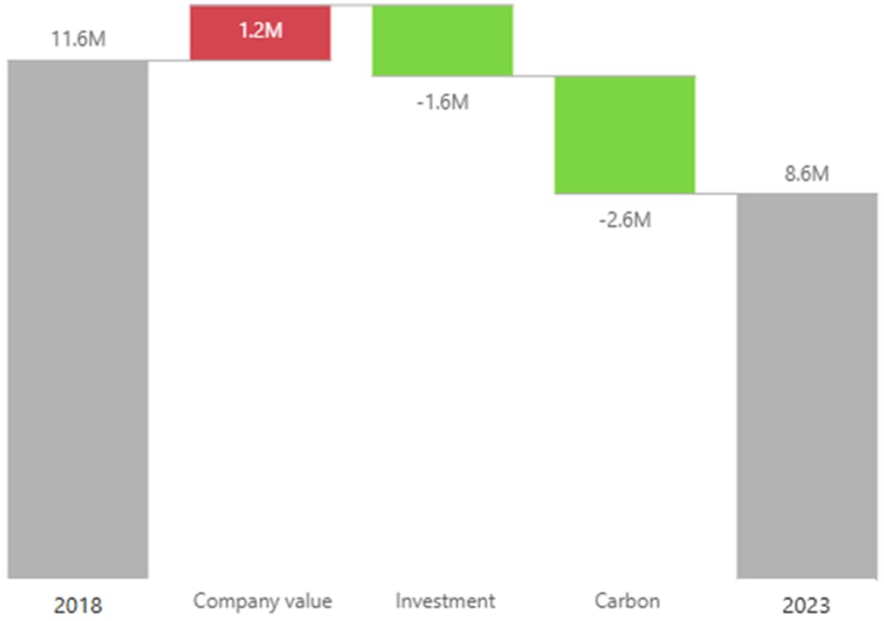
Source: NBB, ECB, ISS

Investment decisions and carbon emission reductions are the main drivers of declining financed emissions

Financial corporations: baseline decomposition



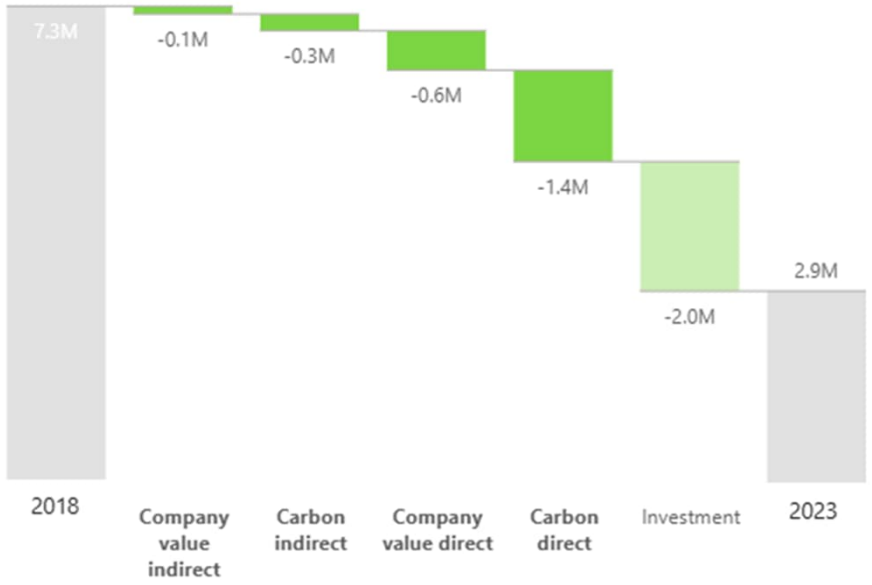
Households: baseline decomposition



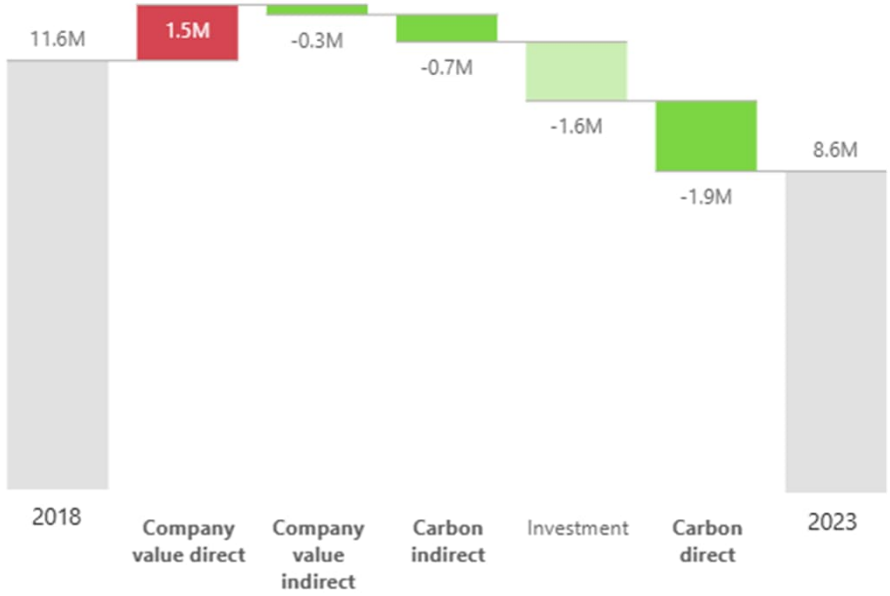
Source: NBB, ECB, ISS

Beneficial impact of emission reductions stems mainly from directly invested firms

Financial corporations: firm characteristics decomposition



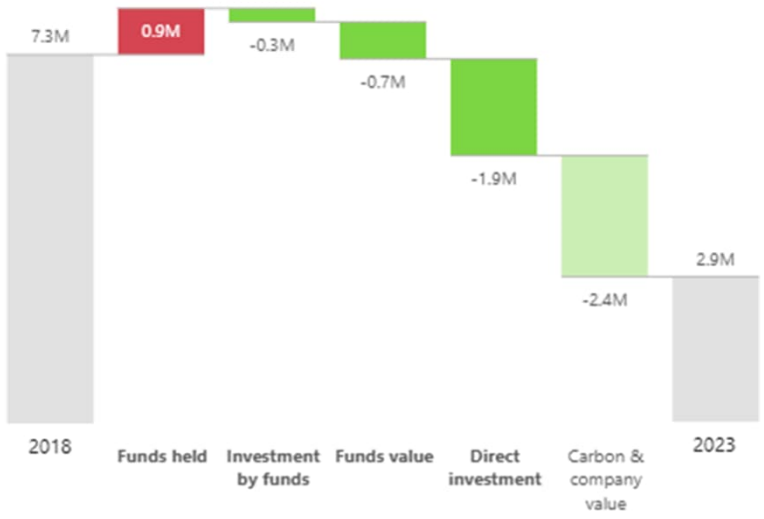
Households: firm characteristics decomposition



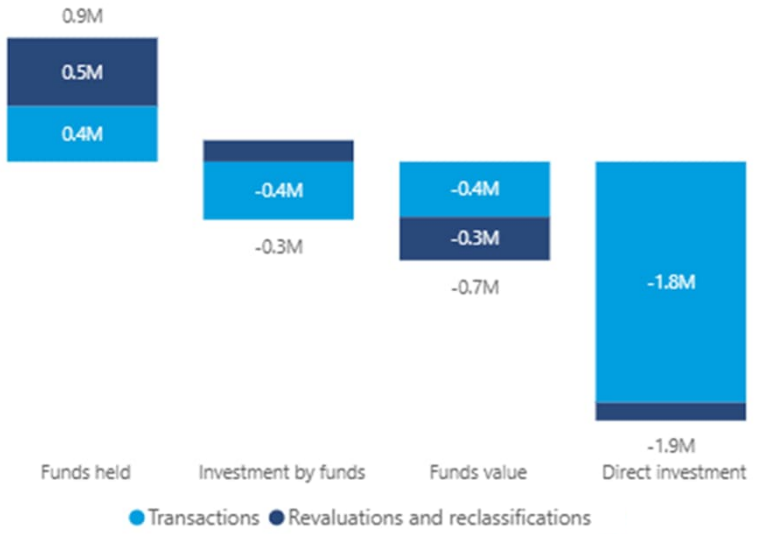
Source: NBB, ECB, ISS

Direct investment transactions have most pronounced impact on emissions financed by financial corporations

Financial corporations: investment components decomposition



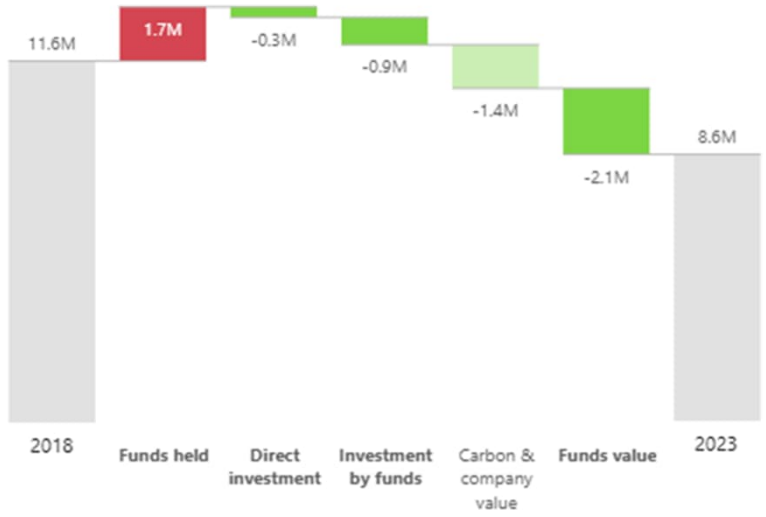
Financial corporations: underlying investment flows (2018-2023)



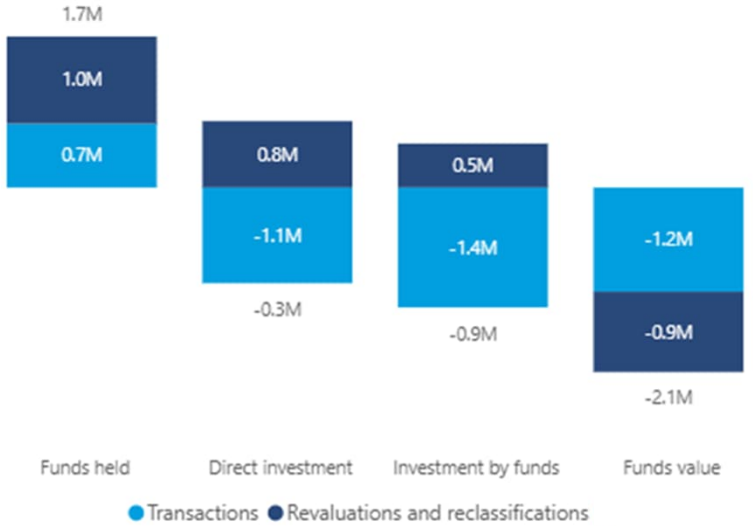
Source: NBB, ECB, ISS

Indirect investments play a key role in reducing household-financed emissions, though aligned direct transactions highlight the need to examine underlying flows

Households: investment components decomposition



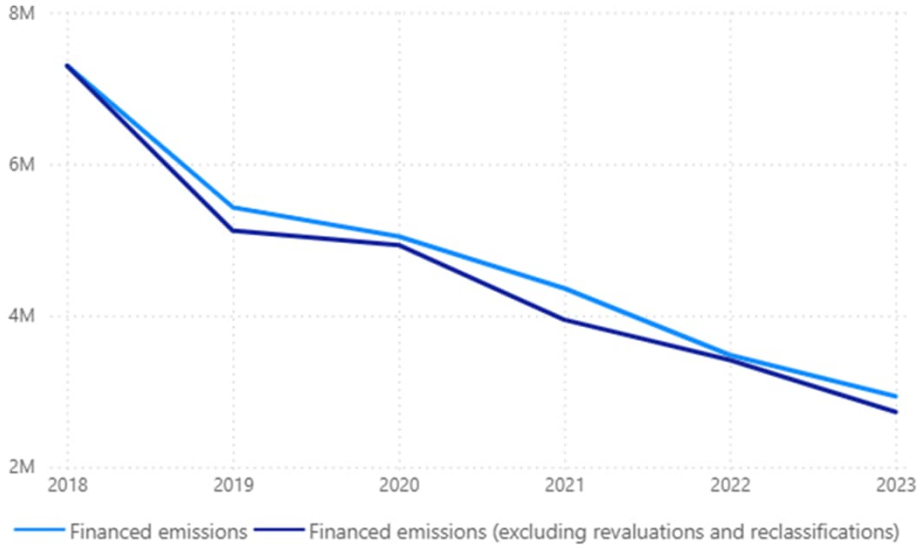
Households: underlying investment flows (2018-2023)



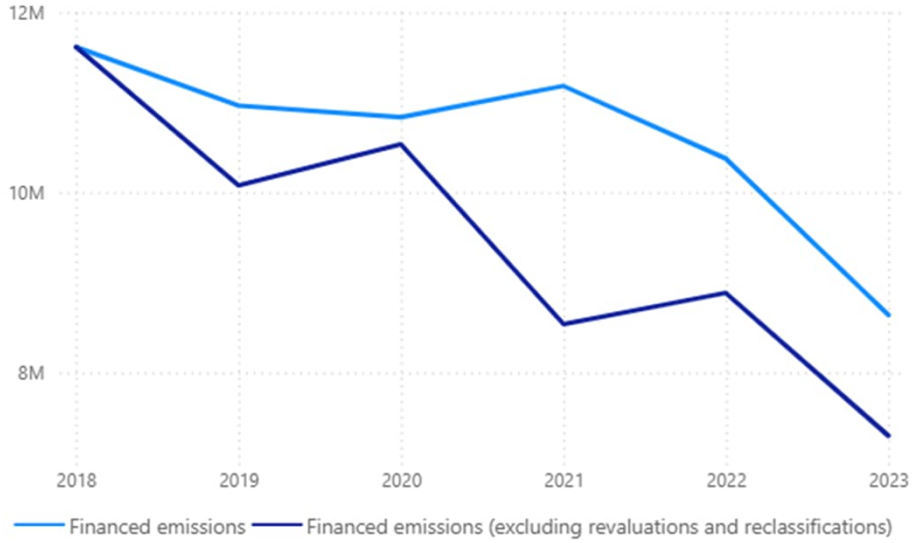
Source: NBB, ECB, ISS

Filtering out revaluation and reclassification effects reveals even stronger decline in financed emissions

Financial corporations: excluding revaluations and reclassifications



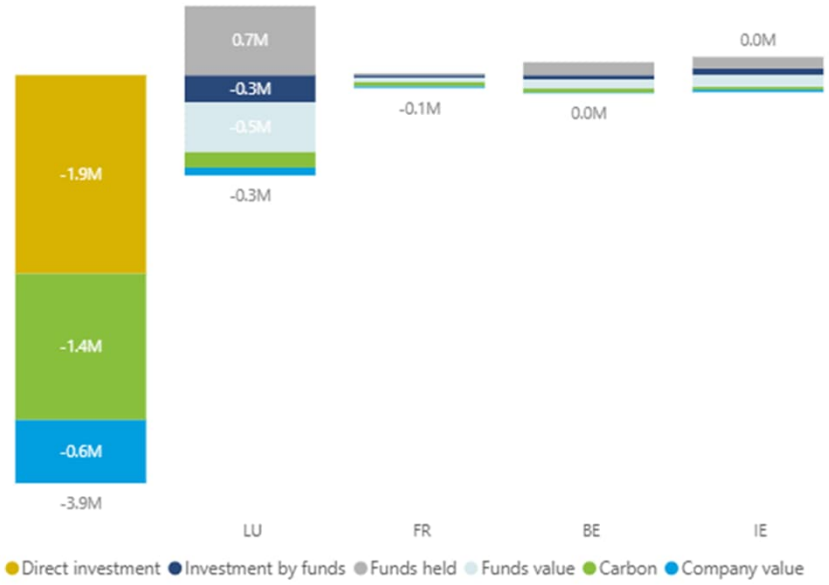
Households: excluding revaluations and reclassifications



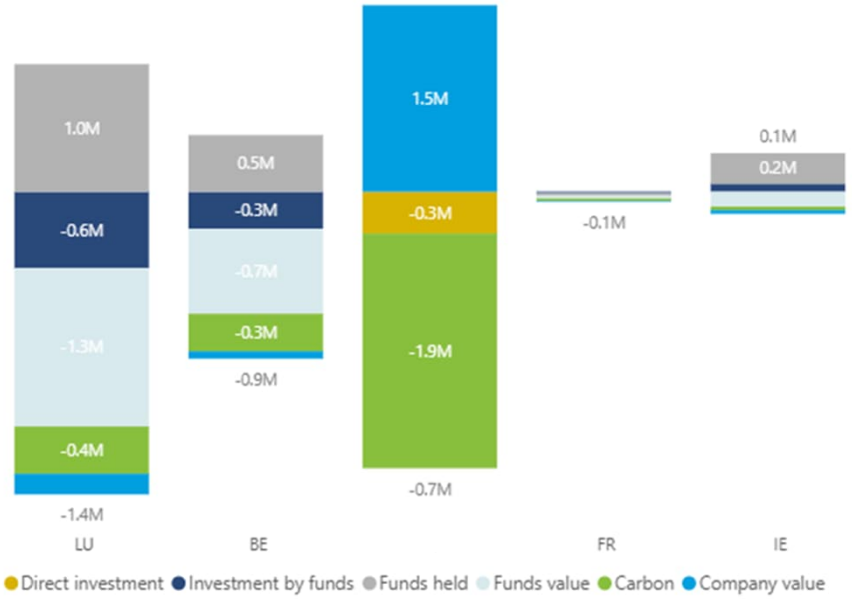
Source: NBB, ECB, ISS

The marshal and his tracker: precision in pursuit along the carbon trails of the great investment plains

Financial corporations: decomposition by fund country (2018-2023)



Households: decomposition by fund country (2018-2023)



Source: NBB, ECB, ISS

CONCLUSIONS AND WAY FORWARD

The Marshall-Edgeworth decomposition provides a powerful framework for monitoring the carbon profile of investment portfolios

Way forward

1. Data improvements (e.g. holdings of individual (Belgian) funds rather than sectoral holdings)
2. Application to other carbon measures (e.g. weighted average carbon intensity)
3. Further deep-dives for data validation (e.g. assessing impact of data imputations) and storytelling

Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

The sustainable data gap in Italy

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This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

The sustainable data gap in Italy

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Abstract

Monitoring climate-related and environmental financial risks requires access to high-quality, highly granular data. However, such data remain scarce and are typically available only for a limited number of counterparty firms. This paper updates the previous work by Lavecchia et al. (2022), providing new evidence on the sustainable data gap in Italy. First, we take stock of the data needs arising from firms' transition plans, net-zero commitments, and financial analyses, as well as from international, European, and national regulations and supervisory requirements. Second, we map the existing data sources related to energy use, greenhouse gas (GHG) emissions, climate indicators, physical and transition risks, and climate scenarios, among others. Finally, we identify the areas where further research is most needed.

Keywords: Sustainable data gap · Climate change · Sustainable finance · Physical risk · Transition risk · Italy · GHG emissions · Energy

JEL classification: C81, Q54, Q48.

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1. Introduction[1]

In the decade following the adoption of the Paris Agreement, global climate commitments and policy actions have proven sufficient to avert the worst-case scenario of a 4°C temperature increase relative to pre-industrial levels. The most recent assessments indicate that the world is currently on a trajectory consistent with an approximate 2.8°C rise by 2100 (UNEP, 2025). Notably, for the first time, the United Nations Framework Convention on Climate Change (UNFCCC) has projected an absolute decline in total global greenhouse gas (GHG) emissions by 2035, estimating a 10% reduction relative to 2019 levels.

Between 2014 and 2024, cumulative global investments in clean energy technologies—including renewable energy, electrification, and energy efficiency—exceeded USD 10 trillion. These sectors now account for slightly more than two-thirds of total energy investments worldwide (IEA, 2025). Despite this significant capital reallocation, current mitigation efforts remain insufficient to achieve the temperature targets established under the Paris Agreement. In 2024, global GHG emissions increased by 2.3%, reaching 57.7 $GtCO_2e$. This growth rate is approximately four times the average annual rate observed over the previous fifteen years and mirrors levels characteristic of the early 2000s (UNEP, 2025).

The underlying drivers of these emissions rebound remain uncertain but are likely multifaceted, encompassing both shortcomings in the design and implementation of climate policies and a potential decline in the effectiveness of natural carbon sinks. Furthermore, the second withdrawal of the United States from the Paris Agreement, coupled with the collapse of a long-negotiated international accord to reduce shipping-sector emissions, underscores the growing fragmentation of global climate governance.

Such developments point toward an increasingly disorderly transition, characterized by asymmetric regional trajectories—where some economies accelerate decarbonization due to technological or economic advantages, while others remain dependent on fossil fuel–based growth models. This emerging divergence has led some observers to describe the situation as an "ecological cold war[2]", reflecting the geopolitical tensions surrounding the global energy transition.

Overall, these dynamics suggest that both physical and transition-related climate risks are likely to intensify, with significant implications for economic systems, financial stability, and corporate strategy over the coming decades.

Several institutional investors have devoted substantial resources to assessing the exposure of their portfolios to physical climate risks[3]. While both demand and supply for asset-level climate risk data have expanded in recent years, these developments remain insufficient to support comprehensive risk evaluation. Investors frequently report that, despite the increased availability of data, determining the materiality of specific assets to overall portfolio risk remains difficult. Persistent information gaps—especially concerning climate vulnerability across value chains and the effectiveness of existing adaptation measures—continue to constrain robust analysis.

Lavecchia et al. (2022) define the deficiencies in the availability, usability, accessibility, and reliability of information relevant to climate change and sustainable finance analysis as the *sustainable data gap*. Legislative initiatives aimed at expanding sustainability reporting are expected to mitigate this gap; however, a recent global retrenchment has been observed, largely due to concerns regarding increased compliance costs. At the same time, commercial data providers continue to invest in this area

[1] The views expressed are those of the authors and do not involve the responsibility of the institutions to which they belong. Corresponding author: Luciano Lavecchia (luciano.lavecchia@bancaditalia.it).

[2] The Coming Ecological Cold War, Foreign Policy, 1 September 2025.

[3] Physical climate risk data: The more you learn, the less you know, Responsible investor, 5 November 2025.

by exploiting new analytical techniques and datasets. Nevertheless, as previously noted, substantial progress remains necessary.

Enhancing the global climate data architecture has therefore become a critical priority. Achieving this objective requires (1) the provision of reliable, comparable, and high-quality data, and (2) the development of harmonized information disclosure standards for climate risks that are as uniform as possible at the global level.

More specifically, ensuring the quality and comparability of climate-related data will depend on three key actions: (1) the rapid adoption of shared disclosure practices at the global level; (2) the establishment of a basic global taxonomy—or at least a common set of classification principles—for sustainable finance; and (3) the development and application of transparent metrics, certifications, labels, and methodologies.

This paper reviews the data necessary to analyse sustainability risks, with a particular focus on climate-related risks (Sect. 2). It then outlines the data required from banks, insurance companies, and other financial institutions operating in Italy to comply with transparency obligations under the current financial regulatory framework (Sect. 3). Subsequently, it examines the existing datasets that could substantially contribute to narrowing the sustainable data gap in Italy (Sect. 4). The paper concludes with a summary identifying the areas in which data deficiencies are most concentrated.

2. The Data required for the financial and economic analyses of Climate Risks

Climate-related financial risks (CRFRs) are commonly classified into physical and transition risks. Physical risk arises when acute or chronic extreme weather events damage the assets and infrastructure of households and firms or impair their capacity to generate income. These repercussions may also affect the financial system, either directly or indirectly, through multiple transmission channels, as described in the Basel Committee's analysis.

Transition risk, by contrast, refers to the potential devaluation of the production and financial assets of carbon-intensive firms or, more broadly, firms relying on "brown" technologies and products. This risk may stem from the abrupt implementation of policies affecting the cost or use of fossil fuels, disruptive technological innovations, or shifts in investor and consumer preferences, generating stranded assets. Transition-oriented policies generally aim to modify the relative prices of energy inputs, rendering carbon-intensive sources less affordable. In the short to medium term, such measures typically increase costs for firms and households, reflecting the need to finance new investments in green technologies, the introduction of carbon pricing mechanisms, and the write-off of stranded assets—investments whose value cannot be recovered and which might accrue to large sums (Carbon Tracker, 2022).

The economic risk faced by an individual agent or business due to a climate shock — physical or transitional — can be expressed as the product of three factors: (1) the likelihood of an adverse event (hazard), (2) the value of the exposed activities (exposure), and (3) the expected loss per unit exposed (vulnerability).

Hazard denotes the probability that an extreme natural event occurs (in the case of physical risk, e.g., floods or landslides) or that new regulations are introduced (in the case of transition risk). Assessing physical risk requires detailed hazard maps that capture the likelihood of extreme weather events linked to climate change, using data as granular as possible. Current classifications are often limited to the provincial or municipal level, a restrictive approximation assigning uniform hazard levels to broad areas.

Ideally, risk classification grids should reach higher spatial resolution (e.g., address or coordinates at plant level[4]), and firm-level geolocation data should be matched with financial information to accurately link risks and exposures. Furthermore, as climate change increases the probability of certain events relative to historical baselines, forward-looking data are essential; reliance solely on historical records poses the risk of systematic underestimation (FSB, 2021).

For transition risk, hazard analysis is typically conducted at the sectoral level, assessing the probability of exposure to policy and regulatory shifts, such as carbon pricing or technology bans. However, sectoral data alone are insufficient, as firms within the same industry may exhibit markedly different emission profiles, a fact that incidentally also underscores the importance of a comprehensive value-chain analysis.

The second component, exposure, measures the economic value of the activities potentially affected. While banks can generally ascertain the value and location of collateralized property owned by households, estimating firms' exposure is more complex. Business registries often provide only the address of administrative offices, rarely including detailed information on production sites, asset values, or turnover. One proxy for exposure is the distribution of employees across geographic areas or production facilities (Meucci and Rinaldi, 2022). For transition risk, exposure depends on sectoral carbon intensity, technological choices, and firm-specific emissions profiles. Ideally, data should include greenhouse gas (GHG) emissions and the firm's energy mix, to evaluate how changes in energy costs might affect financial performance. Yet only a limited number of firms currently disclose such data (see Paragraph 3). Estimating firm-level emissions remains challenging due to insufficient data on energy consumption, raw material use, and process-specific emission factors, particularly for Scope 3 emissions (Busch et al 2022). Advanced machine learning methods can help estimate ESG indicators, especially for equity portfolios (Lanza et al 2020), though they require high-quality training data. Well-designed surveys may, in some cases, yield more accurate results than large-scale data methods, reflecting the so-called big data paradox (Bradley et al 2021).

The final component, vulnerability, represents the expected loss per unit of exposure and captures the share of value lost after an extreme event has materialized. This measure should account for insurance coverage, which can reduce expected losses for intermediaries but simultaneously increase insurers' exposure, particularly when their portfolios are concentrated in affected areas. Assessing vulnerability thus requires information on the protection gap — the difference between total and insured losses — at both firm and macro levels. Such data are typically unavailable, especially at micro scales (Faiella and Lavecchia, 2025). Moreover, not all assets are equally affected by climate events; for instance, floods may damage only the lower floors of buildings. This level of detail, crucial for accurate vulnerability estimation, remains difficult to obtain.

3. The Data Necessary for Financial Intermediaries to Respond to Requests from Supervisors

The General Framework. The role of the financial system in the ongoing transition process is crucial, both to channel financial flows towards a more sustainable economic system and to prevent and mitigate the related risks. The different authorities involved in the various aspects of climate risk and sustainability

[4] Analyses typically focus on firms' headquarters, yet data on local units are crucial for accurately assessing firms' and lenders' exposure (see Loberto and Russo, 2024, on Italian manufacturing firms' exposure to hydrogeological risk).

regulation are making considerable efforts to align legislation and requests to intermediaries wherever possible.

The ECB has included climate and environmental risks among its supervisory priorities and monitors their impacts on significant banks in the euro area. In its 2020 guide to significant banks, the ECB set out its expectations for sound and prudent management of climate and environmental risks, providing non-prescriptive guidance on how to incorporate such risks into the business model, strategic, governance and risk management processes, as well as in the required disclosures to the public. The guide provides practical examples of how to use the existing regulatory framework to integrate climate risks into intermediaries' management processes.

Sustainable finance is a strategic priority area in EIOPA's action plan[5] for the coming years, aimed, in particular, at (i) integrating ESG risks into the prudential framework of Solvency II [6], (ii) supporting the supervision of ESG risks in micro and macroprudential analyses with a view to financial stability and the convergence of supervisory approaches in the EU[7], (iii) promoting disclosure and sustainable business models, (iv) addressing the climate risk insurance protection gap in Europe and (v) promoting the use of open-source models and data concerning the risks associated with climate change.

Entities subject to authorization and supervision by Banca d'Italia are required to comply with the supervisory expectations on climate and environmental risks, published by Banca d'Italia on 8 April 2022 (Banca d'Italia, 2022), regarding the integration of climate and environmental risks into their business strategies, governance, control and risk management systems, as well as market disclosures. These expectations are quite general, and the formalization of the underlying principles at the operational level is deferred to individual intermediaries, who are therefore required to conduct in-depth analyses and assessments to determine the materiality of their risk exposure. Based on these analyses, intermediaries will be able to apply the principle of proportionality, considering their complexity.

Insurance-Specific Surveys. The insurance undertakings supervised by IVASS are required to comply with the Solvency II framework, the prudential regulation of the insurance sector, and the provisions issued by IVASS on the integration of ESG risks into the governance and risk management system, as well as the control and governance requirements for insurance products qualified as 'sustainable'. In 2022, IVASS launched an annual monitoring on natural catastrophes risks and sustainability addressed to all insurers operating in Italy. The Survey consists of quantitative data (as of the end of the previous financial year) on exposure to physical risks in non-life insurance business and transition risks in investment portfolios; and qualitative information (as of the end of the current year) on governance, risk management and the use of climate risk scenarios analysis within the own risk solvency assessment (ORSA).

The monitoring is aimed at collecting hard evidence for the following purposes: (i) assessing the potential impacts of transition risks and physical risks at micro- and macroprudential level on insurers; (ii) identifying vulnerabilities that could affect financial stability, (iii) monitoring the level of natural catastrophe insurance penetration and the protection gap for residential and commercial properties at nationwide, (iv) verifying consistency between national regulations and European legislation and (v)

[5] EIOPA sets out its strategy for 2023 – 2026 (link) to contribute to building up sustainable insurance and pensions, including by addressing protection gaps, for the benefit of citizens and businesses.

[6] See, EIOPA Consultation paper on the proposal for Regulatory Technical Standards (RTS) on management of sustainability risks including sustainability risk plans (December 2024). The Solvency II Directive requires undertakings to implement specific plans to address the financial risks from sustainability factors and mandates EIOPA to specify the elements of the sustainability risks plans (link).

[7] See, EIOPA Opinion on the supervision on the use of climate change risk scenario in own risk solvency assessment (ORSA), (2021) and the Application guidance on how to reflect climate change in aimed mainly at small and medium-sized insurers (2022).

supporting sustainable finance initiative at national and international level. The main results of the survey are published annually (IVASS, 2025).

Disclosure Requirements. Filling the sustainable data gap requires not only an improvement in the statistical coverage of phenomena affecting sustainability and climate risks, but also common and well-defined reporting standards (for further details see Loizzo and Schimperna, 2022). This requires improving transparency and reporting (disclosure), i.e., the dissemination by companies of basic information about the potential risks they face and the effects of their activities (the 'double materiality'). In terms of improved transparency, the international financial community 'institutionalized' the topic of climate risks by establishing the Task Force on Climate-Related Financial Disclosures (TCFD) in December 2015. Since then, reporting requirements for non-financial and financial companies have become increasingly stringent. To complicate things further, the enforcement of these requirements varies according to the scope of the regulatory framework, including the transparency of financial investments (see Lavecchia et al. 2022 for a review).

In Europe, the regulation of non-financial reporting has been innovated with the publication of the Corporate Sustainability Reporting Directive (CSRD)[8] which extended the scope to almost 50,000 companies in the EU (from the previous 11,700) and to about 8,500 in Italy (from the previous 210[9]). However, as part of the process of simplifying and revising the CSRD promoted by the Omnibus package, the European Parliament recently endorsed reduced reporting duties, limiting the scope only to companies employing on average over 1,000 employees and with a net annual turnover of over €450 million. Moreover, the European standards for non-financial disclosure would also be simplified.

Concerning transparency in financial investments, the Sustainable Finance Disclosure Regulation (SFDR; 2019/2088), in force since 10 March 2021, aims to increase and standardize the reporting requirements of ESG investment processes for financial market participants both at entity and product level[10].

The European Taxonomy of Sustainable Investments To foster market confidence and reduce the risk of greenwashing, the Taxonomy Regulation (2020/852), which entered into force on 12 July 2020, introduces a classification system that defines an economic activity that meets specific requirements as environmentally sustainable; furthermore, Art. 8 of the regulation, as supplemented by Delegated Regulation (EU) 2021/2178, sets precise reporting requirements (which apply to undertakings within the scope of the CSRD) in the context of pre-contractual information and periodic reports. As for the CSRD, the Taxonomy framework is under review as part of the Omnibus package.

Pillar 3 Disclosure Requirements As part of the prudential regulation of the banking system, in January 2022 the European Banking Authority (EBA) set harmonized disclosure standards for large institutions with listed securities (Implementing Technical Standards [ITS] P3 ESG ITS). ESG risks should be communicated through tables for qualitative disclosure of environmental, social and governance risks and

[8] In addition to expanding the scope, the CSRD envisaged (i) the use of specific standards provided by the European Financial Reporting Advisory Group (EFRAG), (ii) the requirement of an external auditor, (iii) the inclusion of the non-financial report within the management report and (iv) the adoption of the single electronic reporting format, to improve the dissemination of information.

[9] OIBR, Innovazioni nella Direttiva UE su Reporting di Sostenibilita, 4 July 2022.

[10] The regulation classifies investments as sustainable investments ('Article 9'), investments that reward certain environmental or social characteristics ('Article 8') and the residual category of unsustainable investments ('Article 6'). For each category, there are different disclosure requirements regarding pre-contractual disclosures, periodic reports and communication on corporate websites.

templates for quantitative disclosure of the climate change-related transition risk, climate change-related physical risk and other mitigation actions.

CRR3 has recently extended the scope of ESG Pillar 3 disclosure to all institutions in a proportionate manner. In this scenario, the EBA launched a public consultation on proposed amendments to above-mentioned ITS to i) review the disclosure requirements for large institutions with listed securities, considering the developments in the Omnibus package; and ii) develop simplified and proportional disclosure requirements for large non-listed institutions, other institutions, small and non-complex institutions (SNCIs), and large subsidiaries.

4. Available data

Energy. We first report international (table 1) and national (table 2) sources for energy data. The first is Eurostat Physical energy flow accounts (PEFA) which, as part of the economic and environmental accounts, provides information on estimated energy flows compatibly with the concepts, principles and classifications of national accounts, enabling integrated analyses of economic, environmental and energy issues. The dataset contains data on the supply and use of energy (for intermediate and final consumption and uses relevant to emissions) classified by economic activity (NACE Rev.2), specifically for 21 sections. This information, published annually, complements traditional energy statistics, balances and derived indicators, which are the main source of information for EU energy policies. Information on energy consumption by households and by sector of economic activity is available in the statistics of the Energy Balances, also compiled by Eurostat.

The Global Energy Monitor, a non-profit research organization, provides open access to information to worldwide data on energy infrastructure, resources, and uses, concerning all power plants (coal, gas, wind, nuclear, etc.) built and planned. Data are available in form of interactive database (massive download is allowed). In particular, the Global Integrated Power Tracker lists power plants (coal, gas, oil, nuclear, renewables) with statistics aggregated by country and details on projects under approval, cancelled, and closed plants.

The Joint Research Centre (JRC) of the European Commission publishes a map of the power plants in Europe (Energy and Industry Geography Lab). Different layers (transport infrastructures for gas and power, ETS and E-PRTR plants, etc.) and disaggregation (sector, type of power plant, etc.) are available.

Starting in 1952, British Petroleum (BP) has published, once a year, a key compilation of statistics (Statistical Review of World Energy) of data on energy production, consumption and prices, broken down by source and country. In recent years, the Review has included data on emissions of CO2 and methane caused by and deriving from the use of fossil fuels. This harmonized and freely accessible collection of data is a key point of reference for the world energy community. Starting from 2023, the database is managed by the Energy Institute, a chartered professional membership body for the energy industry.

The Global Power Plant Database – as part of the Resource Watch platform developed by the World Resources Institute - is a free open source database of power plants around the world that covers approximately 30,000 power plants from 164 countries, including both thermal plants (e.g., coal, gas, oil, nuclear, biomass, waste, geothermal) and renewables (e.g., hydro, wind, solar).

As for the national sources, the Ministry of Environment and Energy Security (MASE, in Italian) publishes datasets on mean prices of fuel; oil consumption; consumption and imports of coal and natural gas (Security Energy and Mining Analysis and Statistics). Generally, data are provided with a monthly frequency, data on fuel prices are available also with a weekly frequency.

Additionally, the Ministry of Enterprises and Made in Italy provides a tool ("Osservaprezzi Carburanti" - Fuel Price Observatory) that grants access to real-time information on the selling prices of fuels charged at the distribution plants.

TERNA, the Italian Transmission System Operator (TSO), provides dashboards reporting electricity production and consumption in Italy, with regional and provincial breakdowns. Data are available by sector (consumption) and source (production).

The Italian Regulatory Authority for Energy, Networks and Environment (ARERA) carries on an Annual Survey on Regulated Sectors and publishes a dataset that provides individual information about operators in the electricity and gas sectors, for energy prices and consumption of households and corporations. Data are aggregated by region and user type.

The Italian National Institute of Statistics (ISTAT), periodically conducts a Survey on household energy consumption which provides insights about the energy characteristics of the residential sector in Italy. Tables are available for 2013, 2021 e 2024; the next edition of the survey is scheduled for 2027.

The Italian National Agency for New Technologies, Energy and Sustainable Economic Development (ENEA) collects the Energy performance certificates (EPCs) and publishes aggregated statistics (SIAPE) concerning buildings and real estate units on the number of EPCs, energy class, average GHG emissions, and EP nren/EP ren indices grouped by issuance period, climate zone, property ownership, and size.

GHG emissions and other pollutants. Table 3 collects data on GHG emissions and other pollutants. In this section we have global, European and national resources.

As part of the initiatives promoted by research centres and universities, Carbon Monitor provides regularly updated estimates of CO2 emissions of the main world economies by macro-sector, as well as data on electricity production by energy source. Carbon Monitor has also created the GRACED platform to provide users with near-real-time estimates of daily CO2 emissions from fossil fuel and cement production with high spatial resolution.

The Organisation for Economic Co-operation and Development (OECD) presents trends in man-made emissions of major greenhouse gases and emissions by gas in its OECD Data explorer. Data refer to total emissions of CO_2 (emissions from energy use and industrial processes, e.g. cement production), CH_4 (methane emissions from solid waste, livestock, mining of hard coal and lignite, rice paddies, agriculture and leaks from natural gas pipelines), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF_6) and nitrogen trifluoride (NF_3). Data exclude indirect CO_2. For UNCCCC Annex I countries, data follow the IPCC 2006 guidelines. Territories' coverage is as those defined in the Kyoto Protocol.

Founded in 2016, Kayrros is a global climate technology company and a world leader in environmental intelligence. Kayrros uses satellite imagery, AI, and geo-analytics to help governments, investors and businesses understand the risks posed by the changing climate and energy landscapes and make more informed decisions. On its website, a map of methane emissions, the Kayrros Methane Watch, detected via satellite is available, upon registration.

The International Energy Agency (IEA) provides the Greenhouse Gas Emissions from Energy Highlights, a free extract from Greenhouse Gas Emissions from Energy (an annual time series, updated twice a year, of GHG emissions from energy, a major source of anthropogenic emissions), containing greenhouse gas emissions from the energy sector, broken down by fuel type and country, from 1971 to 2023, with an extended historical series on CO2 emissions from combustion from 1751 to 2022.

The ClimateDeck platform provided by Rodium Group, an independent research provider founded in 2008, provides global and US 50-state greenhouse gas (GHG) emissions inventory data and projections, energy market outlooks, clean investment tracking, and analysis of energy and climate policy

developments. The ClimateDeck equips users with comprehensive datasets, unique and responsive insights, and a robust set of tools for tracking pathways to climate targets and understanding the emissions and economic implications of major developments at the international, national, and state levels.

The Global Monitoring Laboratory (GML) of the National Oceanic and Atmospheric Administration (NOAA), an official website of the United States government, conducts research that addresses three major challenges: greenhouse gas and carbon cycle feedbacks, changes in clouds, aerosols, and surface radiation, and recovery of stratospheric ozone. The website provides measurements of atmospheric concentrations of CO_2, CH_4, N_2O, and SF_6 with charts and historical series (note: the series for N_2O and SF_6 start from the 1990s/2000s, while those for CO_2 and CH_4 start from the 1980s).

Carbon Mapper, a nonprofit organization, leads a coalition of partners — powered by philanthropy — to develop and deploy two satellites with capabilities to detect and quantify methane and CO_2 super-emitters at a level of granularity needed to support direct mitigation action. The data portal includes observations of methane and CO_2 super-emitters across the globe. Data is sourced from multiple sensors onboard aircraft, satellites, and other space-based systems. It's added to the portal on a frequent and ongoing basis.

As for European providers, Eurostat yearly publishes the Air emissions accounts, a collection of greenhouse gas emissions and other pollutants such as particulate matter, NMVOC, ammonia, etc. The archive provides statistics on direct emissions (Scope 1) deriving from production and consumption ("Environmental accounts," "Inventories," and "Environmental footprints"). The European Environment Agency (EEA), instead, publishes every year data on the 'allowances' issued under the EU's main carbon pricing tool, the EU ETS, whose microdata are collected through the European Union Transaction Log (EUTL). For the year 2017 only, the EEA has developed a map with health impacts of road traffic noise and air pollution in selected urban areas, with a 1x1 km grid resolution. No data are available for Italy at the moment.

Another European register with granular data on industrial emissions is the Industrial Emissions Portal Regulation (IEPR), which replaced the European Pollutant Release and Transfer Register Regulation (E-PRTR). It provides public access to key environmental data from about 60,000 large industrial facilities in EU Member States, Iceland, Liechtenstein, Norway, Switzerland, Serbia and the UK through the Industrial Emissions Portal.

The Centre for Research on Energy and Clean Air (CREA) is an independent and nonprofit research organization focused on revealing the trends, causes, and health impacts, as well as the solutions to air pollution. They use scientific data, research and evidence to support the efforts of governments, companies and campaigning organizations worldwide in their efforts to move towards clean energy and clean air. Data on CO_2 emissions, methane flaring in Russia, sanctions against Russia, electricity production by source in various parts of the world are available on CREA website.

The Copernicus Atmosphere Monitoring Service (CAMS) provides free and ready-to-use charts based on its global and European forecasts, allowing everyone to monitor the atmosphere in near-real time and foresee its evolution. CAMS is one of six services that form Copernicus, the European Union's Earth observation programme which looks at our planet and its environment for the ultimate benefit of all European citizens.

CAMS provides forecasts and daily analyses of chemical atmospheric compounds concentrations at the global scale, and of ambient air quality for Europe. The data, available for all on the atmosphere data store (ADS), is used by numerous national and local institutions, international organizations dealing with the environment, and many scientists across the world. Moreover, IT service companies rely on CAMS data to create air quality and atmosphere data applications. In addition to providing the full data for free, CAMS provides visual, intuitive charts of its forecasts and several analysis tools (e.g. the evolution of

Saharan dust transport in Europe or across the Atlantic Ocean or how an ozone or particulate matter pollution episode develops in a city, region or cross-borders).

Finally, as a national source, we signal the average greenhouse gas conversion factors published by the Italian Institute for Environmental Protection and Research (ISPRA) in its report "The environmental challenge for sustainable finance. Methodologies, information and environmental indicators" (2024) mentions conversion factors for energy uses into greenhouse gases (GHG).

Transition risk. The *OECD Climate Actions and Policies Measurement Framework* (CAPMF) is a key initiative developed by the Organization for Economic Co-operation and Development (OECD) to systematically collect and organize information on climate-related policies implemented by member and partner countries (table 5). The CAPMF provides a structured and comparable overview of mitigation and adaptation measures, enabling both cross-country and longitudinal analyses of climate governance strategies. The dataset includes variables covering emission reduction targets, economic instruments, sectoral regulations, fiscal incentives, and public investments in green technologies.

The *Map of the Attribution Studies* dataset provides a comprehensive overview of scientific research assessing the extent to which specific climate-related events can be attributed to anthropogenic climate change. Compiled, maintained, and published by Carbon Brief - a UK-based organization specializing in climate science and policy - the dataset catalogs attribution studies across a wide range of phenomena, including extreme temperatures, precipitation anomalies, droughts, floods, and tropical cyclones. Each entry typically contains metadata such as the event type, geographical location, time period, methodological approach, and key findings regarding the human influence on the event's likelihood or intensity.

Climate Data. Table 4 reports several major databases that collect climate-related information. The U.S. National Oceanic and Atmospheric Administration (NOAA) provides *Climate at a Glance*, a comprehensive global archive containing data on climate anomalies, average temperatures, and precipitation since 1850. The database covers the world as well as the United States specifically, with geographical disaggregation down to the county and city levels. NASA's *GIOVANNI* is a gridded archive offering a wide range of information on aerosols, the cryosphere, and the hydrosphere at the global level, including both historical and modelled data. The International Monetary Fund (IMF) provides a useful dashboard—*Climate Change Indicators*—which offers annual country-level data (since 1990) on climate and economic variables, including indicators of greenhouse gas emissions, financial and risk measures (covering financial, physical, and transition risks), economic indicators (such as those on countries' environmental policies), and other climate-related data. Quarterly emissions data for major global regions are also available.

Physical Risk. The measurement of the potential impacts and damages of climate-related hazards can be summarized in so-called physical risk metrics (table 6 and 7). The construction of these indicators needs thedetailed information on the type of hazard under consideration (e.g. flooding, windstorms, landslides, etc), the exposed asset (population, buildings, financial portfolios, etc) and, if available, its degree of vulnerability based on the intensity of the hazard and the presence of mitigation measures. It follows that detailed information on the localization of the units under analysis is necessary to derive accurate metrics. In this respect, a lot of international and national databases provide useful data inputs.

Measuring climate and environmental risks requires comparable data based on standard rules and classifications among countries. A world-wide overview about the climate-related data on historical and future events and impacts can be assessed by the Climate Change Knowledge Portal maintained by the World Bank Group. Similarly, at world level, the Centre for Research on the Epidemiology of Disasters (CRED) manages the Emergency Events Database (EM-DAT), which collects data on the main natural and technological (mainly industrial and transport accidents) risks of more than 27,000 mass disasters that occurred in the world from 1900 to the present day.

Focusing on the European Union, the Disaster Risk Management Knowledge Center (DRMKC) Risk Data Hub (RDH), developed by the European Commission's Joint Research Center (JRC), is a web platform with an EU-wide geolocation information system that collects information on the location and impact of past natural disasters[11] and presents an analysis of the potential risk of natural disasters. It takes into account the severity of the impact on different resolution grids and reference categories (buildings, population, etc.) and the occurrence probability of the events. Among the resources of the JRC, there is the Agri4Cast portal, a tool dedicated to the publication of climate change databases useful for the agricultural sector. In particular, the database Monthly Heating and Cooling Degree Days in the European Union reports monthly time series since 1979 on the daily maximum and minimum temperatures with a NUTS 3 level of spatial resolution for the geographical area. Among the products developed by the JRC, the EUSO Soil Degradation Dashboard provides data on land degradation processes such as erosion, pollution, and salinization, with global coverage and 16-day hourly forecasts at a 0.25-degree resolution. Based on information collected by meteorological stations, the Copernicus Climate Data Service provides daily meteorological data for Europe offering multiple access channels (API, Cloud infrastructures, open-source codes, etc). The European Storm Forecast Experiment (ESTOFEX) initiative serves as a platform that allows the exchange of information on forecasting of severe weather events (storms, tornadoes) in Europe and other areas. ESTOFEX also provides access to the European Severe Weather Database (ESWD) which collects and provides detailed information on these weather phenomena. The data are collected by national weather service institutes with the cooperation of a network of volunteer observers.

Among the international initiatives aimed at increasing the transparency and accessibility of data, OpenStreetMap collects detailed information on buildings and their characteristics that can be accessed and fed by individual citizens. This information could be useful to create physical risk indicators for the residential estate sector though the coverage and statistical significance of some information details vary between countries[12]. Furthermore, at European level, the EU Building Stock Observatory (BSO) reports accurate information and data on the EU's building stock such as size, energy and GHG efficiencies, etc.

In Italy, detailed information on hydrogeological risk (floods and landslides) and on the national landslide inventory is made available by the Italian Institute for Environmental Protection and Research (ISPRA) through the IdroGEO portal. ISPRA also disseminates a dataset on climate, weather and climate change that collects data, including historical ones, and indicators relating to climate status, variations and trends in Italy. The Institute of Atmospheric Sciences and Climate (ISAC), within Italy's National Research Council (CNR), publishes monthly maps of mean, minimum and maximum temperatures, as well as of the deviations from the 1991–2020 mean, with highly spatially disaggregated since as far back as 2002. Recently, another database has been developed, the MEteorological Reanalysis Italian DAtaset (MERIDA), to provide energy stakeholders with reliable meteorological data to increase the resilience of electricity distribution networks and allows them to implement measures aimed at restoring energy supply in the areas that are more prone to extreme weather events, and which have a major impact on the national electricity system. The project has been developed following the recommendations of the 'Working table for resilience' established by the Regulatory Authority for Energy Networks and the Environment (ARERA).

Climate scenarios. Climate scenarios (table 8) are helpful tools to foresee how economies and financial systems might evolve in response to different climate policies and changes. The Network for Greening the Financial System (NGFS) long-term climate scenarios are a set of forward-looking pathways developed to assess climate-related financial risks on financial stability and economic resilience. In November 2024 the NGFS published the fifth version of the climate scenarios (The NGFS Scenario data). Also, in May 2025 the NGFS published short term scenarios, dedicated to analysing the potential near-term impacts of climate policies and climate change. In Italy,

[11] The database reports events such as floods, earthquakes, wildfires, landslides, droughts, storms, eruptions and tsunamis.

[12] For Italy, where coverage is not very extensive, the data can be accessed with customized queries via the Real Estate Market Observatory (OMI) of the Italian Revenue Agency, which provides details at the municipal micro-area level.

climate scenarios and projections are elaborated by the Euro-Mediterranean Center on Climate Change (CMCC) and the Climate analysis over mediterranean region (CLIMED). The CMCC conducts high-resolution scenario analyses and climate simulations, which have proven useful also to draft the National Plan for Adaptation to Climate Change (NPACC). The CMCC provides access to interactive maps for different types of Italian, mediterranean and global indicators and emission scenarios through its Data delivery system (CMCC DDS). The CLIMED portal has been developed as a tool to support the planning of the National Energy System as well as to support national and local public administrations. It provides climate projections for Italy until 2100 under different global warming conditions.

Sustainable finance. Additional resources concern sustainable finance (table 9), which plays a key role in supporting the ecological transition. The NGFS provides the *Dashboard on Scaling Up Green Finance*, a global dataset offering country-level indicators on climate-related policies, GHG emissions, and green bond issuances, with historical coverage starting from 1970 for some metrics. The *FT Climate Dashboard*, developed by the Financial Times, aggregates information on 193 countries' historical emissions and climate targets, including progress on renewable energy and global rankings. At the national level, the *Osservatorio DNF*, managed by the University of Siena, collects and disseminates Non-Financial Disclosures from Italian companies for the years 2017–2023. For the financial industry, the *Online Tools for the Financial Sector* by UNEP FI provide instruments and datasets aimed at facilitating the implementation of sustainable finance policies and practices in the financial sector. Finally, Borsa Italiana and other exchanges publish the *ESG Bond List*.

Other relevant sources concern nature and broader environmental-economic information (table 10 and 11). The *Ecosystem Services Valuation Database (ESVD)* offers a global dataset with over 10,000 assessments of specific biomes and ecosystems. The *EUSO Soil Degradation Dashboard*, developed by JRC, provides data on land degradation processes such as erosion, pollution, and salinization, with global coverage and 16-day hourly forecasts at a 0.25-degree resolution. In addition, other statistics on European economic and environmental accounts, published by Eurostat, include material flow accounts, environmental tax data, and sectoral accounts for environmental goods and services, covering EU countries from 1990 to 2024. At the national level, the *Ecological Transition Plan and Monitoring Reports* by the Italian Ministry of Environment and Energy Security detail progress toward the 2030 targets, offering annual updates on measures, indicators, and financial resources allocated for the ecological transition.

5. Conclusions

The global energy transition is mobilizing substantial financial resources, estimated at approximately USD 2 trillion in 2024 (IEA, 2025). Depending on the level of climate ambition, these investments could more than double under a net-zero emissions scenario (IEA, 2025). Such significant financial flows, together with the increasing frequency and severity of climate-related extreme events, underscore the intensifying demand for reliable and granular data among financial institutions, insurers, investors, and corporations. Despite this growing demand, a considerable discrepancy persists between the data required for comprehensive climate-risk assessment and the information currently available, a divergence commonly referred to as the *sustainable data gap*.

While numerous legislative initiatives have been introduced in recent years to address this issue, the future trajectory of policy interventions remains uncertain, partly due to concerns regarding regulatory burdens and compliance costs. Concurrently, commercial data providers have increased investment in new datasets and analytical techniques aimed at mitigating informational deficiencies. Building on the framework proposed by Lavecchia et al. (2022), the present study updates and extends the review of data requirements and publicly accessible resources relevant to sustainability and climate-risk analysis.

Persistent weaknesses remain, particularly with respect to data coverage for small and medium-sized enterprises (SMEs) and for energy sources other than electricity and natural gas—the primary vectors typically captured by existing datasets. Although the availability and quality of data on physical climate risks have improved substantially because of recent investments, further progress requires greater integration across information sources. Establishing linkages at the asset or plant level and connecting data along entire value chains represent essential steps toward developing a coherent and comprehensive climate-data architecture.

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Appendix

Energy data (international providers)			Table 1
Name	Provider	Main attributes	Description
Physical energy flow accounts, PEFA	Eurostat/Istat	Geographic area: European Union + Albania, Iceland, Switzerland, North Macedonia, Turkiye and Norway	The database allows access to statistics on energy flows from the environment to the economy (inputs), within the economy (products), and from the economy back to the environment (residuals). The data are annual starting from 2011 and cover all EU countries and some extra-EU countries.
Energy and Industry Geography Lab	JRC	Geographic area: European Union Spatial Unit: Country Period: 2010 – 2022 Further disaggregations: Sector	The JRC has published a map of the power plants in Europe and numerous layers (transport infrastructures for gas and power, ETS and E-PRTR plants, etc.). User guides are available.
Global Energy Monitor	Global energy monitor	Geographic area: world Spatial Unit: singol plant Period: n.a. Further disaggregations: Power plant, industrial plant, transport infrastructures	Interactive database (and with possible massive download) of all power plants (coal, gas, wind, nuclear, etc.) built and planned. In particular, the Global Integrated Power Tracker lists power plants (coal, gas, oil, nuclear, renewables) with statistics aggregated by country and details on projects under approval, cancelled, and closed plants. Presentation article available.
Statistical Review of World Energy	British Petroleum (dal 1952 al 2022)/the Energy Institute (since 2023)	Geographic area: world Spatial Unit: country (EU-27) Period: 1952 – present Further disaggregations: Type of energy source and CO_2 emissions	Collection of information on production, consumption and prices of energy sources, broken down by source and country. Annual publication (since 1952) and free of charge; it is a reference point for analyses of the global energy community. Since 2023, management has passed to The Energy Institute, which also keeps the historical archive (where it is possible to build time series by source and country).
EMBER - Electricity Data Explorer	EMBER	Geographic area: world Spatial Unit: country Period: 2000 – present Further disaggregations:	Data on electricity generation, installed capacity, electricity demand, power sector CO2 emissions, and carbon intensity, by country, from 2000 to today.
Global Power Plant Database	Resource Watch	Geographic area: Worldwide Spatial unit: Countries / specific data points Period: Further disaggregations:	Dashboard with more than 30,000 power plants (installed capacity over 1 MW) from 164 countries worldwide.

Energy data (national providers)			Table 2
Name	Provider	Main attributes	Description
Energy and Mining Analysis and Statistics (Analisi e statistiche energetiche e minerarie)	Italian ministry of environment and energy security (MASE)	Geographic area: Italy Spatial unit: Country Period: Variable; weekly, monthly, or annual frequency Further disaggregations: Type of fuel/combustible	The archive provides datasets on average fuel prices, oil consumption, and coal and natural gas consumption and imports. Data are generally reported with monthly frequency; weekly data are available for fuel prices.
Fuel Price Observatory (Osservaprezzi Carburanti)	Italian ministry of enterprises and made in Italy (MIMIT)	Geographic area: Italy Spatial unit: Country Period: 2015 – present Further disaggregations: Type of fuel/combustible	The tool allows real-time consultation of fuel prices applied at fuel stations. A historical archive of prices (starting from 2015) is also available.
Data on Electricity Production and Consumption	TERNA	Geographic area: Italy Spatial unit: Provinces Period: 2000 – 2022 Further disaggregations: Sector (for consumption), source (for production)	TERNA dashboards reporting electricity production and consumption in Italy, with regional and provincial breakdowns. Data are available by sector (consumption) and source (production).
Annual Survey on Regulated Sectors	ARERA	Geographic area: Italy Spatial unit: Country Period: 1997 – 2023 Further disaggregations: Type of energy source	The dataset provides individual information for operators in the electricity and gas sectors, for energy prices and consumption of households and corporations. Data are aggregated by region and user type.
Survey on household energy consumption (Indagine sui consumi energetici delle famiglie)	ISTAT	Geographic area: Italy Spatial unit: Region Period: 2013, 2021, and 2024 Further disaggregations: Various disaggregations	The survey provides insights about the energy characteristics of the residential sector. Tables are available for 2013, 2021 e 2024, and microdata are available for 2013 and 2021 as MFR; PUF is available only for 2013). Next edition (expected): 2027
Sistema informativo integrato (SII)	Acquirente Unico	Geographic area: Italy Spatial unit: Region/province Period: 2021–2023 Further disaggregations:	The archive contains granular data on electricity and gas consumption by households and businesses. Update frequency and reading details depend on the type of meter installed. ARERA has recently published statistics on monthly consumption and hourly electricity withdrawals (households e businesses) e gas (households only), with provincial level detail, only for the 2021–2023 period so far.

Energy performance certificates' archive (Sistema informativo sugli attestati di prestazione energetica (SIAPE)	ENEA	Geographic area: Italy Spatial unit: Region Period: 2015–present Further disaggregations:	The archive contains aggregated statistics on number of EPCs (energy performance certificate), energy class, average GHG emissions, and EP nren/EP ren indices grouped by issuance period, climate zone, property ownership, and size. Data available for 20 out of 21 regions (Sardinia is missing). Microdata are not available. The database is populated with data from regional registries starting from a specific date, without retroactive data recovery (e.g., Campania region has begun contributing from January 1st, 2025).
Portale PNIEC	GSE	Geographic area: Italy Spatial unit: Country Period: 2022–present Further disaggregations:	Portal for monitoring the 2030 targets of the 2023 PNIEC (Italian National Integrated Plan for Energy and Climate). 9 dimensions are considered.

GHG emissions and other pollutants			Table 3
Name	Provider	Main attributes	Description
Air Emissions Accounts - Database of greenhouse gas emissions and other pollutants such as particulate matter, NMVOC, ammonia, etc.	Eurostat	Geographic area: European Union + EFTA + Serbia and Turkey Spatial unit: Country Period: 1995–2023 Further disaggregations: Economic sector; for energy footprints: CPA08	The archive provides statistics on direct emissions (Scope 1) deriving from production and consumption ("Environmental accounts," "Inventories," and "Environmental footprints"). Annual data from 1995 onward, covering all EU countries plus EFTA members (Iceland, Norway, Switzerland), Serbia, and Turkey.
European Union Transaction Log (EUTL)	European Environment Agency (EEA)	Geographic area: EU Spatial unit: Country and individual operator Period: 2008 – 2025 Further disaggregations: Economic activity sector	The dataset provides information on direct emissions and emission allowances. Data are annual from 2008 and cover all EU countries plus Iceland, Liechtenstein, and Norway. EMBER offers a graphical representation of emissions from European thermal power plants (subject to EU-ETS) and allows downloads. It also provides the historical series of carbon prices. The JRC has created an integrated archive of facilities/companies with ORBIS codes (to obtain financial information). Another system for viewing and bulk downloading data (using JRC's ORBIS classification) is provided by the EUETS.INFO project.
European Emission Industrial Portal	European Environment Agency (EEA)	Geographic area: EU + EFTA + UK Spatial unit: Country Period: 2007 – 2023 Further disaggregations: Economic activity sector	The portal contains data from the European Pollutant Release and Transfer Register (E-PRTR), related to emissions and transfers of pollutants reported by about 60,000 industrial facilities located in the EU, Iceland, Liechtenstein, Norway, United Kingdom, Serbia, and Switzerland.
Stime Carbon Monitor e GRACED	Carbon Monitor	Geographic area: Global Spatial unit: Country Period: 2019 – present Further disaggregations: Economic activity sector	The Carbon Monitor website provides daily estimates of CO_2 emissions by macro-sector for major global economies, as well as data on electricity production by energy source. The GRACED platform offers daily CO_2 emission estimates at fine spatial resolution (1° x 1°) from fossil fuels and cement production.
OECD: Greenhouse gas emissions by country and sector	OECD	Geographic area: Global Spatial unit: Country Period: 1988 – 2023 Further disaggregations:	Greenhouse gas emissions (source: UNFCCC)

Kayrros Methane Watch	Kayrros	Geographic area: Global Spatial unit: Individual emission point / country Period: 2019 - present Further disaggregations:	Map of methane emissions detected via satellite, with download available upon registration.
Greenhouse Gas Emissions from Energy Highlights	IEA	Geographic area: World Spatial unit: Country Time period: 1971 – 2023 Other disaggregations: fuel type	Greenhouse gas emissions from the energy sector, broken down by fuel type and country, from 1971 to 2023 (estimation for 2023), with an extended historical series on CO2 emissions from combustion from 1751 to 2022. Free Excel file available upon registration on the IEA website
ClimateDeck Rodium Group	Rhodium Group	Geographic area: World Spatial unit: Country Time period: 1974 – 2023 Other disaggregations: economic sector	Preliminary estimate of GHG emissions at the global level and for 50 US states through 2030. Historical data on greenhouse gas emissions for over 190 countries, disaggregated by economic sector. Access available upon contact via email with the provider
Global monitoring laboratory	US government	Geographic area: World Spatial unit: Time period: late twentieth century - first half of 2025, monthly data Other disaggregations:	The website provides measurements of atmospheric concentrations of CO_2, CH_4, N_2O, and SF_6 with charts and historical series (note: the series for N_2O and SF_6 start from the 1990s/2000s, while those for CO_2 and CH_4 start from the 1980s). The website states that there will be no further updates to the data
Viewer on combined health impacts from road traffic noise and air pollution in urban areas	European Environmental Agency (EEA)	Geographic area: EU Spatial unit: city, cell of 1x1 km (when available) Time period: 2017 Other disaggregations:	Health impacts of road traffic noise and air pollution in selected urban areas, with a 1x1 km grid resolution. No data available for Italy at the moment
Carbon Mapper	Carbon Mapper	Geographic area: World Spatial unit: grid Time period: variable, generally 2025 data Other disaggregations:	Satellite data on CO_2 and methane emission rates for super-emitters
Center for Research on Energy and Clean Air	CREA	Geographic coverage: Europe / World Spatial unit: Countries / Specific points Period: Further disaggregations:	Data on CO_2 emissions, methane flaring in Russia, sanctions against Russia, electricity production by source in various parts of the world.
Copernicus Atmosphere Monitoring Service (CAMS)	European Commission	Geographic coverage: World (more detailed for Europe) Spatial unit: Grid Period: Further disaggregations: country, region	Detailed maps with daily forecasts for atmospheric compound concentrations and air quality (Europe only). Data are available for download in the Atmosphere Data Store (link).

Average Greenhouse Gas Conversion Factors	ISPRA	Geographic coverage: Italy Spatial unit: country Period: Further disaggregations: n.a.	ISPRA document containing the conversion factors for energy uses into greenhouse gases (GHG).

Climate data			Table 4
Name	Provider	Main attributes	Description
Climate at a Glance	NOAA	Geographic coverage: World Spatial unit: Continents Period: 1850 – present Further disaggregations:	Data on climate anomalies, average temperatures, and precipitation at the global level and for the United States, with disaggregation down to county/city level.
GIOVANNI – NASA	NASA	Geographic coverage: World Spatial unit: Grid Period: n.a. Further disaggregations: n.a.	NASA archive with information on aerosols, cryosphere, and hydrosphere at the global level, including historical and modeled data. Full access requires registration.
Climate Change Indicators Dashboard	IMF	Geographic coverage: World Spatial unit: country Period: 1990 - present Further disaggregations: n.a.	The archive provides a very broad set of information on climate and economic variables, including indicators on greenhouse gas emissions, financial and risk indicators (including financial, physical, and transition risks), economic indicators (e.g., on countries' environmental policies), and climate change data. The data are annual and available by country. Quarterly emissions data for major global regions are also available.

Transition risk			Table 5
Name	Provider	Main attributes	Description
OECD Climate Actions and Policies Measurement Framework (CAPMF)	OECD	Geographic coverage: World Spatial unit: country (53) Period: 2018 - 2023 Further disaggregations: n.a.	The OECD Climate Actions and Policies Measurement Framework (CAPMF) is the most extensive internationally harmonised climate mitigation policy database to date. It tracks 130 policy variables, aggregated into 56 key climate actions and policies
Map of the attribution studies	Carbon brief	Geographic coverage: World Spatial unit: event site Period: n.a. Further disaggregations: n.a.	List of attribution studies referring to 735 extreme weather events. Last updated: November 2024

Physical risk (international providers)			Table 6
Name	Provider	Main attributes	Description
World Bank Climate Change Knowledge Portal	World Bank	Geographic coverage: World Spatial unit: country Period: 1991 – 2021 for some statistics Further disaggregations: NUTS 2	Historical and forward-looking (scenario-based) information on various climate indicators, disaggregated by country and NUTS, available for download.
OSM - OpenStreetMap	OSM Foundation	Geographic coverage: World Spatial unit: country and single building Period: live Further disaggregations: property classification variables	Property data and classification variables. For European comparisons, see also the EUBUCCO v0.1 project.
EU Building Stock Observatory	European Commission	Geographic coverage: EU-27 Spatial unit: country Period: n.a. Further disaggregations: Sector of economic activity for some statistics	Statistics on the building stock of European countries (energy consumption, building elements and technical building systems installed, energy performance certificates, nearly zero-energy buildings and renovation rates, energy poverty and financing aspects)
European Storm Forecast Experiment (ESTOFEX) and European Severe Weather Database, (ESWD)	European Severe Storms Laboratory (ESSL)	Geographic coverage: Europe Spatial unit: city Period: 2007-current Further disaggregations: type of event	The European Storm Forecast Experiment (ESTOFEX) platform publishes daily bulletins with forecasts of hail, strong wind gusts, tornadoes and excessive precipitation in Europe and other areas. The European Severe Weather Database (ESWD) is a repository that collects data on these phenomena in Europe.
EUMETVIEW	European Organisation for the Exploitation of Meteorological Satellites	Geographic coverage: Europe, Africa and South America Spatial unit: grid Period: n.a Further disaggregations: n.a.	Portal with satellite data collection on weather, climate, and environment.
CLIMDEX	University of Sidney (UNSW)	Geographic coverage: World Spatial unit: grid Period: 1953-present Further disaggregations: n.a.	Database of indices on temperature and precipitation extremes recommended by the WMO Expert Team on Climate Change Detection and Indices. These indices were also used in the National Climate Change Adaptation Plan (PNACC – see table XX).
E-OBS (Copernicus Climate change service)	Copernicus Climate Change Service (C3S)	Geographic coverage: Europe Spatial unit: grid Period: 1953-present (daily data) Further disaggregations: n.a.	Daily meteorological data (maximum, minimum, and average temperature; precipitation; humidity; wind speed, etc.), at grid level, for Europe, from meteorological stations.
Climate Reanalyzer	Climate Change Institute at the University of Maine	Geographic coverage: World Spatial unit: Period: Further disaggregations: n.a.	The site offers daily and historical weather maps, satellite photos, daily data on ice thickness, temperatures, and reprocessing of public datasets (list available here).

Risk Data Hub (RDH) of the Disaster Risk Management Knowledge Centre (DRMKC)	JRC	Geographic coverage: Europe Spatial unit: different breakdowns based on the indicator Period: 1980 - present Further disaggregations: type of risk and potential loss	The archive contains information on losses associated with historical events and potential impact analyses for different physical risks. Two main modules: historical events and risk analysis. A list of catastrophic events is also available (here).
Agri4Cast	European Commission	Geographic coverage: European Union Spatial unit: country, region and other based on the indicator Period: 1979 -2022 Further disaggregations: different breakdowns based on the indicator	Agro-meteorological grids, irrigation grids, indices of low and high temperature days, crop statistics. Registration required.
EM-DAT	Centre for Research on the Epidemiology of Disasters (CRED)	Geographic coverage: World Spatial unit: country Period: 1900 - 2022 Further disaggregations: different breakdowns based on the indicator	The archive considers the main natural risks (geophysical, meteorological, hydrological, climatic, biological and extraterrestrial) and technological risks (mainly industrial and transport accidents).
SIGMA Explorer	Swiss RE	Geographic coverage: World Spatial unit: country Period: 1970 - 2021 Further disaggregations: n.a.	SwissRe's database of natural disasters, man-made disasters, and earthquakes and insurance premiums.
Dashboard EIOPA on the insurance protection gap	EIOPA	Geographical area: European Economic Area Spatial unit: country Period: 2022-2024 Further disaggregations:	Dashboard on European insurance protection gap. It focuses on natural catastrophe risks (Windstorm, Flood, Coastal flood, Wildfire, Earthquake). Results are represented by a score varying from 1 (no protection gap) to 4 (very high protection gap).
FIRMS - Fire information for resource management system	NASA	Geographical area: world Spatial unit: specific locations Period: 2000 - present Further disaggregations:	Data on wildfires locations worldwide collected via satellites (coordinates, radiative power and other variables for each event).
Global Wildfire Information System (GWIS)	GEO/Copernicus Climate Change Service (C3S)	Geographical area: world Spatial unit: Period: 2002 - present Further disaggregations: country, region	Data on wildfires and lightning occurrence (both historical and forecast up to 10 days in advance) with statistics provided at national level and for regions of interest.
City-scale climate hazards	World resource institute	Geographical area: world Spatial unit: city (0.25-degree resolution) Period: Further disaggregations:	This dataset contains estimated average magnitudes and probabilities of extreme-magnitude exceedance for 14 climate hazards, calculated for the 996 cities larger than 500,000 in population, at recent historical level and 1.5°C, 2.0°C, and 3.0°C of global warming above pre-industrial baseline. Concerning Italy it covers six cities (Rome, Milan, Turin, Naples, Genoa and Palermo).

EIOPA Catastrophe data hub	EIOPA	Geographical area: European Economic Area Spatial unit: country Period: Further disaggregations:	The sample includes 35 large European groups active in non-life business and 9 non-life and composite solo undertakings with relevant exposure to fire and other damages to property business. Data: overall value or replacement value of the commercial or residential buildings insured. Incurred claims for buildings and other claims reported by the insurance undertakings or groups in the sample.

Physical risk (national providers)			Table 7
Name	Provider	Main attributes	Description
Sistema informativo nazionale ambientale	ISPRA	Geographical area: Italy Spatial unit: Municipality (for some indicators) Period: different time ranges based on the indicator Further breakdowns: different breakdowns based on the indicator	Inland waters, physical agents, environment and health, environmental sustainability, air, climate, weather, climate change, environmental controls and inspections, circular economy, geology, soil, contaminated sites, environmental indicators, sea and coast, nature and biodiversity, waste, chemicals.
Piattaforma nazionale adattamento cambiamenti climatici	ISPRA	Geographical area: Italy Spatial unit: Period: 1960-present Further breakdowns:	Data and information on climate change in Italy, including national impact indicators (and regional case studies), management and adaptation.
Sistema nazionale di raccolta, elaborazione e diffusione dei dati climatici (SCIA)	ISPRA	Geographical area: Italy Spatial unit: Italy/station/grid Period: 1860 – present (daily, weekly, monthly, yearly frequency) Further breakdowns:	Database containing climate variations and trends in Italy (average minimum and maximum temperatures, humidity, wind, precipitation, etc.) compiled by ISPRA.
Mappe su temperature (e deviazioni) medie, minime e massime del CNR-ISAC	CNR	Geographical area: Italy Spatial unit: Period: 2002 – present Further breakdowns:	Maps of average, minimum and maximum temperatures, with deviations from historical averages (1991-2020) produced by ISAC-CNR for civil protection - full database here.
MEteorological Reanalysis Italian DAtaset (MERIDA)	Ricerca sul Sistema Energetico (RSE)	Geographical area: Italy Spatial unit: grid 21-7 e 4 km (HRES version) Period: 1990-2023 (2022 for HRES) Further breakdowns:	Historical series of meteorological variables (list here) with fine spatial granularity.

Climate scenarios			Table 8
Name	Provider	Main attributes	Description
Scenario portal NGFS	NGFS	Geographical area: Worldwide Spatial unit: Country (where downscaling is possible) Period: Different periods depending on the type of scenario Further breakdowns: Scenarios are distinguished by physical risks and transition risks	The archive contains the fifth edition of the NGFS long-term scenarios (previous versions are also available). The NGFS IIASA Scenario Explorer allows for the analysis of transition scenarios, while the NGFS CA Climate Impact Explorer allows for the analysis of physical risk scenarios. It is possible to both explore the scenarios and download them.
Centro Euro-Mediterraneo sui Cambiamenti Climatici - Data Delivery System (CMCC-DDS)	CMCC Foundation	Geographical area: Italy, Mediterranean, with possible extensions to larger scales for some global data Spatial unit: various Period: different periods depending on the dataset Further breakdowns: various, depending on the type of dataset	Multiple datasets: High-resolution climate scenarios for Italy for various emission scenarios (RCP 4.5 or RCP 8.5) and periods (2021-2050, 2041-2070, and 2071-2100). Lower resolution global data. Climate variables (average daily temperature, days of intense precipitation, days of intense cold, etc.).
Climate analysis over MEDiterranean Region (CLIMED)	RSE	Geographical area: Italy Spatial unit: Country Period: 2021-2050, 2041-2070, and 2071-2100 Further breakdowns: emission scenario (RCP 2.6, 4.5 or 8.5) and climate models (Euro-CORDEX, Med-CORDEX, ENSEMBLES)	Historical data (1971-2000) and prospective data (2021-2050; 2041-2070; 2071-2100) for different scenarios, at grid level for different climate variables. (average/maximum/minimum temperature, total rainfall, wind intensity, hot days, tropical nights, etc.).

Sustainable finance			Table 9
Name	Provider	Main attributes	Description
Dashboard on scaling up green finance	NGFS	Geographical area: World Spatial unit: Country Time period: 1970 – present (for some indicators) Further breakdowns: multiple, depending on the indicator	The dashboard provides links to websites where 21 annual indicators on ecological transition in countries are available, including, for example, greenhouse gas emissions, national policies, and green and social bond issuances.
FT climate dashboard	Financial Times	Geographical area: World Spatial unit: Country Period: 1990–2021 Further breakdowns:	Dashboard with information on total GHG emissions, per capita, global ranking, year-on-year change, summary of climate pledges, % of renewables in the electricity production mix
Osservatorio DNF	University of Siena	Geographic coverage: Italy Spatial unit: regions Period: 2017-2023 Further disaggregations: economic sectors	The archive contains annual data obtained from the Non-Financial Reporting of the main Italian companies, including those on their direct and indirect emissions.
Online Tools for the Financial Sector	UNEP FI	Geographic coverage: World Spatial unit: country Period: 2017-2023 Further disaggregations: asset class	Useful tools for financial sector agents
ESG Bond Lists	SSE e Borse Valori (Borsa Italiana, LSE, Euronext)	Geographic coverage: World Spatial unit: country Period: 2017-2023 Further disaggregations: asset class	Asset ESG: green and sustainable bonds

Nature and others			Table 10
Name	Provider	Main attributes	Description
ESVD - Ecosystem services valuation database	ESVD	Geographic coverage: World Spatial unit: specific area Period: Further disaggregations:	Database containing more than 10,000 assessments of specific biomes/ecosystems. For a description of the contents, see Brander et al. (2024).
EUSO Soil Degradation Dashboard	JRC	Geographic coverage: World Spatial unit: 0.25 degree Period: 16-day hourly forecast Further disaggregations:	Dashboard on land degradation (erosion, pollution, salinization, etc.) created by the European Commission's Joint Research Centre (JRC). Here for a list of resources.
Other statistics on European economic and environmental accounts	Eurostat	Geographic coverage: EU Spatial unit: country Period: 1990-2024 Further disaggregations:	Other statistics (full list here) include: Material Flow Accounts, Environmental Tax Data, Environmental Goods and Services Sector Accounts, and Environmental Protection Expenditure Accounts.
Ecological Transition Plan and Monitoring Reports	Italian ministry of environment and energy security (MASE)	Geographic coverage: Italy Spatial unit: country Period: 2019-2030 Further disaggregations:	The PTE is the strategic plan for the ecological transition, divided into eight themes. By law, a report will be published annually, detailing progress and comparing it with the 2030 target (here is the first report, May 2022).

Climate and Environmental Risk Data in Italy

Katia Specchia

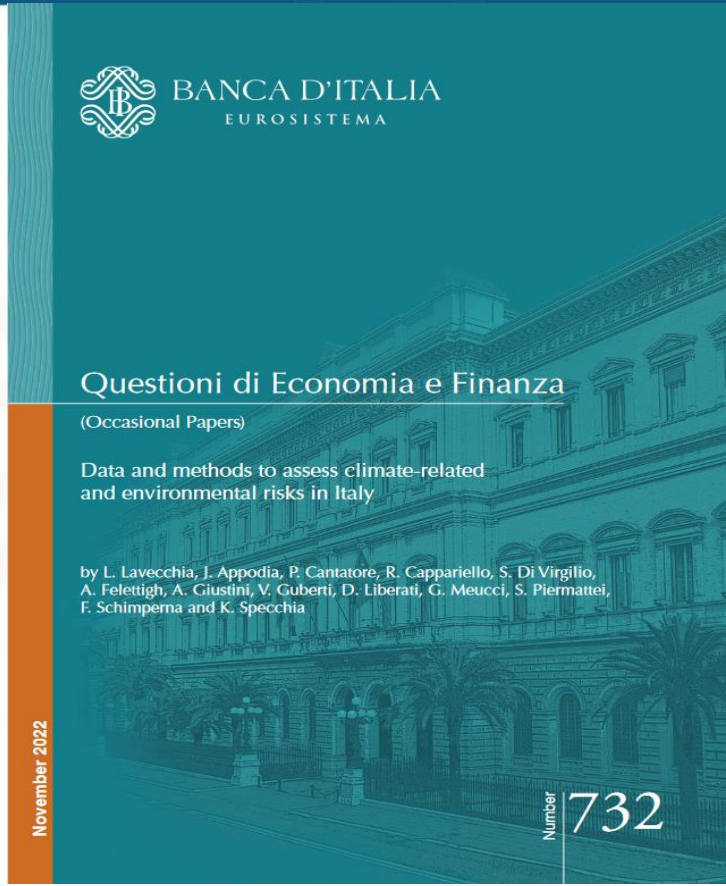
Supervisory Regulations and Policies Directorate
Insurance Supervisory Authority (IVASS)

IFC Satellite Seminar on "Sustainability data issues and central banks' experience“

Amsterdam, 4 October 2025

Agenda

1. **Foreword and Structure of the paper**
2. **The sustainable data gap in Italy**
   - Data required for economic and financial analysis of climate risks
   - Data required by financial intermediaries to respond to requests from supervisors
   - Available data
   - Data available but not accessible
3. **Conclusions**



Foreword and Structure of the paper

- **Research context and motivation: Rising Demand for Climate Data**

Mitigation and adaptation to climate change are top priorities. Lots of public-private resources needed. Global initiatives have increased demand for climate-related data in sustainable finance and risk management.

- **Regulatory Pressure in Europe: Data Requirements**

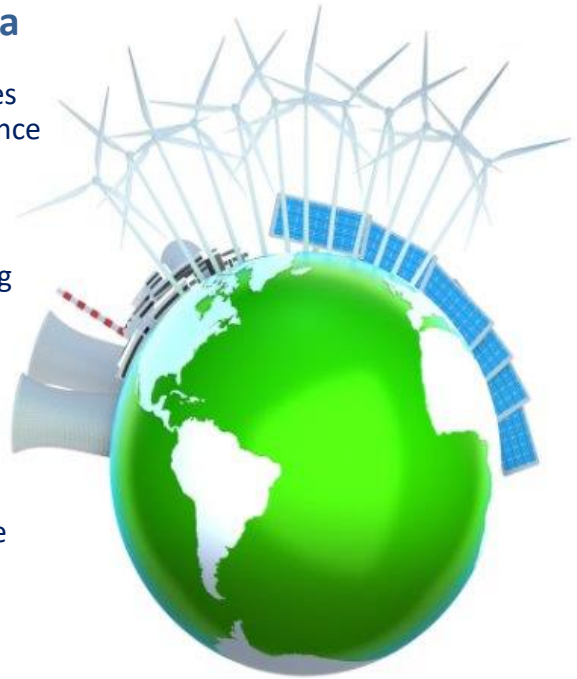
European regulations push firms for comprehensive climate disclosures, intensifying reporting expectations. Goal is to enhance risk management and ensure compliance with regulatory climate requirements set by supervisory authorities and regulatory frameworks.

- **Sustainable Data Gap Challenges**

Huge demand for high-quality microdata.
Missing/insufficient data concern: GHG emissions, energy use, physical/transition risk exposures; insurance protection gap and peril-specific economic losses; integration of climate scenarios into financial models; granular data for SMEs.
Private data providers offer partial solutions, but suffer from low transparency on the methodology involved and inconsistency (uncorrelation among scores/ratings).
The study maps available sources, assessing accessibility and quality for risk management.

- **Italy's Data Limitations and constraints**

Research focuses on identifying sustainable data gaps related to climate and environmental risks in Italy.



What about existing public data sources?

1. What data is required?
2. What data is already available?
3. Where is the *sustainable data gap* in Italy?

The data required for economic and financial analysis

- **Physical Climate Risks**: physical risks result from extreme weather damaging infrastructure and disrupting operations.
- **Transition Climate Risks:** transition risks arise from policy changes and market shifts affecting asset values
- **Risk Evaluation and Mitigation:** comprehensive data is crucial to assess impacts and develop mitigation strategies. Accurate risk assessment depends on detailed data like geolocated risk maps and firm-level energy use.

- Pressure from stakeholders to commit to Net zero; align firms' performances to climate benchmarks
- Define mitigation/adaptation plans
- Measure and manage physical and transition risks
- Decline climate scenarios
- Country view: current exposure, vulnerability and available insurance coverage for climate risks

	Ante 2022	2022	2023	2024	2025	2026	…
NFD		*Disclosure ESG as defined in the NFRD*		*Disclosure ESG as defined in the CSRD/EFRAG schemes*			
Scope		*Large listed undertakings, banks, insurances (relevant Public interest entities - PIEs)*		*Relevant PIEs*	*Relevant PIEs and large non-listed undertakings*	*(As 2025) + listed SMEs, small and non-complex credit institutions and captive insurance undertakings*	
Taxonomy Reg.							
NFCs within the NFRD/ CSRD's scope		• % of *Capex, Opex, turnover* from *taxonomy **eligible** activities.*		• *% Capex, Opex, turnover* from *taxonomy **aligned*** and *taxonomy **eligible** activities.*			
Banks within NFRD/ CSRD's scope		• % Total assets from *taxonomy-**eligible** activities.*		• *Green Asset Ratio* (GAR) for lending and debt assets from firms covered by the NFRD/CSRD, computed according to the Capex and turnover from *taxonomy **aligned** activities*. % of guarantees from *taxonomy **aligned** activities.*	• % revenues from services different from *lending* from *taxonomy **aligned** activities* and GAR from trading activity		
Insurances within NFRD/ CSRD's scope		• % Total assets from *taxonomy-**eligible** activities.* • % Total non-life insurance gross premiums written from *taxonomy-**eligible** underwriting insurance activities*		•% Total assets from *taxonomy-**aligned** activities.* •% Total non-life insurance gross premiums written from *taxonomy-**aligned** underwriting insurance activities*			
Pillar 3							
Large Institution		• Quantitative and qualitative disclosure of ESG risks		• Integration of quantitative disclosure with the *Green Asset Ratio* (GAR).			
All banks					• Integration of quantitative disclosure with the *Banking Book Taxonomy Alignment Ratio* (BTAR), *scope 3 GHG emissions* and alignment metrics.		
					• Extension of Pillar 3 to all banks		
Pillar 2/3							
Insurances		• identify any material exposure to climate change risks and, where relevant, assess the impact of climate change scenarios on their business (in the ORSA Report and public disclosure)					
Survey IVASS							
Insurances		• Investments broken by NACE code, data on taxonomy eligible activities, on carbon footprint and green bonds. *Data on nat cat risk impact underwriting and on taxonomy **eligible** insurance activities*		• Investments broken by NACE code, data on taxonomy eligible and taxonomy aligned activities, on carbon footprint and green bonds. *Data on nat cat risk impact underwriting and on taxonomy **eligible*** and taxonomy ***aligned** insurance activities*			



Available data - 1

From official statistical sources and other public resources	• Eurostat environmental accounts (Air Emissions Accounts; Physical Energy Flow Account; Eurostat/Material flow accounts, Environmental taxes revenues, National expenditure on environmental protection by institutional sector) • Climate Change Knowledge Portal, EIOPA Catastrophe data Hub • Emissions data for EU ETS installations (EU transaction log; EUTL) • European Pollutant Release and Transfer Register (E-PRTR) • Dashboards: IMF - Climate change indicators, NGFS Dashboard on scaling up green finance, EIOPA Dashboard on insurance protection gap, FT Climate • CO2 emissions data: Greenhouse Gas Emissions from Energy, Carbon Monitor and GRACED • Real estate data: OpenStreetMap and OMI • Data on severe weather events: European Storm Forecast Experiment (ESTOFEX) and European Severe Weather Database (ESWD)

Available data - 2

National sources	• ISPRA: national GHG inventory + data on water, air, sea and coasts, nature and biodiversity, climate, waste, environmental indicators, hydrogeological risk maps (IdroGEO portal); • MASE (formerly MITE): monthly data on fuel prices, oil, coal and natural gas consumption + fuel price monitoring (real-time prices) and Ecological Transition Plan; • ARERA: annual survey on regulated sectors; • DNF Observatory (University of Siena and Sustainability makers); • Istat: Household expenditure survey, household energy consumption surveys;
Risk indicators	• JRC: DRMKC - RiskData Hub and Agri4Cast; WWF risk filter suite, Sigma Explorer, EIOPA Dashboard on Insurance Protection gap, Emergency Events Database (EM-DAT)

Available data - 3

Green finance	• UNEP Finance Initiative UNEP-FI • Sustainable Stock Exchange Initiative (SSEI)
Scenario data	• NGFS: scenario data on the IIASA and Climate Analytics platform • RSE: Meteorological Reanalysis Italian Dataset (MERIDA) • CMCC: data and scenarios • OECD Climate Actions and Policies Measurement Framework (CAPMF)

The unavailable data

1. The Sistema informativo integrato (SII) by Acquirente Unico
2. Sistema Informativo sugli Attestati di Prestazione Energetica (SIAPE) by ENEA

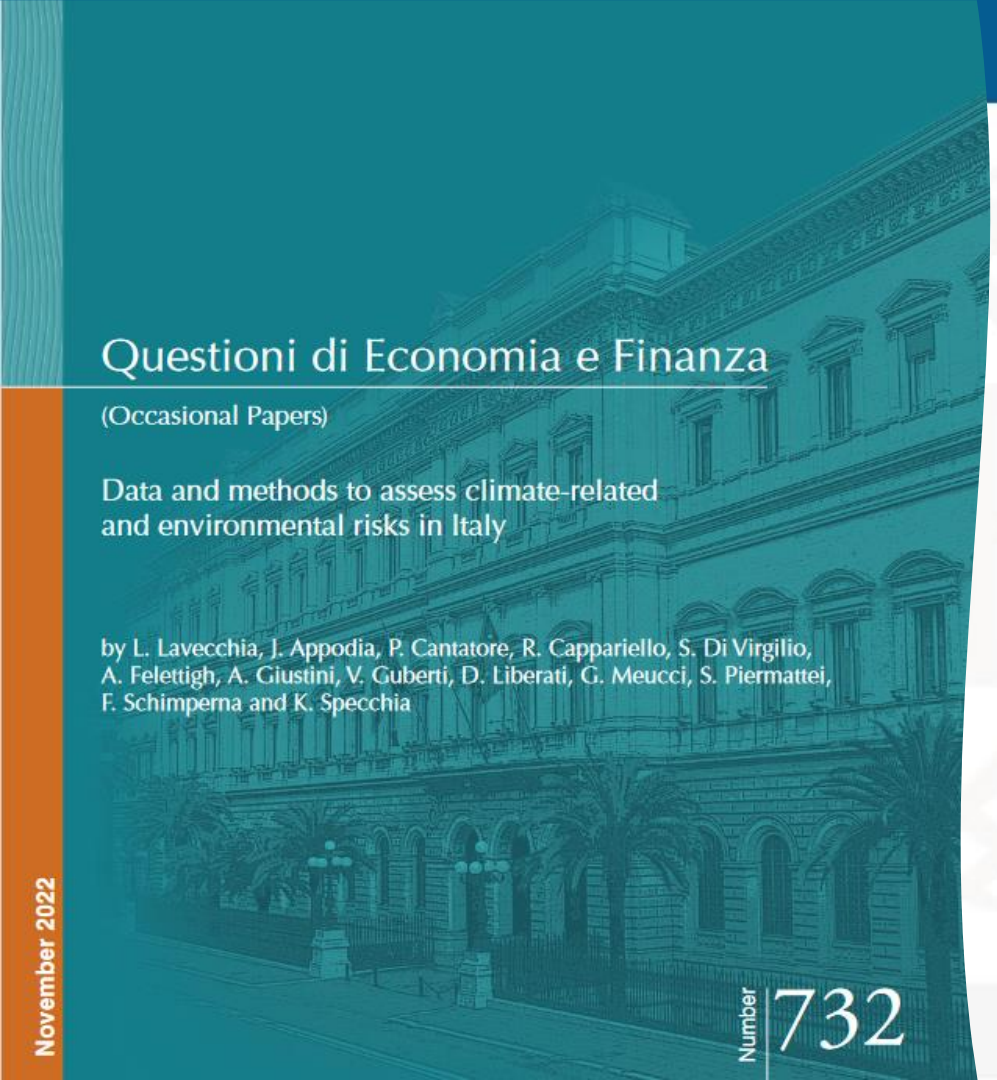


The sustainable data gap in Italy

- The sustainable data gap is concentrated :
  - By theme: energy (use, prices, expenditure), for HHs and firms; GHG emissions; climate scenarios data; natural catastrophe risks coverages and economic losses
  - By regulations: Pillar 3, CSRD
  - By firm size: micro and SMEs

Conclusions

- **The financial system is increasingly committed to supporting the green transition**, yet data limitations remain a critical bottleneck, especially in assessing and managing natural catastrophe risks
- **Bridging the data gap is not just a technical challenge**—it's a strategic imperative for a resilient and sustainable financial system:
  - **High-quality, granular and forward-looking data** are essential for: internal risk analysis and transition plans, regulations, financial stability monitoring, insurance underwriting and pricing;
  - **Public data sources offer valuable insights**, but accessibility, interoperability and granularity are still insufficient
  - **The sustainable data gap persists**, notably in: Energy consumption and GHG emissions, SME-level disclosures, Insurance protection gap and peril-specific economic losses, Integration of EPCs and climate scenarios into financial risk models
- **Coordinated action is needed**: Among statistical agencies, regulators, financial institutions and data providers; To harmonize standards, improve data sharing, and support the development of robust climate risk analytics



Thank you

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Irving Fisher Committee on Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

An experiment to measure physical climate risks in FDI between France and Italy

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This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

An experiment to measure physical climate risks in FDI between France and Italy

Mapping FDI vulnerability to physical climate change risks

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Jorge Diz Dias, Nadia Accoto, Rocco Incardona, Veronique Genre

Abstract

Economic activity worldwide is increasingly exposed to the adverse effects of climate-related risks. Extreme weather events — such as floodings, heatwaves, wildfires, and rising sea levels — are causing economic losses that in the European Union alone amounted to €208 billion between 2021 and 2024 (European Environmental Agency)[1]. The G20 has emphasised the need to address critical data gaps in related statistics, calling for improved measurement of emissions, exposure to financial and physical climate risks, and indicators to monitor the economic impact of the transition to a low-carbon economy.

Foreign direct investment (FDI), as a key driver of globalisation, is particularly relevant in this context. Assessing its exposure to physical climate risk can offer valuable insights for both policy development and economic analysis. This paper contributes to this effort, by proposing a methodology to quantify the vulnerability of FDI to the associated risks. We apply this framework to a case study involving France and Italy, assessing the exposure of bilateral FDI to current and projected physical climate change risks.

Our contribution builds on the literature examining how external risks affect FDI strategies, a body of work that has primarily focused on political instability and regulatory uncertainty. Few studies have directly addressed the role of physical climate risks in shaping FDI patterns. Our approach establishes an empirical link between FDI and climate risk at both regional and economic activity levels, leveraging firm-level data with detailed locational information shared by Italy and France. The locational data are matched with a geospatial mapping of climate-related physical risks providing a measure of risk exposure of French-owned FDI in Italy and of Italian-owned FDI in France, in the past, present and future under different climate scenarios. We also address methodological challenges related to the application of this methodology to multinational enterprise structures, including issues of indirect ownerships and overlapping affiliations.

While quantifying the effects of erratic and stochastic climate events remains challenging, our framework offers a foundational approach to incorporating physical climate risks into FDI measurement. In doing so, it supports more informed financial decisions and equips policymakers and investors with actionable insights for fostering climate-resilient FDI strategies.

Keywords: climate-related risks, foreign direct investment (**FDI**), physical climate risk, geospatial data, firm-level analysis, bilateral FDIJEL classification: Q56, F21, C81, Q54

[1] https://www.eea.europa.eu/en/analysis/indicators/economic-losses-from-climate-related?

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1. Introduction

In recent decades, the world economy has become increasingly intertwined with the planet's climate system. Climate change has emerged as an active and relevant variable in economic developments, shaping the contours of risk and opportunity across regional, sectoral, and temporal dimensions. The Copernicus Climate Change Service (C3S) reported that 2024 was the hottest year on record[2]. Extreme weather events (heatwaves, droughts, floods, wildfires, hurricanes, and coastal surges) are becoming more frequent and intense, and they do not only cause havoc or disruptions: they are rapidly translating into actual financial losses. In the European Union alone, the cumulative economic damage from climate-related events between 2021 and 2023 is estimated to have reached €162 billion (European Environmental Agency, 2024), a trend which has been on the rise since the last four decades. These impacts are unevenly distributed across time and space. Some regions and economic activities are more exposed than others, albeit reliable data on how exposure varies along these dimensions remains scarce. Understanding which industries and geographies bear the greatest risk is essential for designing effective policy responses and for allowing better investment decisions.

This shifting reality and information needs have prompted growing attention from policymakers, central banks, and multilateral institutions. The G20, among others, has highlighted the need to close data gaps in climate-related statistics, particularly those concerning the physical and financial risks linked to climate change.

Foreign direct investment (FDI) is particularly exposed to this challenge, as it is not only a channel for capital transfer but also a mechanism for technology diffusion, supply chain integration, and firm-level strategy. Unlike portfolio flows, FDI involves long-term commitments, frequently entailing the establishment of physical assets and organizational infrastructure in host countries. Such investment decisions are made with certain expectations about market stability, regulatory frameworks, and — crucially — the viability of operating conditions over time. As those conditions are increasingly shaped by climate events — a flood that disables a logistics hub, a heatwave that strains the power grid, or a wildfire that forces temporary shutdowns — investors and policymakers alike face a new class of uncertainty. A central question hence becomes: how exposed is FDI to these types of risks, and how can we measure that exposure systematically?

To date, most of the empirical literature on FDI and risk has focused on political or institutional uncertainties — regime volatility, regulatory instability, or expropriation threats. While these remain undoubtedly important, they now tell only part of the story. Physical climate risk has remained an underexplored dimension, not because it is unimportant, but because it is hard to measure. Unlike tax incentives or investment treaties, climate hazards are spatially specific, governed by probabilistic risk assessments, and often characterized by stochastic dynamics over time. Their impacts are also mediated by a range of local conditions: infrastructure quality, adaptation capacity, and even firm-level resilience strategies. Yet ignoring these risks amounts to assuming they are negligible — a stance increasingly at odds with reality.

This paper proposes a methodological framework to empirically assess the exposure of FDI to physical climate risk, with an application to a bilateral case study of France and Italy. These two countries are particularly well-suited for such an analysis. Both are major economies within the European Union with deep mutual investment ties and rich statistical systems. Their bilateral FDI relationship spans multiple economic activities — including manufacturing, energy, finance, and services — and features significant firm-level granularity in the available administrative data. Moreover, both countries face growing climate challenges, albeit with regional and climatic variation. France's southern regions are increasingly vulnerable

[2] https://climate.copernicus.eu/copernicus-2024-first-year-exceed-15degc-above-pre-industrial-level

to wildfires and droughts, while its Atlantic and Mediterranean coastlines face rising risks from sea-level rise and storm surges. Italy, on the other hand, confronts repeated flooding in the north, increased landslide risk in the Apennines, and heat-related stress in urban areas and in the southern regions, especially during the summer months. These contrasts offer useful evidence for testing how localized climate risk affect cross-border direct investment.

Our approach integrates firm-level locational and balance-sheet data with high-resolution geospatial information on physical climate hazards — such as flood maps, wildfire probability, and extreme heat projections — both current and under future climate scenarios, opening a new way to quantify the vulnerability of FDI positions to climate risks. By linking the geographic coordinates of firms to spatially granular risk indicators, we can assess the risk exposure of the resident direct investment enterprises and, subject to data constraints, of their local production units.

Crucially, this methodology also addresses technical challenges that often plague empirical work in this space: for instance, how to treat multinational enterprise structures, account for indirect ownership links, and manage overlapping affiliate networks. These are not mere methodological details, but crucial decisions if we are to move from stylized facts to rigorous empirical insight.

The broader aim of this study is to lay groundwork for a climate-informed theory and measurement of FDI. We do not claim to forecast FDI developments under climate change with precision — the underlying uncertainties are far too great, and the phenomena too complex. But what we can do is offer a replicable method to assess exposure, one that helps illuminate which sectors and regions are more at risk, and why, and to track how the exposure evolves over time. This is a first step toward building better risk assessments for investors, more resilient strategies for firms, and more targeted policies for governments concerned with both economic competitiveness and climate adaptation.

The paper is structured as follows: Chapter 2 reviews the literature. Chapter 3 covers the details on the methodology and its main phases. Chapter 4 provides details on the data used in the analysis. Chapter 5 presents and discusses the results for France and Italy. Chapter 6 offers a thorough discussion of the methodological difficulties encountered in the exercise. Finally, Chapter 7 presents some concluding remarks.

2. Literature review

The connection between FDI and climate risks has been a growing concern for investors and policymakers alike. As climate change becomes more evident from extreme weather events to rising sea levels, the related financial impacts also affect corporate financial performance and ultimately decisions about FDI location.

Several theoretical frameworks have been used to relate climate and FDI. The international risk theory, as outlined by Buckley et al. (2016), suggests that multinational enterprises (MNEs) take into account host country risks — including climate vulnerabilities — when making investment decisions. Similarly, Dunning's OLI (Ownership, Location, Internalization) paradigm emphasizes how locational advantages, potentially undermined by climate risks, play a crucial role in shaping FDI flows (see Shear et al. 2023). These frameworks provide a theoretical basis for examining climate risk as one of the determinants of FDI patterns.

The literature has highlighted the influence of climate physical risks both in FDI host countries (where the direct investment enterprises are located) and in FDI home countries (where direct investors are residing). Empirical evidence consistently points to a negative impact of physical climate risks on FDI inflows. Gu and Hale (2023) evaluate the response of FDI to extreme weather events, finding that countries

experiencing higher climate vulnerability attract significantly lower investment. Similar patterns emerge from panel studies spanning multiple decades and countries, which show that climatological indicators — such as average annual temperature and precipitation intensity — negatively correlate with inward FDI (see Jihad Ait Soussane et al. 2022). The type of climate hazard also plays a consistent role in deterring investment: floods, landslides, and cyclones have a much stronger negative impact compared to extreme heat and wildfires. This differentiated response underscores the complex relationship between specific climate hazards and FDI decisions.

The literature also shows considerable heterogeneity across economic activities and geographies. Agriculture, forestry, fishing, mining, and manufacturing emerge as the most climate-vulnerable sectors for FDI, with heat stress, water scarcity, and flood risk representing the primary threats. Meanwhile, in manufacturing and construction, increased flood risk from rising sea levels can lead to direct asset damage and indirect operational losses, impacting FDI investments. Such observation regarding sectoral variation reflects key differences in exposure to climate hazards and country adaptive capacity.

From a geographical perspective, FDI in the Caribbean, the Middle East, and Southeast Asia is exposed to the highest levels of climate risks (Li et al. 2022). Developing economies are disproportionally affected, as the negative effects of climate change on FDI tend to be more severe in countries with more agriculture-dependent economies and with limited investment in research and development. This geographical disparity underscores the uneven distribution of climate vulnerability across the global economy.

A relatively innovative concept introduced by Xing et al (2022) is "climate risk distance," defined as the difference in climate risks levels (as measured with Germanwatch data) between the home and the host countries in FDI relationships. Evidence shows that when the climate risk distance is positive (host country has higher risk than home country) FDI is less likely to occur. Conversely, when climate risk distance is negative (home country has a higher climate risk than host country), FDI is not significantly deterred, which the authors interpret as evidence that investors from higher-risk home countries may possess internalized knowledge or experience to manage climate risks. This asymmetric relationship suggests that countries with high climate risks may hold competitive advantages — such as enhanced resilience or adaptive capabilities — that help them overcome climate-related barriers when investing abroad. The concept provides a nuanced understanding of how relative, rather than absolute, climate risk affects cross-border investment patterns.

These finding suggest that investments in climate adaptation and resilience generate not only environmental benefits but also enhance a country's attractiveness to FDI. The potential for policy interventions to mitigate some adverse effects of physical climate risks can play a critical role in improving FDI attractiveness.

The literature has developed diverse methodological approaches to assess the relationship between climate risk and FDI. These include panel econometric models based on climate vulnerability indices (e.g. Shear et al. 2023, Jihad Ait Soussane et al. 2022) and firm-level analyses of investment decisions (e.g. Gu and Hale 2022). Recent advances involve the integration of geospatial climate risk data with facility-level information, allowing for more granular assessments of physical risk exposure (e.g. Li et al. 2022).

Nonetheless, some methodological and measurement challenges persist. Quantifying erratic and stochastic climate events remains difficult, while capturing the complexity of FDI chains — including indirect ownership structures and overlapping corporate affiliations — requires the development of detailed and integrated statistical databases. These limitations are reflected in several outstanding research gaps. In particular, few studies have measured the relationship between FDI and physical climate risk at the firm level, with detailed geographic and sectoral resolution. Our study contributes to closing this gap by proposing a framework that combines firm-level FDI data with geospatial mapping of climate hazards,

applied to a case study of bilateral investment between France and Italy. This approach provides an empirical basis for integrating climate risk into FDI analysis.

3. Methodology

This chapter presents the methodological framework developed to quantify the exposure of bilateral FDI between France and Italy to physical climate risks. FDI refers to cross-border investments involving a 'lasting interest', where an investor from one country acquires control (defined as 50% or more of voting rights) or a significant degree of influence over the management (defined as 10% or more of voting rights) of a company located in another country (OECD, 2025). The proposed approach is conceptually organized into three sequential phases, each addressing a key aspect of the measurement strategy. The overarching objective is to construct a granular, replicable, and interpretable measure of physical risk exposure at the level of bilateral FDI positions, by linking firm-level data to climate hazard maps.

The scope is restricted to the non-financial sector. Financial institutions such as banks and insurance companies are excluded, as their climate risk exposure stems primarily from their financial portfolios than from their physical location. An exception is made for financial holding companies, which are retained to preserve the integrity of the ownership chains including non-financial entities. These choices ensure that the resulting measure captures the physical vulnerability of direct investment, rather than intermediated financial risks. In addition, the analysis focuses exclusively on the equity component of FDI, which best reflects ownership structures and avoids potential distortions arising from the debt component. This narrower scope allows for full control over data quality and detail at firm level, providing valuable insights at this early stage of integrating FDI with climate risk metrics.

Phase 1: decomposition of FDI positions

The first phase decomposes aggregate inward FDI positions into elementary units. This involves identifying the Direct Investment Enterprises (DIEs) residing in France (Italy) that are linked to an Italian (French) direct investor, along with their domestic ownership chain, including related establishments or production sites. Branches are also included when treated as DIEs in official FDI statistics. The output of this phase is a list of DIEs associated with bilateral FDI positions, together with their downstream affiliates and establishments in the respective host economy. We shall refer to the elements in this list as the elementary units.

With respect to the domestic ownership chain, only controlled entities are included. Specifically, the chain is followed downstream only when the participation link involves an equity share of at least 50%. While minority stakes (e.g. 25%) may confer a degree of influence, they typically reflect arm's-length contractual relationships rather than full vertical integration. The literature on ownership and value chains suggests that effective control – and thus strategic vulnerability to physical shocks – rests primarily with majority-owned affiliates (Grossman and Hart, 1986; Gereffi, Humphrey and Sturgeon, 2005).

Caution is warranted when official FDI statistics are derived from sample-based surveys rather than from a census. This issue is particularly relevant when analysing the relationship between FDI and climate risk, where the geographic location of enterprises plays a crucial role. In sample-based surveys, enterprises are assumed to be representative of the broader population, and their reported values are extrapolated to the national level using expansion coefficients. While this approach is appropriate for estimating aggregate measures (e.g., total FDI values), it is less reliable for capturing granular details, such as the precise geographic distribution of enterprises. For this reason, the dataset used for the analysis

should be drawn from comprehensive administrative sources, which provide detailed information on enterprise equity, ownership shares, and the residency status of shareholders.

We focus on immediate ownership, and the DIE list includes only bilateral FDI positions between France and Italy (i.e., French-owned entities in Italy and Italian-owned entities in France) and their respective domestic chain of entities (i.e. non-resident units belonging to the same DIE group are not included). In adopting this approach, we do not adjust for potential round-tripping in the identification of DIEs. Round-tripping refers to situations in which domestic investors route capital through foreign jurisdictions for several strategic or financial reasons, and subsequently reinvest it in their home country, creating the appearance of foreign ownership and potentially benefiting from tax or regulatory advantages.[3] While it is possible that some enterprises in our sample reflect round-tripping structures, the phenomenon is expected to be limited in this bilateral context. Indeed, since France and Italy have broadly similar legal and tax frameworks, the incentives for round-tripping between the two countries are likely to be weak, and the volume of such transactions relatively low.

Phase 2: Geolocation and climate risk mapping

The goal of the second phase in our methodology is to assign a climate risk score to each elementary unit identified in Phase 1. In principle, this would require geolocating each unit – i.e. retrieving its address from national registers and converting the address into geographic coordinates – and overlaying it with high-resolution climate hazard maps to obtain the associated risk score. However, rather than conducting this process independently, we rely on an enhanced version of the ECB's Register of Institutions and Affiliates Database (RIAD+). This version integrates firm-level geographic coordinates and physical climate risk indicators from specialized climate data sources (see Section 4.2 for further details).

RIAD+ allows us to assign the risk scores in two ways. When an elementary unit from our sample appears in RIAD+, we directly use its climate risk score. This applies to about 20% of units, as most establishments lack separate identifiers distinct from their parent companies, and RIAD was originally designed with a focus on financial institutions and large corporates. For the remaining units, we apply a two-step geolocation and spatial interpolation method. Each unit's address is first geocoded with OpenStreetMap to obtain latitude and longitude coordinates.[4] Using these coordinates, each non-RIAD+ unit is matched with its five closest neighbors in RIAD+. Specifically, we compute the median physical risk score of its five nearest neighbors, identified using the haversine distance in combination with a Ball Tree search algorithm (Moore, 1991). [5] Using the median reduces the influence of extreme values, ensuring more robust and representative imputations. This spatial approach is supported by the strong local autocorrelation of climate variables (e.g. temperature, flooding, water stress). As shown in Chart 1, over 95% of matched neighbors are within 1 km.

Phase 2 produces a vector of climate risk scores for each of the elementary units identified in Phase 1. Scores are remapped to their original scales (e.g., probabilities, expected losses) to enable the

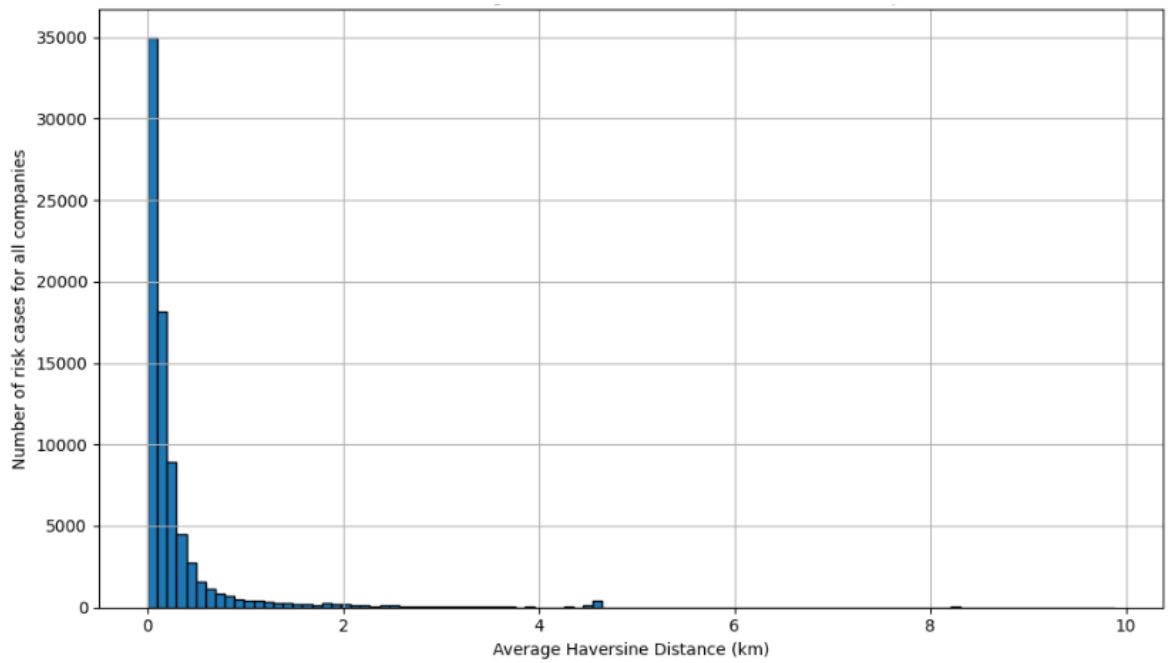
[3] As an illustrative example, consider the case of a DIE residing in Italy with a French direct investor, which is itself ultimately controlled by an Italian entity (round-tripping). This DIE would be included in our analysis, since, under the immediate investor perspective, it is an Italian firm controlled by a French investor.

[4] Most entities are successfully geolocated, while a small number are excluded due to invalid address records or locations outside mainland France. For France, we only consider units located in the "metropolitan France", i.e. we exclude overseas regions, departments, and territories.

[5] The haversine formula calculates great-circle distances between two points on a sphere, making it suitable for geographic coordinates. The Ball Tree is a hierarchical data structure that organizes points into hyper-spherical nodes to enable efficient nearest-neighbor searches. Combined, these methods significantly reduce computational costs compared to brute-force distance calculations and provide a statistically robust approximation for missing climate scores.

subsequent aggregation. Before Phase 3, we exclude entities associated with negative FDI positions to facility the calculations and without any impact on the results.

Distribution of Average Haversine distances (km) for nearest neighbours Chart 1



Sources: authors' own calculation on Italian and French elementary units' dataset

Phase 3: Aggregation of risk scores at FDI-level

The final phase aggregates the unit-level climate risk scores into a consolidated assessment of FDI exposure to physical climate risk. The aggregation process follows a structured, hierarchical approach.

First, climate risk scores assigned to elementary units (establishments or affiliates) are consolidated at the level of the DIE. This step captures how the FDI capital of a single enterprise, potentially spread across multiple locations, is exposed to physical risks. We weight each unit by the number of employees, as a proxy for its operational scale and economic significance.[6]

Second, DIE-level risk measures are aggregated by NACE economic activity, using each DIE's total equity as a weight. This produces sectoral climate risk indicators that combine both the exposure of individual firms and their relative importance within the sector.

Finally, sectoral climate risk indicators are combined into an overall measure of the inward FDI position. Each NACE economic activity is weighted by its share of the total FDI equity, ensuring that the

[6] Tangible capital, such as non-financial assets, would be a relevant basis for weighting the consolidation of risk scores at the DIE level. However, data on tangible capital are limited, especially at the level of elementary units. Employment is therefore used as the preferred proxy, as it is widely available and strongly correlated with value added, effectively capturing the relative economic scale of each unit.

final indicator reflects both the granular exposure of local production units and the economic weight of each unit within the broader investment structure.

Critical assumptions include the availability and consistency of data on the number of employees and equity, as well as the comparability of risk metrics across establishments and sectors. Transparency in these assumptions remains essential for robustness and replicability. Together, the three phases define the complete set of data requirements needed to implement this type of analysis.

4. Data and Descriptive statistics

4.1. National microdata on FDI firms

To implement the proposed three-phase methodology, the following microdata are required:

1. Equity value: pro-rata equity of DIEs.
2. NACE activity: the economic activity classification of DIEs.
3. Number of employees: employment data for all enterprises, including their local subsidiaries and their establishments.
4. Address of all elementary units (DIE, their subsidiaries, and their establishments)

These data were provided by the French and Italian national central banks (NCBs), which sourced them from national business registers. Both French and Italian dataset are methodologically consistent as both countries follow international standards and Eurosystem guidelines to compile FDI data. For example, data are reported at Own Funds at Book Value (OFBV), meaning that equity positions are valued according to the accounting records of the resident enterprise, capturing both initial capital contributions and retained earnings. This accounting-based approach ensures internal consistency across data sources and provides a reliable basis for linking FDI positions to the geographic distribution of productive assets and, ultimately, to their exposure to climate-related risks.

4.1.1 The Italian case

In the case of Italy, the identification of the list resulting from phase 1 relies on national business register and Italian NSI's ASIA-GRUPPI database, which is the Italian contribution to the European Group Register (EGR).

The domestic ownership chains were reconstructed sequentially. Starting with the list of Italian enterprises with French shareholders (Level 0), the affiliated enterprises controlled by these entities (Level 1) were identified using the ASIA-GRUPPI database, and so on. For each enterprise (with French shareholders and reconstructed ownership chains), establishments were also identified and the respective number of employees obtained from the national business register.

For the enterprises under study, official Italian FDI data are derived from sample-based surveys. A comparison between official FDI data and data used for this study (derived from administrative sources and referred to the entire population) is therefore necessary. This comparison based on 2022 data demonstrates a near-perfect overlap in terms of amounts (Table 1).

Comparison between official FDI data and FDI from administrative sources

Table 1

	Number of enterprises	Sample not grossed up OFBV (M €)	Sample grossed up OFBV (M €)
Sample	132	33,902	42,304
Population	2,626	-	42,316

Sources: Banca d'Italia

4.1.2 The French case

In France, equity capital positions of inward FDI are identified as all non-resident holdings exceeding 10% of the equity capital of resident enterprises. This information is compiled using mainly three administrative sources.

SIRENE is the national business register, maintained by INSEE, the national statistical institute. It provides exhaustive coverage of all enterprises and establishments operating in France, whether public or private, and assigns them unique identifiers. The database includes detailed information on legal form, sector of activity, size, and geographic location, and is continuously updated through administrative sources such as tax records, social security, and commercial court registries.

The identification of corporate groups in France draws on INSEE's *Liaisons financières entre sociétés* (LIFI) database, which records equity links between companies as of December 31 each year. LIFI reconstructs group structures by identifying both DIE parent and its elementary units, relying on multiple sources such as Banque de France's financial data, fiscal records from the Ministry of Finance, and the European Group Register. An algorithm establishes financial control and group heads (including foreign ones). Originally survey-based, LIFI has since evolved into an integrated database covering nearly 190,000 groups in 2023, making it a central tool for mapping ownership structures and multinational linkages in France.

Finally, ESANE (*Élaboration des Statistiques Annuelles d'Entreprises*) integrates accounting, tax, and survey data to produce harmonized indicators on equity, employment, value added, and other financial characteristics of French enterprises.

Together, these sources enable the detailed mapping of inward FDI positions, domestic ownership structures, and the geographic distribution of investments necessary for linking FDI to climate risk exposure.

4.2. Overview of Physical Risk Data

As anticipated in Chapter 3, this study leverages RIAD+, an enhanced version of RIAD that integrates firm-level geolocation with climate physical risk data developed by the ESCB Statistics Committee Expert Group on Climate Change and Statistics (STC EG), in collaboration with the Working Group on Securities Statistics (WGSS)[7]. The physical hazard data were retrieved by the STC EG entirely from public sources such as Copernicus[8] and the European Commission DRMKC RDH[9], and they are developed and maintained by the

7 See SPS https://www.ecb.europa.eu/pub/pdf/scpsps/ecb.sps48~e3fd21dd5a.en.pdf

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

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

Joint Research Centre (JRC). The climate scenarios rely mostly on climate projections developed by the European Coordinated Regional Downscaling Experiment (EURO-CORDEX) – and are based on earlier models expressed in Representative Concentration Pathways (RCPs)[10]. These indicators are built at the firm-level and aim to quantify the exposure of corporations to physical climate hazards (see Table 1 in the appendix for a detailed overview of the different climate scores and how they are computed). Climate risk scores across various dimensions typically range from 0 (low risk) to 5 (high risk). An exception is the risk score associated with the precipitation index, which is distributed between -3 (extremely dry) and 3 (extremely wet).

These data enable the assessment of both current and future vulnerabilities, with a focus on medium-term time horizons to support climate risk analysis and evaluations. Climate scenarios are inspected, where relevant, to enhance the understanding of potential risks and inform appropriate mitigations strategies.[11]

European firms are exposed to a wide array of climate-related hazards, which can be broadly grouped into acute and chronic risks. Acute risks refer to event-driven hazards such as floods (coastal and river), windstorms, wildfires, landslides and subsidence, which can cause abrupt and severe disruptions to economic activity. By contrast, chronic risks capture long-term, persistent and gradual shifts in climate conditions, notably droughts, water stress, and precipitation anomalies (measured for instance through consecutive dry days or the Standardised Precipitation Index). A recent ECB study (Boldrini et al, 2023) indicates that while acute hazards tend to generate losses concentrated in specific regions or sectors, chronic risks – particularly prolonged drought and increasing water scarcity – affect all Europe, with various degrees of intensity, bearing significant implications for agriculture, energy production, and manufacturing.

4.3 Descriptive Statistics on elementary units

After completing phase 2, we were able to draw the following descriptive statistics for the elementary units in France and Italy and their related FDI positions (Table 2). The figures reported show a coverage slightly above 52% if we consider official total bilateral FDI investments in Italy and France for end-2022 and close to 100% if we consider official FDI data for the corporations covered in our analysis[12] (as explained in Chapter 3). Finally, on average, French DIEs tend to be larger when looking at average employees and median FDI value. However, the largest DIEs in the dataset are located in Italy (larger average FDI value).

[10] RCP 4.5: Stabilization pathway. Radiative forcing reaches about 4.5 W/m^2 by 2100. Emissions peak around mid-century, then decline due to mitigation policies. Leads to moderate warming (~2–3°C by 2100 relative to preindustrial). RCP 8.5: High baseline pathway. Radiative forcing reaches 8.5 W/m^2 by 2100. Assumes continued high emissions, heavy reliance on fossil fuels, little mitigation. Leads to stronger warming (~4–5°C by 2100).

[11] Climate scenarios are standardized projections of future climate conditions based on different assumptions about greenhouse gas emissions and socio-economic developments. Commonly used scenarios include the Representative Concentration Pathways (RCPs) adopted by the IPCC, such as RCP4.5 (moderate mitigation) and RCP8.5 (high emissions). These are widely used by policymakers and institutions (e.g. European Commission, NGFS) to assess physical climate risks under alternative futures.

[12] That is excluding real estate investments, banks and insurance companies.

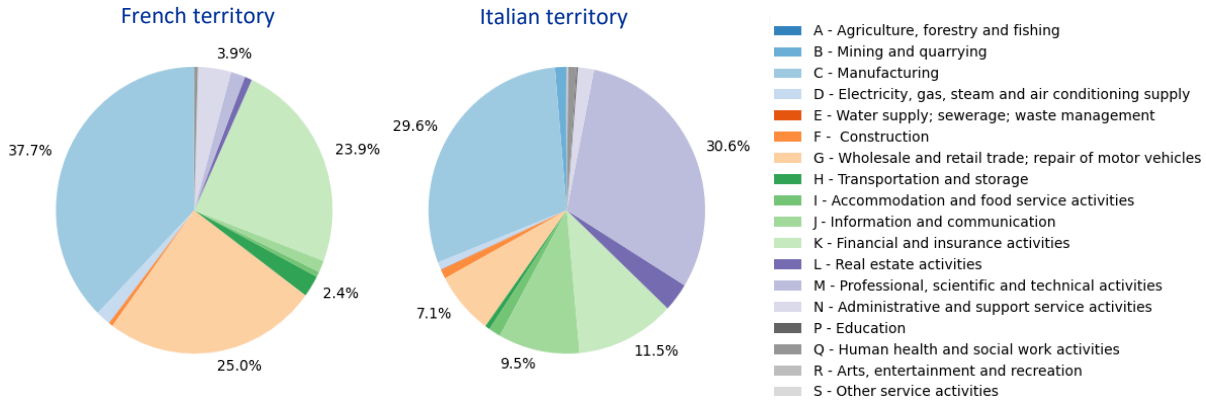
Comparison between French and Italian territory (year 2022) Table 2

	French territory	Italian territory
Number of DIEs	1,504	2,580
Total number of employees	332,372	336,241
Bilateral FDI value (M €)	13,898	41,899
Median FDI value (M €)	769.0	89.8
% of official total bilateral FDI	52%	55%
% of official FDI enterprises in the analysis	100%	97%

Sources: authors' own calculation on Italian and French elementary units' dataset

Looking at the economic activity (NACE level 1) breakdown in Chart 2, most of French FDI value in Italy (pie chart on the right) is focused on (M) Professional, scientific and technical activities, which includes also head offices, (C) Manufacturing, (K) Financial and insurance activities and (J) Information and communication. Most of Italian FDI value in France (pie chart on the left) is concentrated in (C) Manufacturing, (G) Wholesale and retail trade and (K) Financial and insurance activities (see also Table 1 in appendix). We should expect companies involved in Agriculture, Manufacturing and Construction to be more exposed to climate risk rather than, for instance, those in Financial and insurance activities (see next section), which in the scope of our analysis only include holding companies.

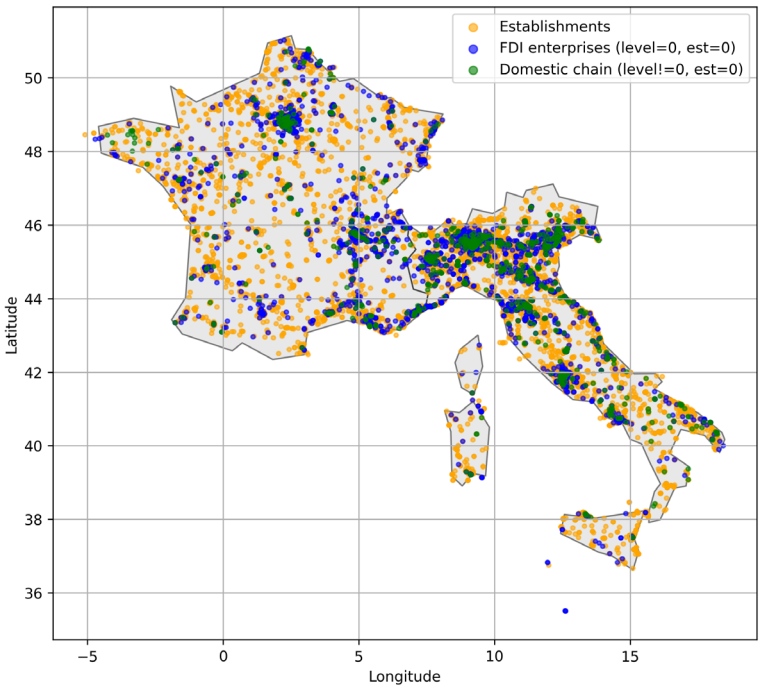
Distribution of FDI value in French and Italian NACE activities Chart 2



Sources: authors' own calculation on Italian and French elementary units' dataset
Notes: Financial and insurance activities include only holdings as specified in the methodological Chapter 3

An analysis of the geographical distribution of the list of elementary units (i.e. including domestic chain and establishments) reveals that DIEs enterprises are heavily concentrated in major urban centres (Chart 3). In contrast, domestic chain (i.e. local subsidiaries) and establishments are more widely dispersed throughout the territories. This spatial disparity highlights the necessity of incorporating these establishments into FDI-weighted climate score calculations for a more comprehensive assessment.

Geospatial distribution of elementary units Chart 3



Sources: authors' own calculation on Italian and French elementary units' dataset

Furthermore, inspecting the distribution across the domestic chain (Table 3), we find that the majority of entities are either DIEs at Level 0 or their local subsidiaries (and their associated establishments) at Level 1. We define "daughter companies" or establishments as being one level down their parent DIE.

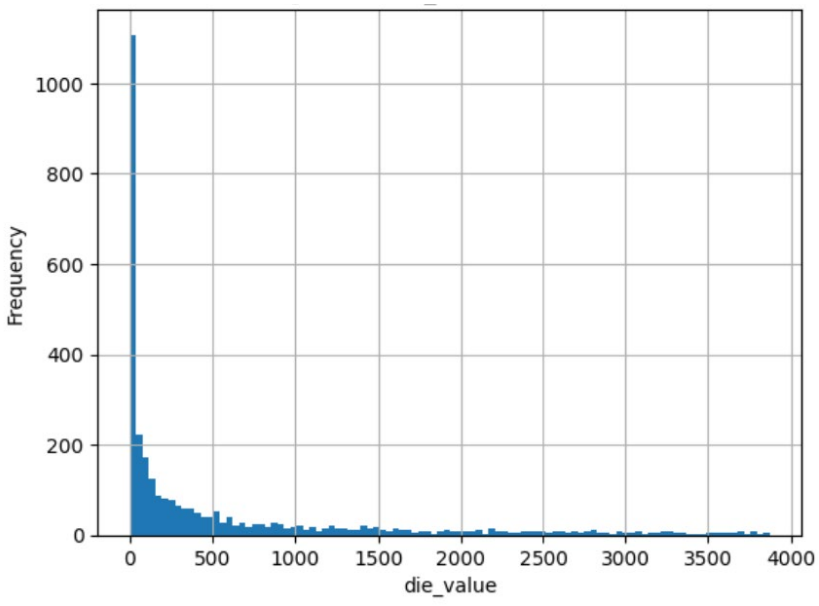
Distribution of elementary units along the different levels — Table 3

	French territory		Italian Territory	
	Establishments	**Enterprises**	**Establishments**	**Enterprises**
Level 0	0	1504	0	2580
Level 1	3800	211	4313	751
Level 2	572	70	3787	272
Level 3	126	35	557	67
Level 4	75	7	112	25
Level 5	4	1	56	2
Level 6	0	0	1	0

Sources: authors' own calculation on Italian and French elementary units' dataset

Finally, an examination of the FDI values reveals a highly skewed distribution (Chart 4), where a few companies have extremely large FDI values while the vast majority have very small or even zero values. This is often referred to as a power-law distribution and has significant implications for analysis: this skewness makes a simple average misleading, as it would be heavily inflated by the few large companies, giving a false impression on the overall investment landscape.

Histogram of FDI values in the French and Italian territories (year 2022) — Chart 4

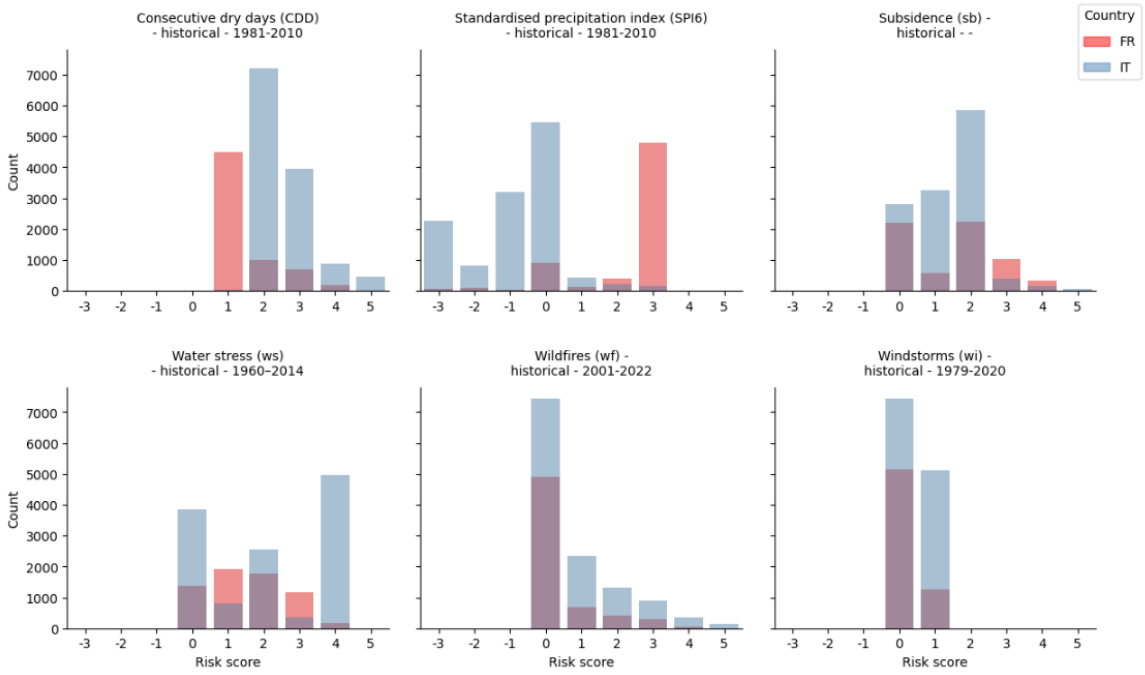


Sources: authors' own calculation on Italian and French elementary units' dataset

4.4 Descriptive Statistics on climate risk scores

The graphs below present the matching results between the full list of identified entities (18,928 units) and the climate physical risk dataset, separately for French and Italian territory. Examining the distribution of enterprises and establishments across different hazard types (Chart 5), we find that French and Italian firms are frequently exposed to hazards related to prolonged climatic stress, such as consecutive dry days, water stress, or precipitation anomalies (standardized precipitation index). Approximately one-third of total entities are highly exposed to prolonged drought conditions and around 18% face a significant risk of wildfire. By contrast, risks such as coastal or river flooding affect only a small number of entities, with most enterprises recording a risk score of zero (see Chart 1 in appendix).

Number of entities in each risk bucket in French and Italian territories — Chart 5



Sources: authors' own calculation on Italian and French elementary units' dataset

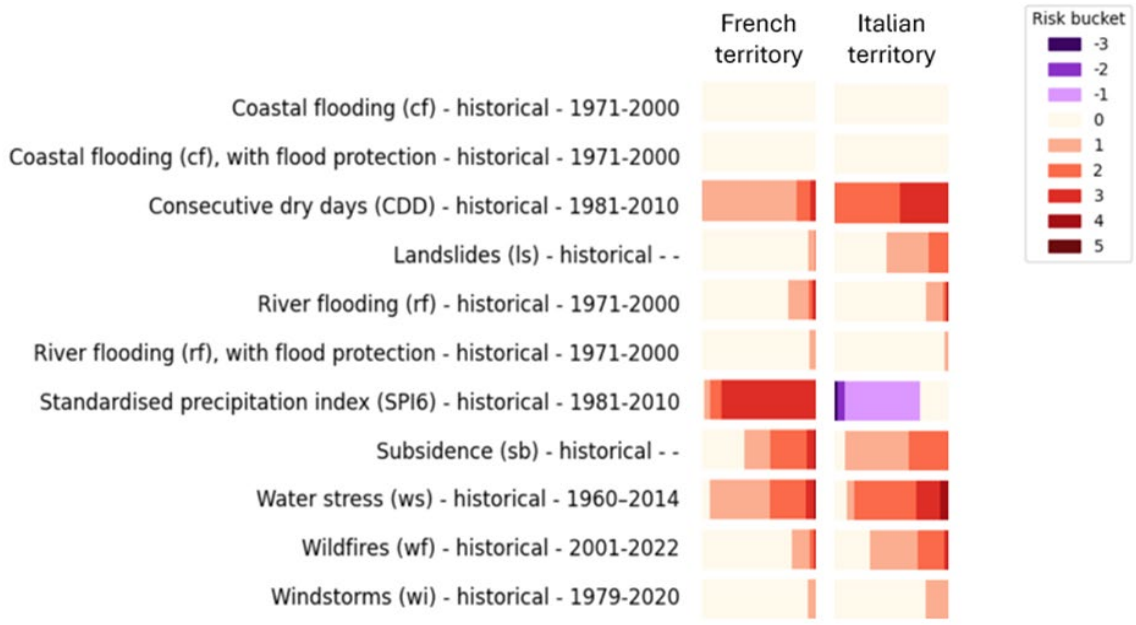
5. Results

Our results provide a detailed understanding of the variability in climate risk exposure across different hazards, sectors, and countries. They also shed light on the spatial and economic distribution of these risks. Unless otherwise specified, the following charts display weighted risk scores, based on the methodology outlined in Chapter 3. In evaluating the results, we consider a qualitative assessment of climate hazard exposure, because, at this stage, we are not able to quantify the financial impact of climate risks, i.e. to express the risk in terms of expected losses. Additionally, we do refrain from adding climate risk assessment across different risk categories; due to the way we build scores, comparisons across different hazard types are not meaningful.

5.1 Aggregate Climate Risk Exposure

Chart 6 shows the distribution of weighted climate risk scores for FDI in the French and Italian territory. Climate risk scores at the level of bilateral FDI positions reveal significant variability across different hazards and regions. Some hazards affect only a few firms, but risks such as water stress, wildfires, consecutive dry days, subsidence and the SPI index show greater variability.

Distribution of weighted climate risk scores for DIEs — Chart 6



Sources: authors' own calculation on Italian and French elementary units' dataset and climate scores from STC EG

While France is more exposed to extreme wet conditions, for Italian inward FDI the opposite is true (Standardised precipitation index is negative). The same picture is showed by the consecutive dry days score, since both the measures are capturing the intensity of draughts. French direct investment in Italy is also more exposed to wildfires, water stress, landslide, subsidence, windstorm and coastal flooding.

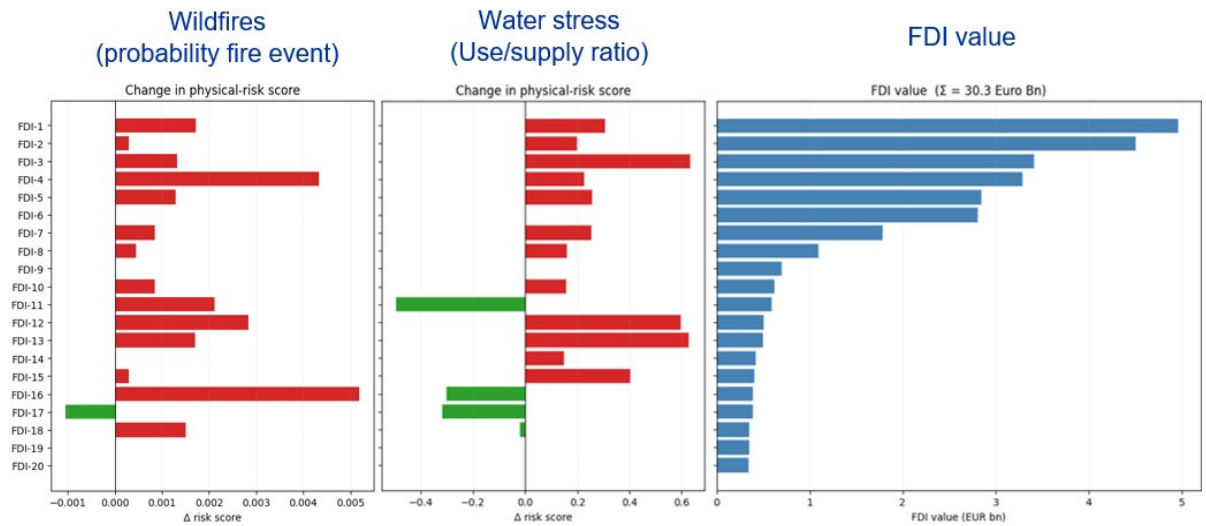
5.2 The importance of domestic subsidiaries and local establishments

The twenty largest foreign investors in our sample account for €30.3 billion, roughly 55 percent of the entire inward FDI equity stock that Italy and France reported at year-end 2022. Because these conglomerates dominate the aggregate position, any mismeasurement of their exposure to climate hazards can contaminate macro-level indicators and the risk assessments used by regulators and policy makers.

A frequent shortcut in the empirical FDI literature is to proxy an enterprise's physical-risk exposure with the hazard score of its legal domicile or head-office location. Our results show that this simplification produces a pronounced downward bias. FDI parent companies are typically located in capital regions or major business centres that enjoy better infrastructure and lower climate vulnerability than the peripheral sites where production takes place. By extending the analysis to the full domestic corporate ownership chain, we reveal a more comprehensive and heightened assessment of climate risk exposure.

Chart 7 illustrates the point for two relevant hazards, based on score variability: (i) wildfires and (ii) water stress risk. For most firms, and particularly for the ten largest investors, the score associated with the domestic corporate ownership chain is markedly higher than the score associated with the DIE only. The implication is two-fold. First, climate risk is systematically under-estimated in conventional FDI datasets that stop at the parent-company address. Second, policy interventions, such as targeted adaptation support, should focus on the geographical footprint of corporate groups rather than on their legal seats.

Change in climate risk scores after including subsidiaries and establishments — Chart 7



Sources: authors' own calculation on Italian and French elementary units' dataset and climate scores from STC EG

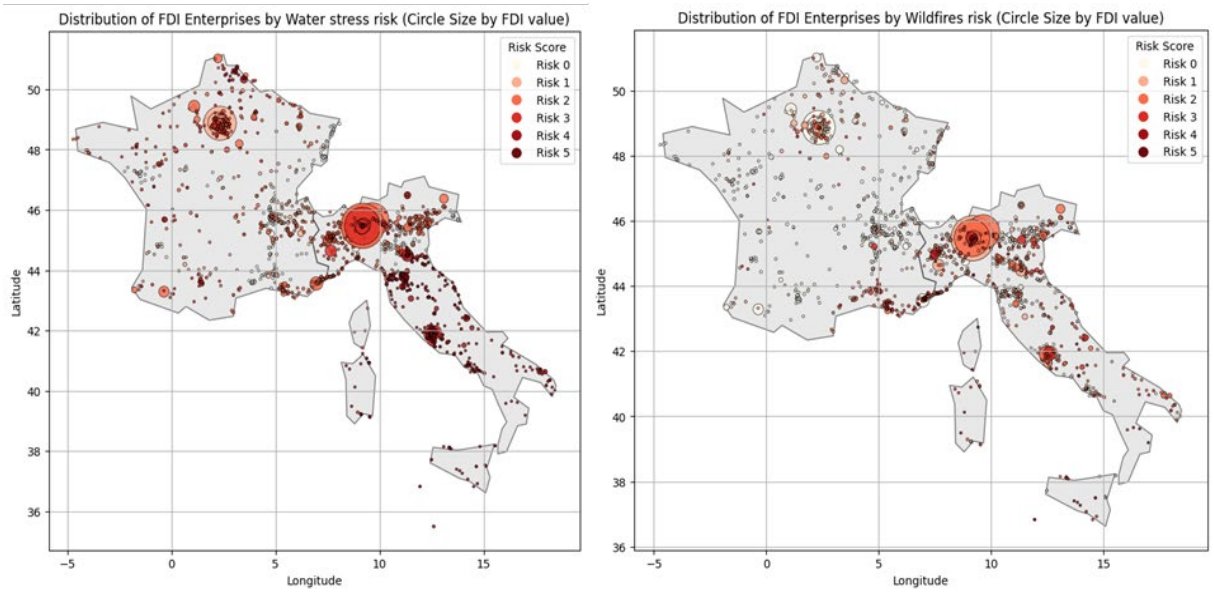
As a confirmation of this result, we also compare the raw climate risk scores between entities that are establishments and those that are not, finding a statistically significant difference for most indicators. As expected, establishments tend to be exposed to higher climate risks than their parents, given their more diverse geographical distribution. A similar pattern is also observed in another recent study on euro area firms (Rang, 2025).

5.3 Geographic distribution of physical risks

Inspecting the geographic distribution of the elementary units in our sample and their risk scores, we observe the localized nature of certain hazards. Acute risks, such as wildfires, are concentrated in specific geographic areas, while chronic risks, such as consecutive dry days, exhibit a broader distribution but with less intensity. Furthermore, large enterprises (in terms of FDI value) tend to be less exposed to risks compared to smaller ones.

Chart 8 shows where high-risk FDI enterprises are located, with bubble size reflecting FDI value and bubble colour reflecting risk class. We observe that regions with higher climate risk exposure often host less FDI value overall. Another point is that firms located in the same area can still record different scores, depending on where their subsidiaries are spread.

Geospatial distribution of FDI and climate risk scores — Chart 8



Sources: authors' own calculation on Italian and French elementary units' dataset and climate scores from STC EG

5.4 Distribution of physical risk across sectors of economic activity (NACE)

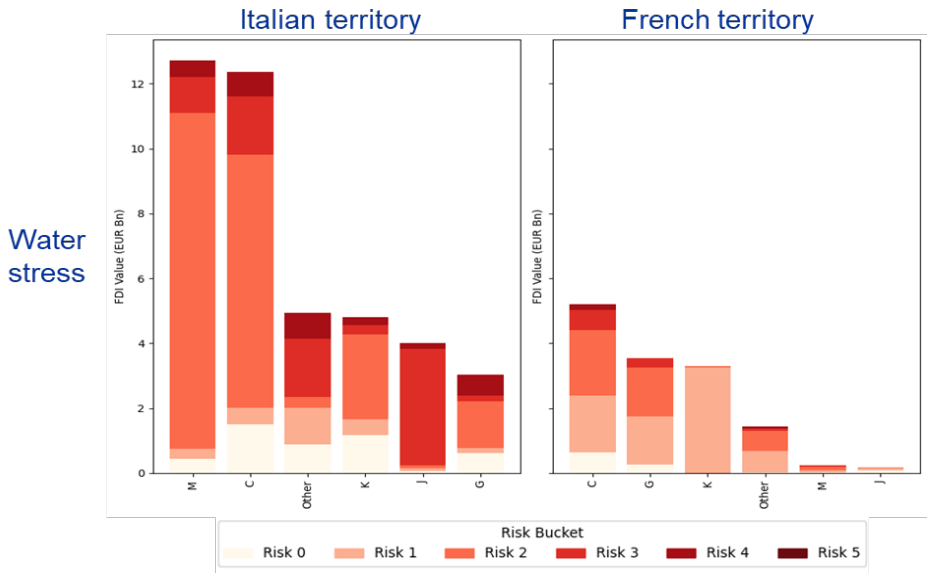
Our analysis also uncovers differences in the climate risk exposure of economic activities. Certain industries, such as manufacturing and agriculture, are disproportionately exposed to specific types of physical risks due to their geographic concentration and reliance on climate-sensitive resources. By aggregating risk scores at the level of DIEs and further consolidating these scores by activity, we can inspect which economic activities are more exposed to specific type of risks.

FDI is mostly concentrated in a few key activities: Professional, scientific and technical activities (M), Manufacturing (C), Financial holdings (K)[13] and wholesale (G) (Chart 9). These activities are also

[13] Since the financial sector was originally excluded from this analysis, this group should be interpreted as a 'miscellaneous' sector, as it is made up by holdings whose domestic chains are not related with financial services.

associated with lower physical risk scores on average, reflecting the fact that they are made up by a few large FDI firms.

FDI and climate risk distribution across NACE activities — Chart 9



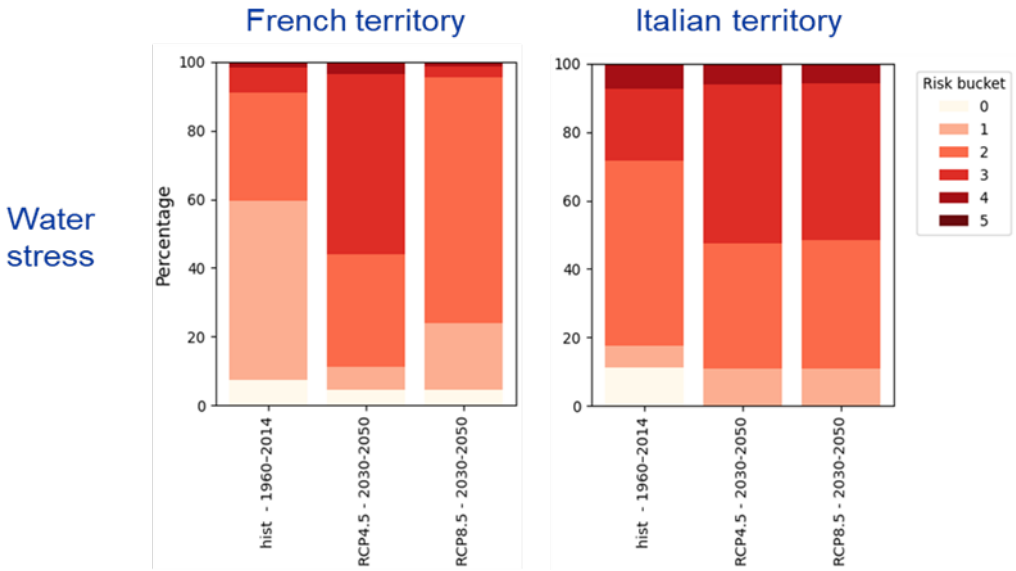
Sources: authors' own calculation on Italian and French elementary units' dataset and climate scores from STC EG

Disregarding the FDI absolute value, the NACE activities most exposed to climate risks show a clear territorial variation. For example, French FDI in Italy exhibits significantly greater historical wildfire risk exposure across sectors like Agriculture, Mining, and Transportation compared to Italian FDI in France within those same activities (see Appendix, Chart 2).

5.5 Risk evolution under RCP 4.5 and RCP 8.5

To evaluate the potential evolution of risks and its impact on FDI under different climate scenarios, the analysis incorporates projections based on the IPCC's Representative Concentration Pathways (RCP4.5 and RCP8.5). These scenarios imply an increase in risk exposure under moderate and high-emission pathways.

Water stress risk evolution under RCP 4.5 and RCP 8.5 Chart 10



Sources: authors' own calculation on Italian and French elementary units' dataset and climate scores from STC EG

As an example, Chart 10 shows the projected evolution of the exposure to water stress under the two scenarios. For French FDI in Italy, the results indicate an increasing exposure to this risk, following a similar trajectory under both the moderate- and high-emission pathways. In contrast, for Italian FDI in France, the exposure is higher under the moderate-emission scenario than under the high-emission scenario. This outcome aligns with the findings reported in the climate physical risk data developed by the Statistics Committee Expert Group on Climate Change and Statistics (STC EG), in collaboration with the Working Group on Securities Statistics (WGSS)[14].

6. Main challenges and future prospects

While this study provides valuable insights into the exposure of bilateral FDI to physical climate risks, several limitations and sensitivities must be acknowledged. One primary challenge stems from **data gaps**, particularly in climate score calculations, geolocation accuracy, or the availability of fixed assets and precise employment data at the establishment level. These gaps introduce uncertainties in the aggregation of risk metrics, potentially leading to overgeneralizations or underestimations in specific regions or sectors. Furthermore, the comparability of risk metrics across hazard types, economic activities, and geographies requires careful interpretation, as the climate scores do not accurately depict the FDI expected losses in the case of adverse climate events.

An additional limitation is that an integrated view of the climate risk exposure of FDI requires considering also the **banking and insurance sectors**, which are exposed to risks through a different channel: not through their geographical location but through the composition of their balance sheet

[14] See SPS https://www.ecb.europa.eu/pub/pdf/scpsps/ecb.sps48~e3fd21dd5a.en.pdf

assets. Similarly, FDI includes real estate, which is also subject to physical risks but has been excluded from this analysis due to both its modest share on total FDI and to the lack of information on its geographical location.

Another relevant caveat for our analysis is that it does not account for risk mitigation measures. For instance, a firm located in a high-risk area may be hedged or insured, making it less exposed than a non-insured firm in a medium-risk region. Moreover, hazard maps often account for physical mitigation measures only with a significant lag. This is particularly relevant for risks such as flooding or wildfires, where prevention actions (embankments, levees, firebreaks), albeit expensive, can be very effective in reducing risk exposure.

A minor limitation, which is nonetheless worth mentioning, involves the temporal misalignment between the snapshot of FDI values (captured at the end of 2022) and the historical or projected climate indicators used in the analysis. This mismatch may distort the relationship between FDI exposure and climate risks. A more rigorous approach would involve linking FDI values to climate risk data from corresponding time periods, ensuring a temporally consistent representation of FDI exposure and associated risk distributions.

The findings highlight the challenge of creating aggregate hazard scores that can serve as the best Expected Loss Assessment (ELA) for all hazards. Such scores could then be used to calculate expected losses from FDI assets due to physical hazards. This requires further development of robust and comprehensive climate indicators.

Another area worth exploring is differentiating between immediate and ultimate perspectives in FDI climate risk analysis. Immediate perspectives focus on the direct exposures of FDI enterprises, while ultimate perspectives consider the broader economic and operational linkages between FDI investors and their enterprises. Future research could also calculate the "FDI climate distance" measuring the gap in climate risk exposure between FDI investors and their enterprises. This metric could provide insights into the alignment (or misalignment) of climate resilience strategies across value chains.

Finally, future extensions of this work could explore integrating transition risks, such as firm-level carbon emissions, to complement the analysis of physical climate risks.

7 Concluding remarks

This study presents a rigorous framework for assessing the vulnerability of FDI to physical climate risks, leveraging firm-level locational data and granular geospatial climate hazard indicators. By examining bilateral FDI positions between France and Italy, it demonstrates the feasibility of linking FDI statistics to climate risk data, addressing critical gaps in the literature and advancing our understanding of climate-related vulnerabilities in FDI. The findings underscore significant disparities in exposure to acute risks, such as geographically concentrated wildfires, and chronic risks, like more broadly distributed water stress.

Methodologically, the structured aggregation approach ensures that the resulting metrics are both granular and economically relevant, enabling more robust and replicable assessments of FDI exposure to climate risks. At the same time, the analysis highlights key limitations, particularly related to data availability for detailed physical risk score calculations, which, if addressed, could further enhance the reliability and depth of these findings.

By bridging the intersection of FDI statistics and climate risk assessment, this study lays the foundation for a more detailed and statistically robust understanding of how climate change influences international investment patterns. It also demonstrates the feasibility of calculating FDI climate risk

statistics, particularly for inward FDI and outlines an empirical methodology for doing it. Future research should focus on expanding these datasets with additional transitional risk scores, improved geolocation accuracy, and dynamic risk metrics over time to allow a further refinement of these statistics. These advancements will equip both policymakers and researchers with the information and the analytical insights needed to address the challenges at the nexus of international economics and climate change.

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Appendix

Appendix Table 1 – Physical climate risks and their groupings

Hazard	Short description	Score scale groupings
Coastal flooding	Risk based on water level rise (meters) due to extreme events intensities (per return period). Climate scenarios: 1971-2000 (baseline), 2021-2050, 2071-2100 under RCP 4.5 and RCP 8.5. Return period: 10, 30, 100, 300,1000 years.	Based on expected annual loss (EAL)[15]: *Low risk* (scores 0-1): EAL<20% of maximum EAL *Medium risk* (scores 2-3): 20%<EAL<60% of maximum EAL *High risk* (scores 4-5): EAL>60% of maximum EAL
River flooding	Risk based on water level rise (m) due to extreme events intensities (per return period). Climate scenarios: 1971-2000 (baseline), 2021-2050 under RCP 4.5 and RCP 8.5. Return period: 10, 30, 100, 300,1000 years.	Based on expected annual loss (EAL)**Error! Bookmark not defined.**: *Low risk* (scores 0-1): EAL<20% of maximum EAL *Medium risk* (scores 2-3): 20%<EAL<60% of maximum EAL *High risk* (scores 4-5): EAL>60% of maximum EAL
Windstorms	Risk based on wind gust speed (meters/second) due to extreme events intensities (per return period). Climate scenarios: 1979-2020 (baseline). Return period: 10, 50,100, 500 years	Based on expected annual loss (EAL)**Error! Bookmark not defined.**: *Low risk* (scores 0-1): EAL<20% of maximum EAL *Medium risk* (scores 2-3): 20%<EAL<60% of maximum EAL *High risk* (scores 4-5): EAL>60% of maximum EAL
Landslides	Risk based on terrain characteristics and daily maximum precipitation (score 1-5). Return period: 10, 50, 100, 500 years.	Based on expected annual loss (EAL)**Error! Bookmark not defined.**: *Low risk* (scores 0-1): EAL<20% of maximum EAL

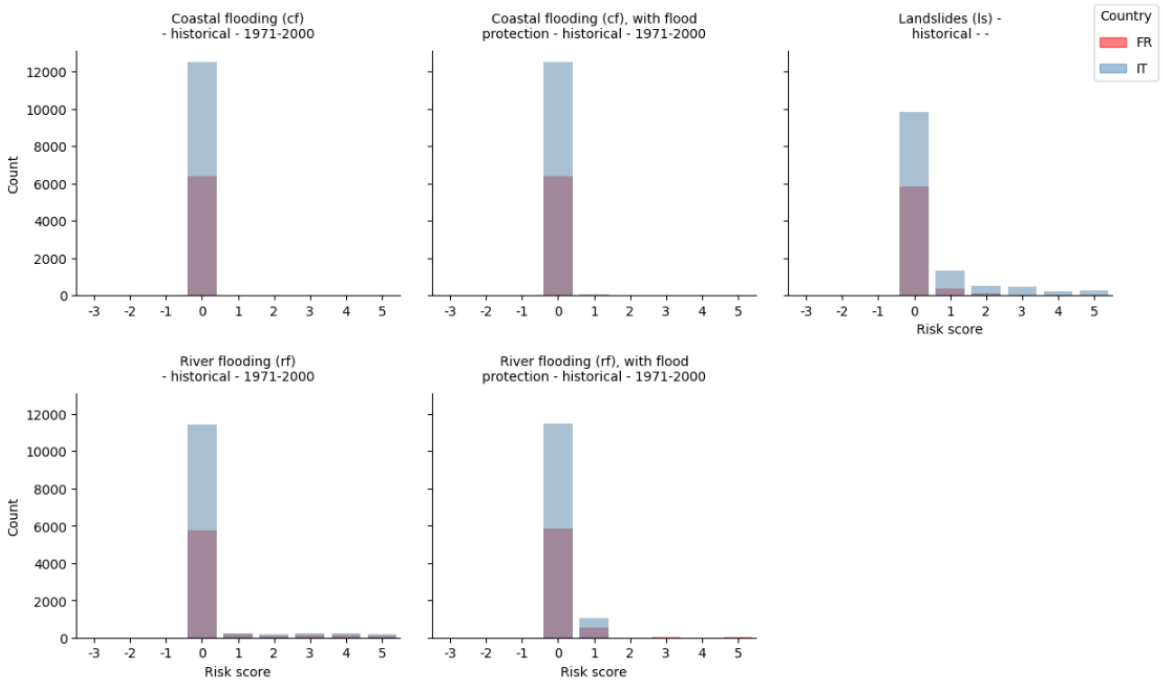
[15] As computed in SPS Annex 6.4 https://www.ecb.europa.eu/pub/pdf/scpsps/ecb.sps48~e3fd21dd5a.en.pdf

		Medium risk (scores 2-3): 20%<EAL<60% of maximum EAL *High risk* (scores 4-5): EAL>60% of maximum EAL
Subsidence	Risk based on soils' clay content.	*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%)
Wildfires	Risk based on the probability of a fire event using Fire Weather Index, land cover, and burned areas. Climate scenarios: 2001-2022 (baseline), 2023-2050 under RCP 4.5 and RCP 8.5.	*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)
Water stress	Risk based on the ratio of water demand and water supply. Climate scenarios: 1960-2014 (baseline), 2030-2050 under RCP 4.5 (SSP2) and RCP 8.5 (SSP3).	*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%
Consecutive dry days	Risk based on the maximum number of consecutive dry days (precipitation < 1mm/day). Climate scenarios: 1986-2005 (baseline), 2021-2040, 2041-2060 under RCP 4.5 and RCP 8.5.	*No risk*: < 15 days *Low*: 15-20 *Medium*: 20-30, 30-40 *High*: 40-50, >50 days
Standardized Precipitation Index (SPI)	Risk based on cumulative precipitation for 6 months compared to long-term precipitation distribution. Climate scenarios: 1986-2005 (baseline), 2021-2040, 2041-2060 under RCP 4.5 and RCP 8.5.	*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)

Notes: RCP stands for Representative Concentration Pathways. RCP 4.5. corresponds to radiative forcing of 4.5 W/m^2 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/m^2 by 2100, and is considered a worst-case scenario.

Number of entities in each risk bucket in French and Italian territories

Appendix Chart 1

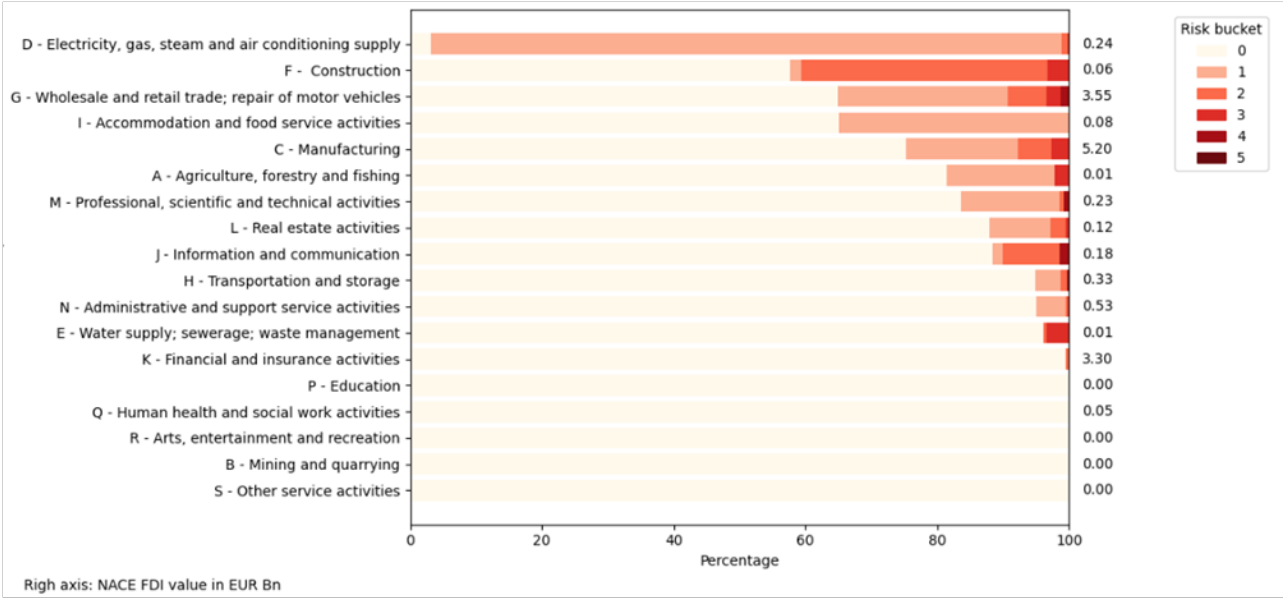


Sources: authors' own calculation on Italian and French elementary units' dataset

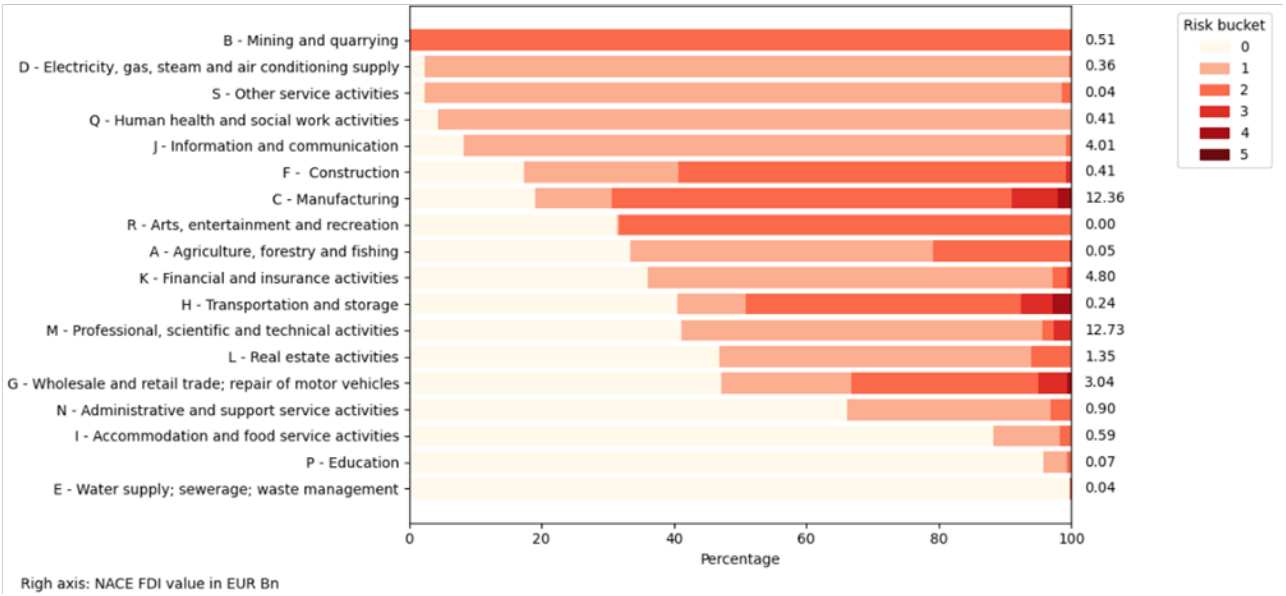
Wildfires risk distribution across NACE activities

Appendix Chart 2

French territory



Italian territory



Sources: authors' own calculation on Italian and French elementary units' dataset and climate scores from STC EG

BANQUE DE FRANCE
EUROSYSTÈME

BANCA D'ITALIA
EUROSISTEMA

EUROPEAN CENTRAL BANK
EUROSYSTEM

An experiment to measure physical climate risks in FDI between France and Italy

Mapping FDI vulnerability to physical climate change risks



04/10/2025

Chiara Torri, Daniele Di Pietro, Francois Robin, Giacomo Oddo, Jorge Diz Dias, Nadia Accoto, Rocco Incardona, Veronique Genre

Motivation

Climate change impact

- Increasing exposure to extreme weather events (floods, heatwaves, wildfires) causing significant economic losses (€162 billion in EU between 2021-2023).

FDI relevance

- Foreign Direct Investment (FDI) is a key driver of globalization, involving long-term investment commitments. Physical climate risks threaten the long-term viability of FDI. Implementing active climate-resilient strategies help mitigate risks.

Data gaps

- G20 Data Gaps initiative emphasizes need to improving measurement of climate change statistics (physical and transition risks, green house gas emissions).

Research gap

- Limited empirical literature on the role of physical climate risks in shaping FDI patterns.

Main objective

- Develop statistical methodological framework, with case study to test it

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Our contribution

Main innovations

- **First firm-level framework to map FDI exposure to physical climate risks** (floods, wildfires, heat) using geospatial hazard data.
- **Addresses FDI domestic ownership chain complexity** in host country: considering affiliates and establishments
- **Links FDI firms' geo location with high-resolution climate risk maps** with risk assessments (historical projections contrasted with future climate scenarios).
- **Cross-sectional analysis**: economic activities (e.g. agriculture, manufacturing, mining) and regional climate disparities (e.g., French mediterranean wildfires vs. Italian northern floods) regarding FDI.

Policy-relevant insights

- Identifies more climate vulnerable economic activities/regions, guiding climate-resilient FDI strategies.
- Supports information on targeted policy interventions (e.g., adaptation investments).

Why this matters for statistical community

- Develop extensible statistical framework: showcase the feasibility to develop relevant FDI climate change indicators applicable to EU countries
- Actionable evidence: Moves beyond theoretical frameworks to empirical, data-driven insights.

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Methodology (1)

Objective: measuring the exposure of bilateral FDI positions between FR and IT to physical climate risks.

Scope: Financial corporations excluded, except financial holding companies and head offices

- Indirect “balance sheet” exposure vs direct physical exposure
- Real estate is also excluded, due to data constraints (geolocation).

Focus: equity component of FDI

Structure: three phases:

- (1) decomposition of FDI enterprises into elementary units;
- (2) risk assessment of elementary units, based on geolocation;
- (3) aggregation of risk score at FDI level.

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Methodology (2)

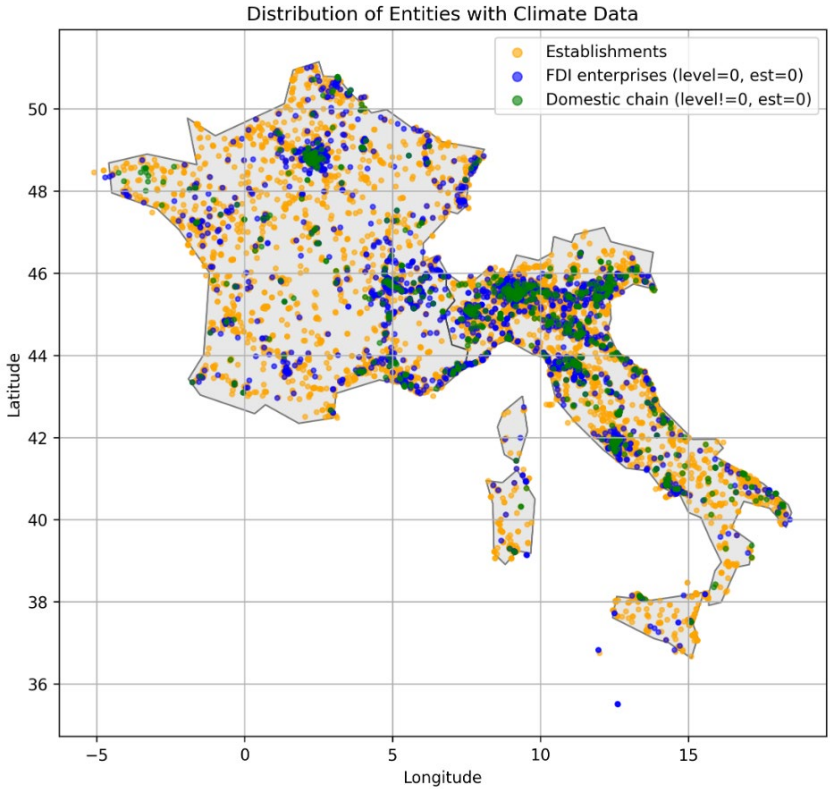
Phase 1: Top-down decomposition of inward bilateral FDI into elementary units



Phase 1 output: **list of elementary units** (DIE + subsidiaries + establishments), including their addresses and number of employees

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Distribution of entities in the dataset



Country	French territory	Italian territory
Nr of DIE	1,545	2,413
Employees (total)	324,528	332,274
Bilateral FDI value (EUR mln)	13,811	41,521
% of total bilateral FDI (end 2022)	52%	55%

- DIEs and domestic chain units tend to cluster in big cities
- Establishments are more equally spread across the territories

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Methodology (3)

Phase 2: assign climate risk scores to each elementary unit identified in phase 1.

Geocoding

For each elementary unit, use the address and OpenStreetMap to obtain latitude and longitude coordinates

Mapping each location with risk scores

Leverage the innovative dataset developed by the ESCB STC Expert Group on Climate Change, which enriched ECB's RIAD (Register of Institutions and Affiliates Dataset) with physical hazard data from Copernicus, EC Risk Data Hub, Delft University of Technology, IPCC, Aqueduct WRI.

RIAD+ allows to assign scores in various risk dimensions (wildfires, water stress…) to our set of firms in two ways:

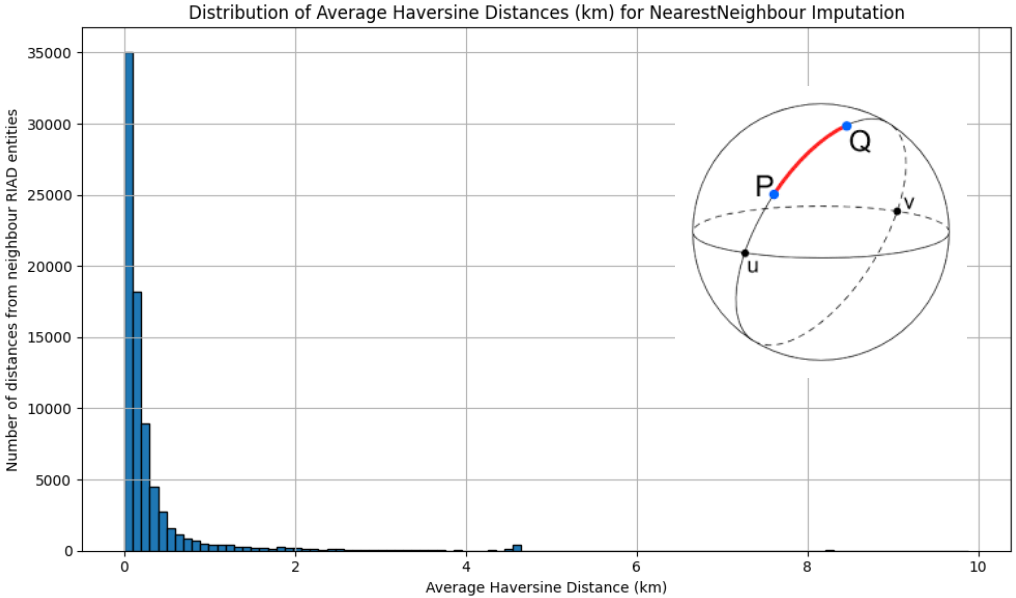
- *Directly*: If the elementary unit is included in RIAD+, its risk scores are directly retrieved (~ 20% of entities are covered)
- *Indirectly*: if the unit is not included, its risk scores are assigned through **spatial interpolation**, using 5 nearest neighbors in RIAD+

ECB SPS: Climate change-related statistical indicators

Methodology (4)

Spatial interpolation for missing risk scores:

- We compute haversine distance of potential neighbors. Through Ball Tree algorithm we select the nearest 5 and take their **median** score
- Justification: strong spatial autocorrelation of climate hazards and high density of RIAD+:
- Average haversine distance of nearest neighbors is very small. In 95% of cases is less than 1 km.



Phase 2 output: **Risk scores computed at the elementary unit level**, remapped to their original scales (probabilities, expected annual losses, etc.) to enable Phase 3 calculations.

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Methodology (5)

Phase 3: aggregation of elementary units' risk scores into FDI positions.
Bottom-up, hierarchical consolidation of risk scores

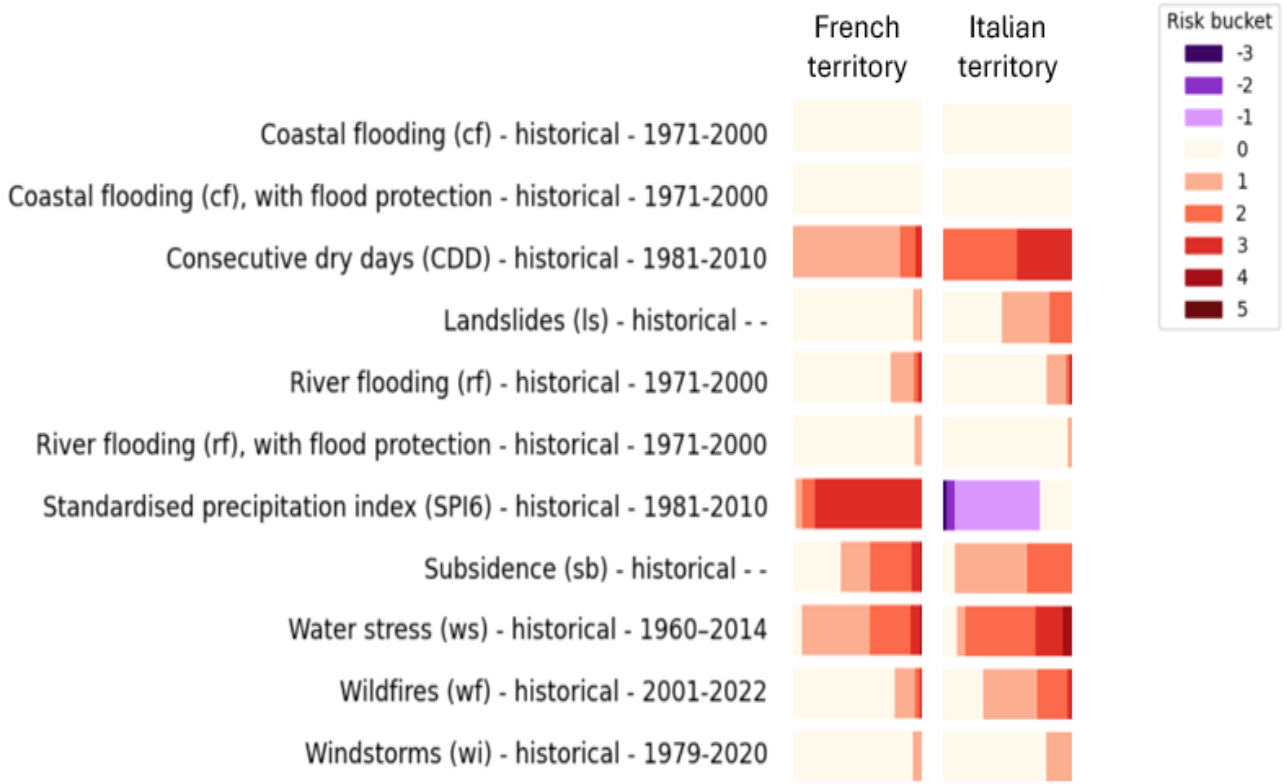


Phase 3 output: Climate physical risk scores of FDI positions, with scores reassigned to their original ordinal values and detailed breakdowns.

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Results: Exposure of bilateral FDI to climate risk dimensions

- Several climate scores have been computed both for historical and Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios
- Scores typically range: **0 (low risk) to 5 (high risk),** except for Standardized precipitation index
- Bilateral FDI investments in France and Italy are exposed to different type of risks
- e.g. **French FDI in Italy is exposed to higher risk of drought** (negative SPI6 and higher nr of consecutive dry days)



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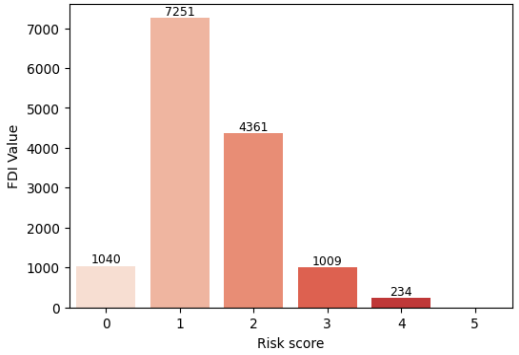
Results: FDI distribution by buckets of risks

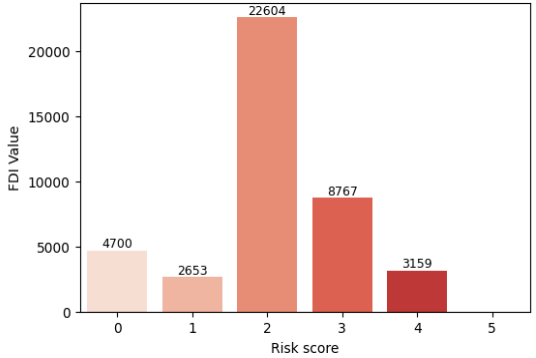
- FDI bilateral stocks allocated to different **buckets of risks**
- Some hazards affect very few enterprises
- **Scores with widest distribution across risk categories**: water stress, wildfires, consecutive dry days, subsidence, SPI

French territory

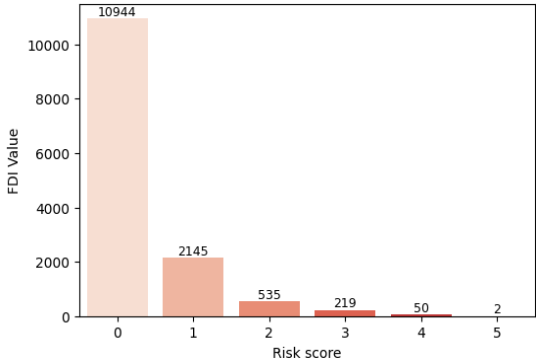
Italian territory

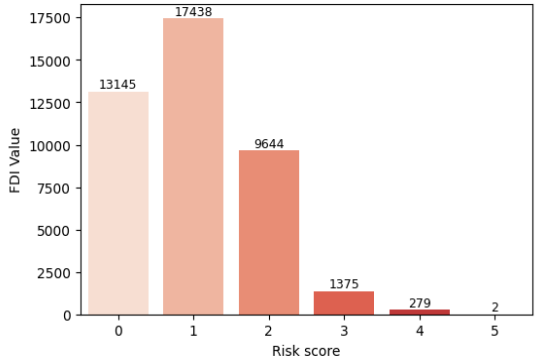
Water stress





Wildfires





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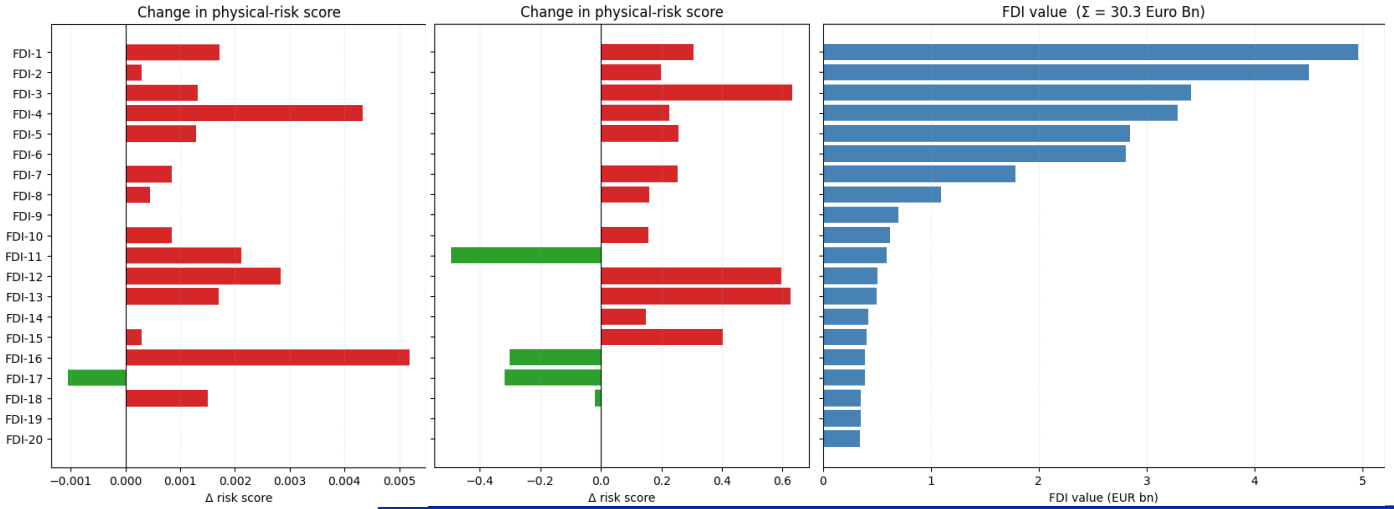
Results: The impact of subsidiaries and establishments

- Including subsidiaries and establishments **increases,** on average, the risk scores of the top 20 FDI enterprises (by FDI value)
- The top 20 FDI enterprises account for 55% of the total FDI value in the dataset (end-2022)

Wildfires (probability fire event)

Water stress (Use/supply ratio)

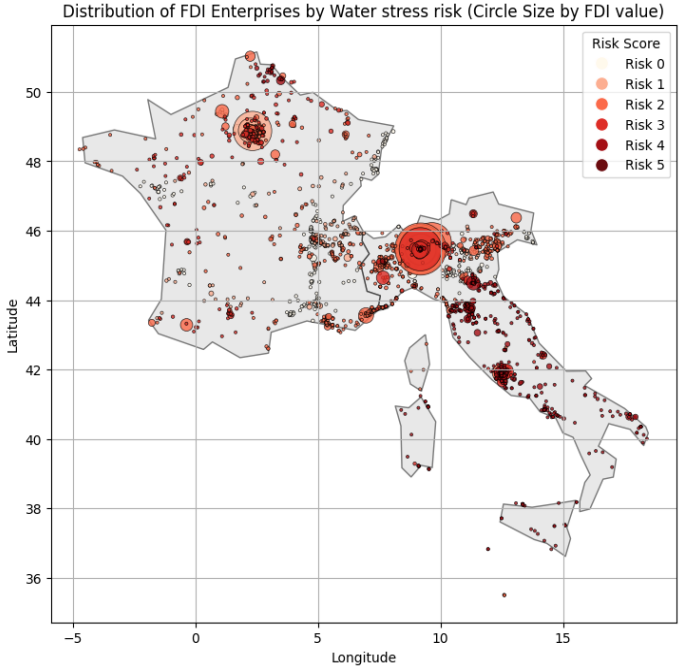
FDI value

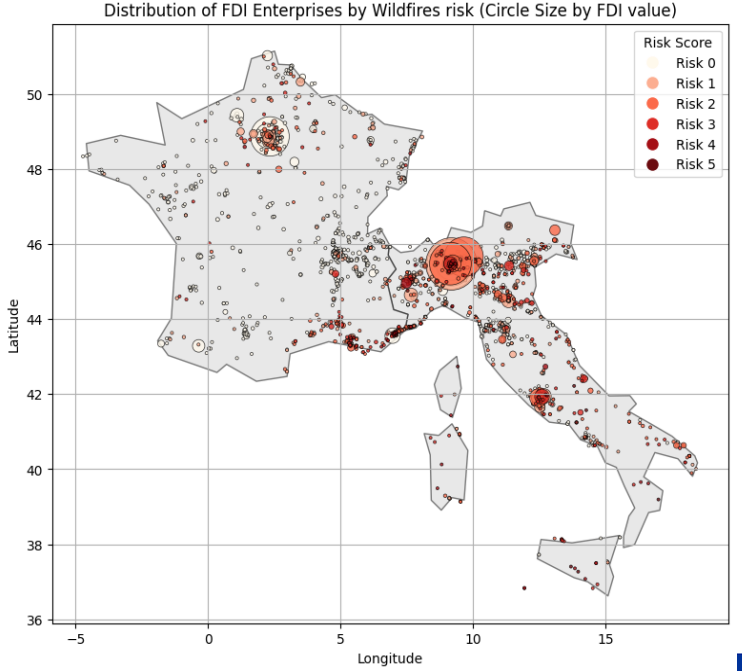


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Results: Geographic distribution of risks

- In this dataset, regions where DIEs are exposed to higher risks tend to have lower FDI investments
- FDI enterprises located in the same area might have different risk scores due to the different distribution of subsidiaries or establishments



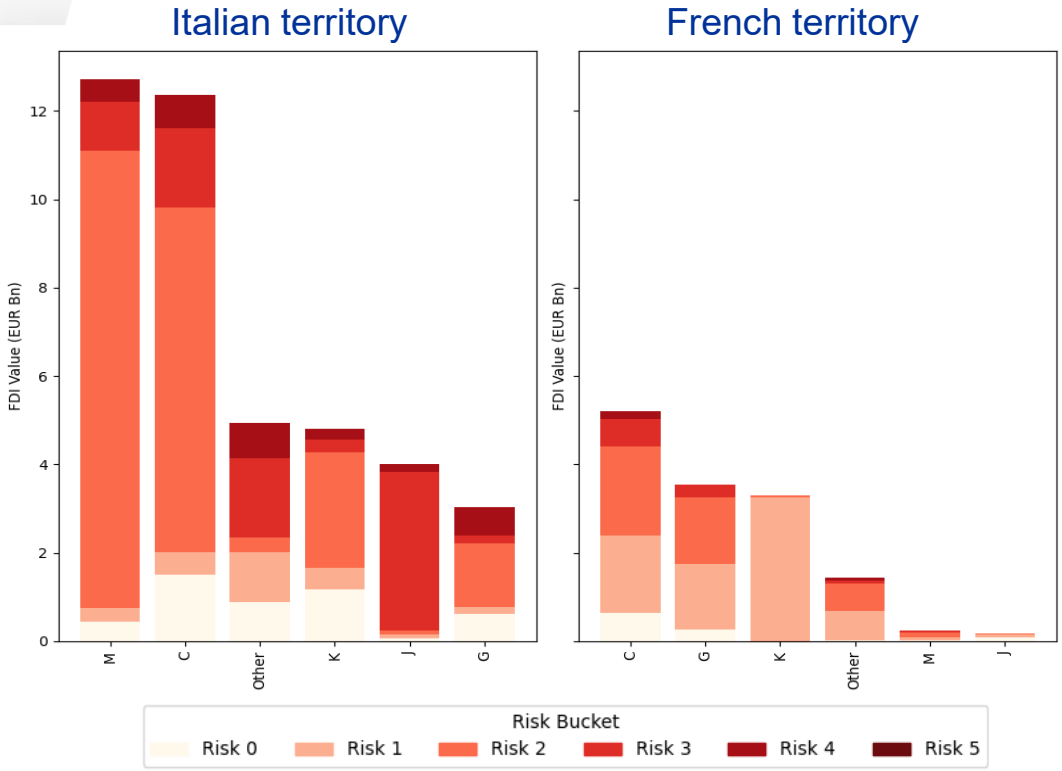


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Results: Risk distribution across NACE activities

- NACE activities like agriculture or mining are highly exposed to water risk but account for a relatively small share of total FDI.
- The **most relevant activities** in terms of FDI and risk exposures are Manufacturing (**C**), Professional, scientific and technical activities (**M**), Wholesale and retail trade (**G**) and Information and communication (**J**).
- Financial and insurance activities (K) include financial holding companies and head offices.

Water stress

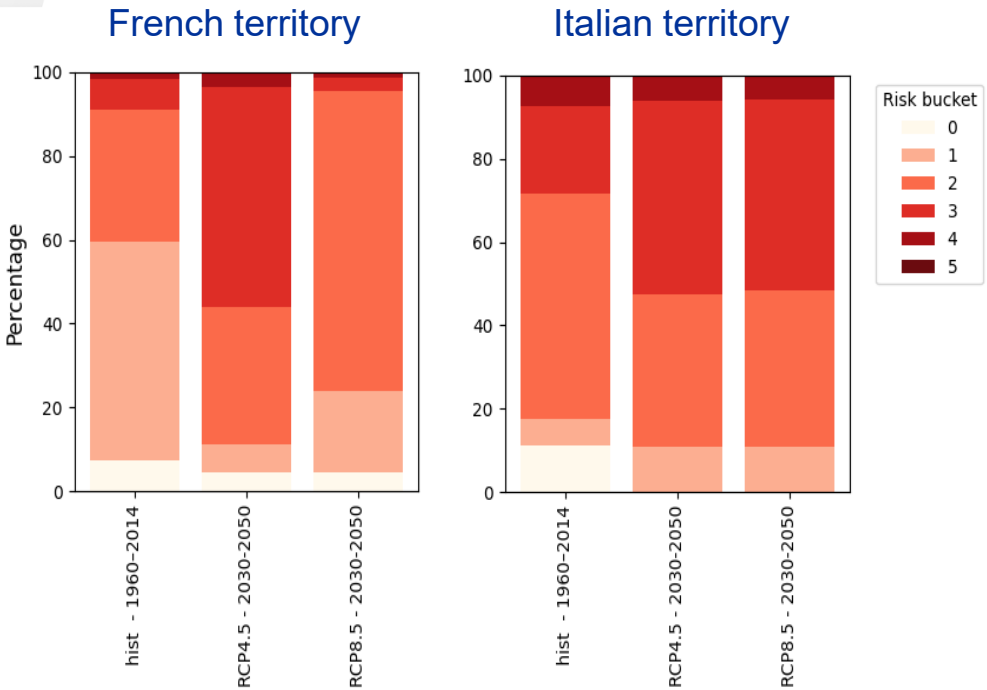


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Results: Risk evolution under RCP 4.5 and RCP 8.5

- For French FDI in Italy, the results show increasing exposure to water stress on both RCP 4.5 and 8.5 pathways.
- In contrast, for Italian FDI in France, the exposure is higher under the moderate-emission scenario than under the high-emission scenario.

Water stress



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Conclusions and next steps

Key takeaways

- **Innovative methodological framework**: First firm-level methodology quantifying FDI exposure to physical climate risks (floods, wildfires, water stress) using geospatial hazard data.
- **Considering the domestic chain and establishments** is critical for accurate climate physical risk assessment.
- Applied to France–Italy bilateral FDI: reveals geographic concentration of acute risks (e.g. wildfires) and broader distribution of chronic risks (e.g. water stress).
- **Economic activity heterogeneity**: Some NACE activities like agriculture or mining are highly exposed to physical risk but account for a relatively small share of total FDI.
- **Policy Implications**: High-risk regions and specific industries require targeted adaptation strategies to protect FDI stocks. Investors must account for climate risks in long-term strategy, prioritizing resilience in vulnerable activities/locations.

Limitations and challenges

- Data gaps in geolocation accuracy, firm-level asset/employment data, and effects of erratic and stochastic climate events remains challenging to address.
- Indirect exposure of FDI in financial sector (banking and insurance).
- Local hazards maps for acute risks are usually delayed with respect to updates of the global climate models.

Future directions

- Pursue climate experts to develop expected annual losses for physical hazard risks and link it with FDI for composite physical risk statistics expressed in probability monetary losses.
- Directly link the location of FDI elementary units and detailed physical hazard maps (by-passing the use of RIAD).
- Explore "FDI climate distance" to assess misalignment of resilience strategies between direct investors and direct investment enterprises.
- Perform the analysis for several years (timeseries perspective).

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Thank you!

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Appendix

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Literature review

Theoretical FDI frameworks

- International risk theory (Buckley et al., 2016)
- Dunning's ownership, location and internalization (OLI paradigm) (Shear et al., 2023)

Empirical evidence

- Negative impact of physical climate risks on FDI inflows (Gu and Hale, 2023; Jihad Ait Soussane et al., 2022)
- "Climate risk distance" (Xing et al., 2022): home vs. host risk matters with FDI flows higher when home country has greater climate risk
- Economic activity heterogeneity: Agriculture, forestry, fishing, mining, construction and manufacturing most vulnerable
- Geographical disparities: Higher risks in Caribbean, Middle East, Southeast Asia (Li et al. 2022) and in other developing countries

Methodological approaches

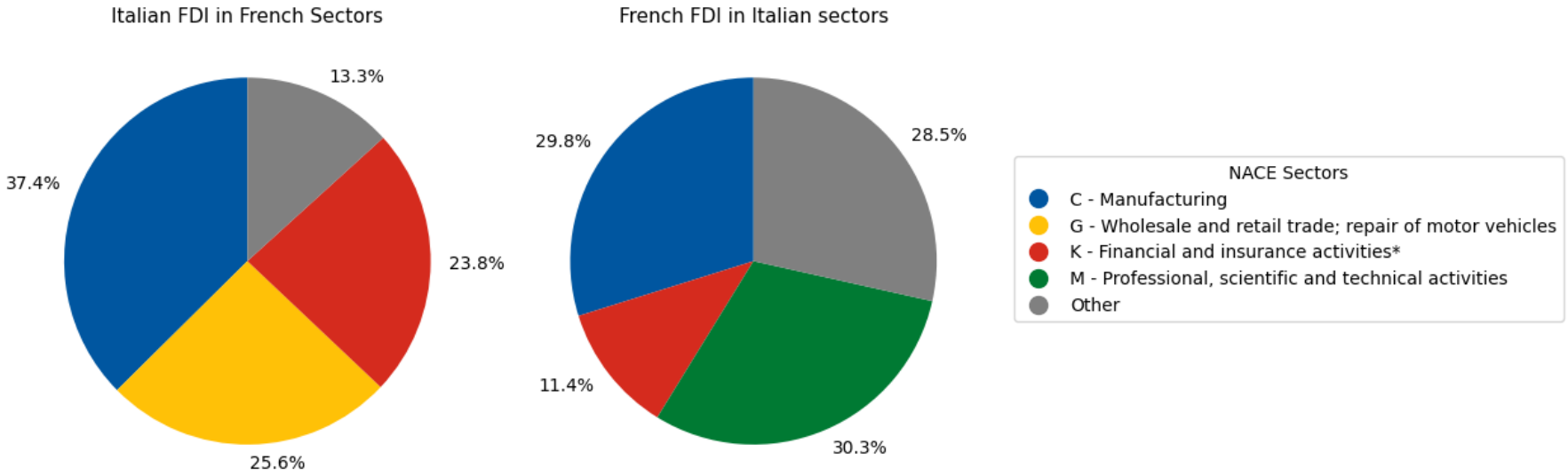
- Panel econometric models
- Limited firm-level analyses
- Integration of geospatial climate risk data with facility-level information

Research gaps

- Limited firm-level measurement between FDI and physical climate risks at geographical and economic activity levels

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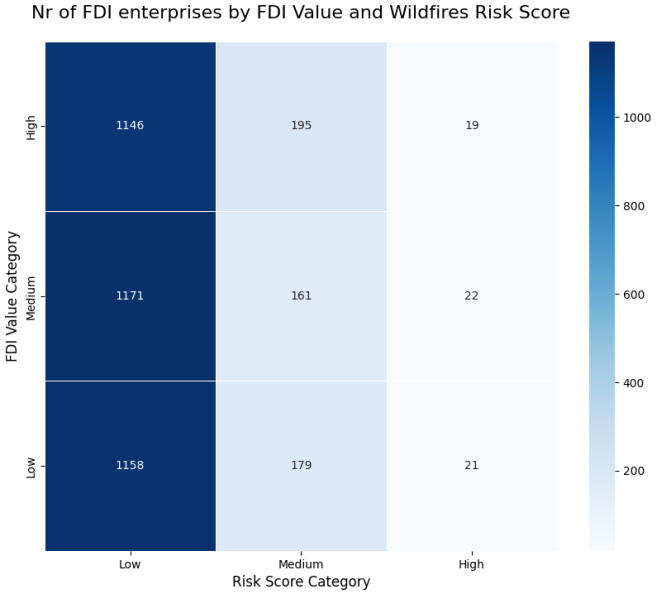
Results: Descriptive statistics on FDI

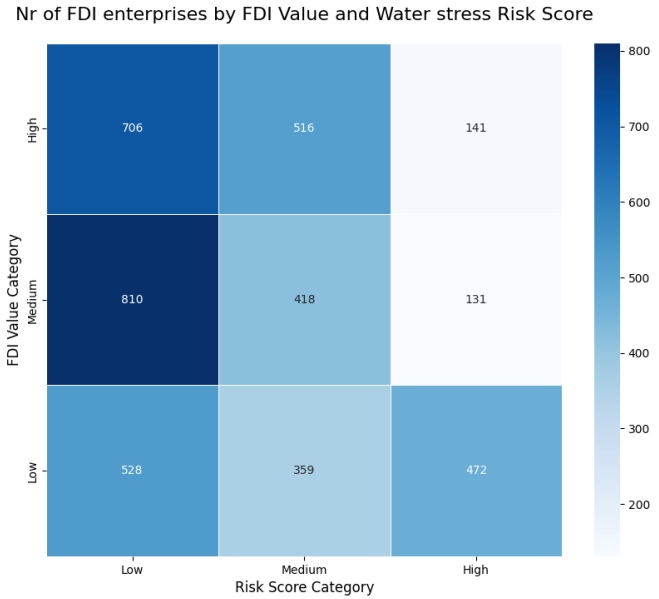


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Results: Clustering

- Wildfire risk seems to affect similarly small and large FDI enterprises (localized risk)
- Water stress is affecting smaller FDI enterprises proportionally more than larger ones





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Irving Fisher Committee on Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Pilot compilation results for climate finance debt securities

Soohoon Choi,
Bank for Korea

This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

Pilot Compilation Results for Climate finance debt securities

「G20 Data Gaps Initiatives 3(DGI-3)」 Climate Finance(#4)

2025. 10. 4.

Soohoon Choi

Economic Statistics Division,
The Bank of Korea

BANK OF KOREA

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Ⅱ. Key Elements of the DGI-3 Climate Finance Task

Ⅲ. Compilation Methodology

Ⅳ. Pilot Compilation Results

Ⅴ. Implications and Next Steps

I Background of Pilot Compilation

- **The G20 DGI has selected "Climate Finance" as a new task under DGI-3.**
  - Monitoring the transition to a low-carbon economy.
  - Tracking the growth trend of climate finance.
  - Expanding internationally comparable statistics.

→ **The G20 WGSD decided to compile statistics for climate finance debt securities as part of this initiative.**

- **Compilation results(issuance, holding, and interconnectedness) are to be submitted to BIS and ECB.**

⇒ **The BOK prepares implementation plan for the climate finance debt securities task and sharing of pilot compilation results.**

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Ⅱ Key Elements of DGI-3

- **Scope of Climate finance debt securities**

- **Green debt securities :** use of proceeds restricted to financing/refinancing activities that improve the the **environment.**

- **Sustainablility debt securities :** use of proceeds restricted to financing/ refinancing activities that improve the **environment and society.**

- **Sustainability-linked debt securities :** debt securities whose financial terms(e.g., cash payments) are linked to achieving environmental or social objectives.

Ⅱ Key Elements of DGI-3

- **Based on Handbook on Securities Statistics(HSS)**

  - By bond type, stock/net transaction amounts, valuation method, currency, maturity, market of issuance.

- **Timeline**

  - Core data: 2025-2027
  - Advanced ambitions data: end of 2027

DGI-3 Scope[1] and Timeline

No	Data	Timeline
①	**(Green bond)** Issues(Stock) ■ Valuation / Currency / Maturity	end-2025
②	**(Green bond)** Issues(Net Transaction) ■ Valuation / Currency / Maturity	end-2027
③	**(Sustainablity·Sustainability-linked)** Issues(Stock) ■ Valuation / Currency / Maturity	end-2027 (priority)
④	**(Total)** Holdings(Stock and Net Transactions) ■ Valuation / Currency / Maturity / Domestic·Foreigner	
⑤	**(Total)** Issues(Stock and Net Transactions) ■ Maturity / Interest rate / Market of issuance	end-2027
⑥	**(Total)** Holdings(Stock and Net Transactions) ■ Maturity / Interest rate / Market of issuance	
⑦	**Interconnectedness**	

Note: 1) Depending on priorities and the feasibility of data aggregation, data are classified into core data and advanced ambitions data. The shaded areas indicate core data.

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Ⅲ Compilation Methodology

- **Source Data**

  - **(Issues) KRX「ESG Bond Information Platform」**

ESG[1] Bond Information Platform(example)

Issuer	ISIN	ESG Type	Bond Name	Date of Issue	Maturity date	Coupon rate	Nominal (million won)	Bond type
AAbank	**KR123456G125**	Green	AAbank123-1(G)	06/05/2021	06/05/2031	2.58%	400,000	Corporate
BBcorp	**KR876543G210**	Sustainablity	BBcorp456(S)	30/03/2022	30/03/2027	3.16%	50,000	Special

Note : 1) Inclueds green, social, sustainablity, sustainibility-linked bonds.

  - **(Issue/Holdings) BOK-BOMIS「Bond Market Information System」**

Depository Status by Investor Type(example)

Depositior	Depositor Group	Bond name	Nominal (million won)	ISIN	Market value (mil won)	Interest rate[3]
CCbank	**Domestic bank**	AAbank123-1(G)	50,000	**KR123456G125**	45,971	Fixed
National Pension	**Government**	〃	200,000	〃	183,888	Fixed
EEsecurities (customer)	**Securities company**	〃	150,000	〃	137,916	Fixed
FFbank	**Domestic bank**	BBcorp456(S)	20,000	**KR876543G210**	18,317	Fixed
GGbank(foreigner)	**Foreign Bank**	〃	30,000	〃	27,476	Fixed

- **Methodology**

  - **Match ISIN codes between KRX and BOK-BOMIS.**

  - **Use microdata instead of survey aggregation.**

<Reporting Template>

Table 1.1a: Green Bonds Issues by Sector, Currency, Maturity, Interest Rate and Market of Issuance. Stocks at Nominal Value

Orange cells: Core data to be transmitted by end-2025
White cells: Advanced ambitions data to be transmitted by end-2027

Issuer / Currency, Maturity, Interest rate, Market of issuance	Residents (S1)												All resident issuers (S1)
	Non-financial corporations (S11)	Financial corporations (S12)						General government (S13)		*Memo item:* public sector	Households and NPISH (S14+ S15)		
			Central bank (S121)	Other deposit-taking corporations (S122)	Money market funds* (S123)	Other financial corporations (S124 to S127)	*Of which:* Securitisation corporations (S125A)	Insurance corporations and pension funds (S128,S129)		*Of which:* Central government (S1311)			
Total													
By domestic currency													
By foreign currency													
Short term at original maturity													
Long term at original maturity													
More than 1 year and up to and including 2 years													
More than 2 years and up to and including 5 years													
More than 5 years and up to and including 10 years													
More than ten years													
Of which: Long term at original maturity, with a remaining maturity up to and including 1 year													
Fixed interest rate													
Variable interest rate													
Inflation-linked													
Interest rate-linked													
Asset price-linked													
Domestic market													
International market													

*) Money market funds do not issue debt securities. 2008 SNA codes are used for sectors and subsectors.

Ⅲ Compilation Methodology

<Reporting Template(example of KOREA)>

Table 1.1a: Green Bonds Issues by Sector, Currency, Maturity, Interest Rate and Market of Issuance. Stocks at Nominal Value

Orange cells: Core data to be transmitted by end-2025
White cells: Advanced ambitions data to be transmitted by end-2027

Currency Maturity Interest rate Market of issuance	Residents (S1)												All resident issuers (S1)
	Non-financial corporations (S11)	Financial corporations (S12)							General government (S13)		*Memo item:* public sector	Households and NPISH (S14+ S15)	
			Central bank (S121)	Other deposit-taking corporations (S122)	Money market funds* (S123)	Other financial corporations (S124 to S127)	*Of which:* Securitisation corporations	Insurance corporations and pension funds (S128,S129)		*Of which:* Central government (S1311)			
Total	19,474,641	7,360,767	-	2,760,000		4,600,767	470,767	-	495,100	300,000	7,820,100	-	27,330,508
By domestic currency	19,474,641	7,360,767	-	2,760,000		4,600,767	470,767	-	495,100	300,000	7,820,100	-	27,330,508
By foreign currency	-	-	-	-		-	-	-	-	-	-	-	-
Short term at original maturity	120,000	120,000	-	120,000		-	-	-	-	-	120,000	-	240,000
Long term at original maturity	19,354,641	7,240,767	-	2,640,000		4,600,767	470,767	-	495,100	300,000	7,700,100	-	27,090,508
More than 1 year and up to and including 2 years	1,935,000	1,850,000	-	1,200,000		650,000	-	-	70,000	-	1,035,000	-	3,855,000
More than 2 years and up to and including 5 years	13,149,641	4,100,767	-	650,000		3,450,767	470,767	-	425,100	300,000	3,865,100	-	17,675,508
More than 5 years and up to and including 10 years	2,520,000	1,050,000	-	660,000		390,000	-	-	-	-	1,050,000	-	3,570,000
More than ten years	1,750,000	240,000	-	130,000		110,000	-	-	-	-	1,750,000	-	1,990,000
Of which: Long term at original maturity, with a remaining maturity up to and including 1 year	3,833,000	1,220,000	-	600,000		620,000	-	-	70,000	-	1,620,000	-	5,123,000
Fixed interest rate	19,374,641	6,900,767	-	2,760,000		4,140,767	470,767	-	495,100	300,000	7,820,100	-	26,770,508
Variable interest rate	100,000	460,000	-	-		460,000	-	-	-	-	-	-	560,000
Inflation-linked	-	-	-	-		-	-	-	-	-	-	-	-
Interest rate-linked	100,000	460,000	-	-		460,000	-	-	-	-	-	-	560,000
Asset price-linked													
Domestic market	19,474,641	7,360,767	-	2,760,000		4,600,767	470,767	-	495,100	300,000	7,820,100	-	27,330,508
International market													

*) Money market funds do not issue debt securities. 2008 SNA codes are used for sectors and subsectors.

Ⅲ Compilation Methodology

- **Compilation results(summary)**

Issues of Climate Finance Debt Securities
(as of end-2024)

(stock, market value, trillion won)

	Total	Non-Financial	Financial	Government
▪ Total	**44.4**	**22.8**	**21.1**	0.6
<Bond type>				
▪ Green	27.4	19.5	7.4	0.5
▪ Sustainability	16.6	3.2	13.4	0.1
▪ Sustainability-linked	0.4	0.1	0.3	0.0
<Currency>				
▪ Domestic(KRW)	44.4	22.8	21.1	0.6
▪ Foreign	0.0	0.0	0.0	0.0
<Maturity[1]>				
▪ Short-term(less than 1yr)	0.5	0.1	0.4	0.0
▪ Long-term(longer than 1yr)	43.9	22.6	20.7	0.6
- 1y~2y	5.2	2.0	3.2	0.1
- 2y~5y	**25.6**	16.0	9.1	0.5
- 5y~10y	8.6	2.7	5.9	0.0
- over 10y	4.5	2.0	2.5	0.0
- Remaining mat ≤ 1y	8.7	4.6	4.1	0.1
<Interest rate>				
▪ Fixed	**43.7**	22.5	20.6	0.6
▪ Variable	0.7	0.2	0.5	0.0
- Inflation-linked	0.0	0.0	0.0	0.0
- Interest rate-linked	0.7	0.2	0.5	0.0
- Asset price-linked[2]	-	-	-	-
<Market of Issuance>				
▪ Domestic Market	43.7	22.5	21.1	0.6
▪ International Market[2]	-	-		

Note: 1) Classified by original maturity
2) Compilation currently not feasible due to lack of source data

Source: KRX, BOK

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● Issuance Statistics (as of end-2024)

KRW 44.4trn

Domestic issues(stock)

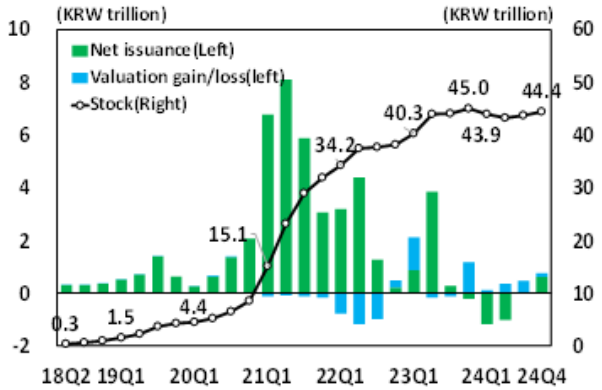
11.8%

Annual growth rate(2021~2024)

562

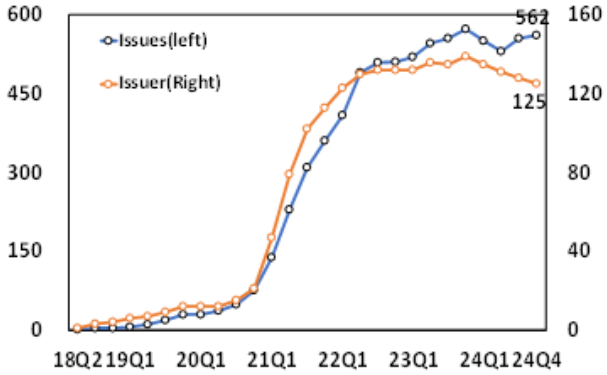
Number of bond issues

Domestic Outstanding Amount of Climate Finance Debt Securities



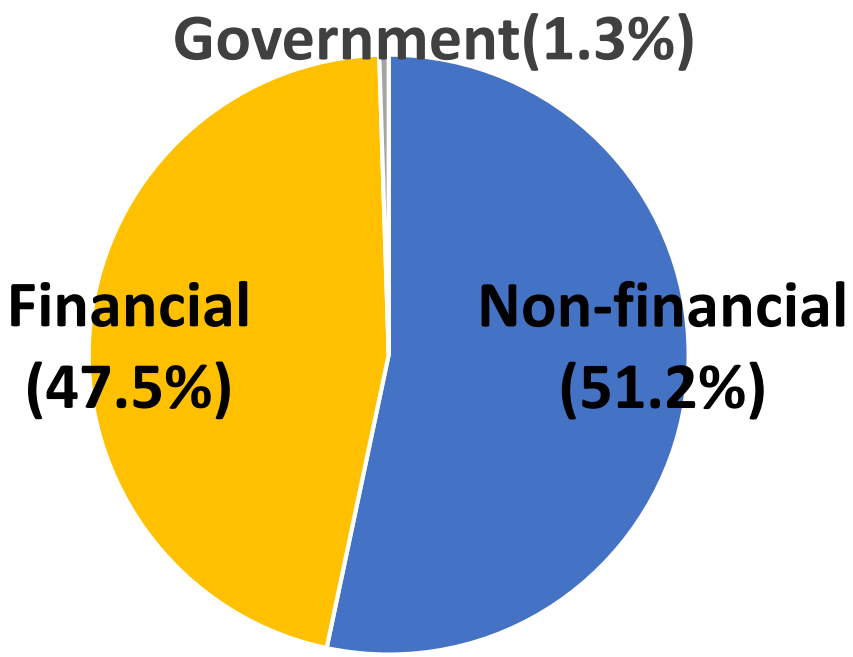
Source: KRX

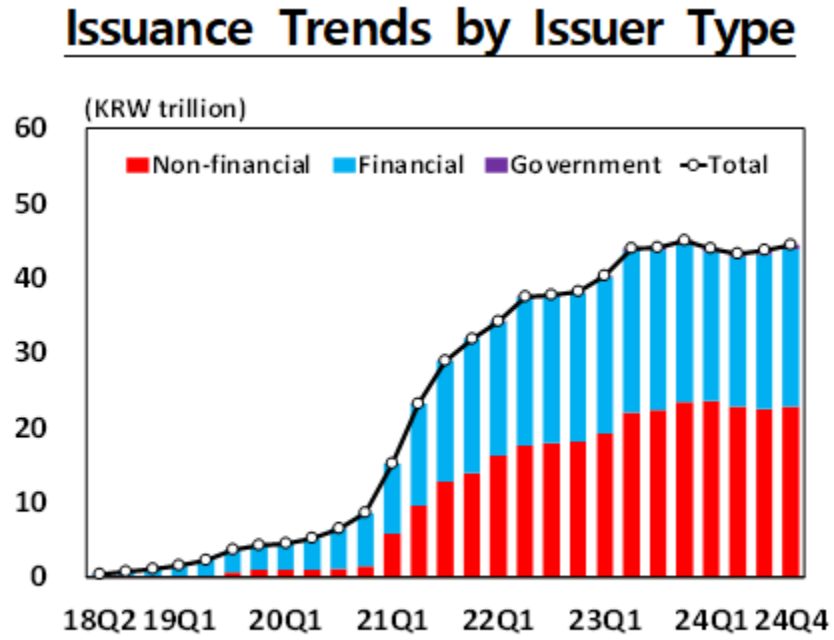
Number of Issues and Issuers



Source: KRX

• Issuance Statistics (as of end-2024)



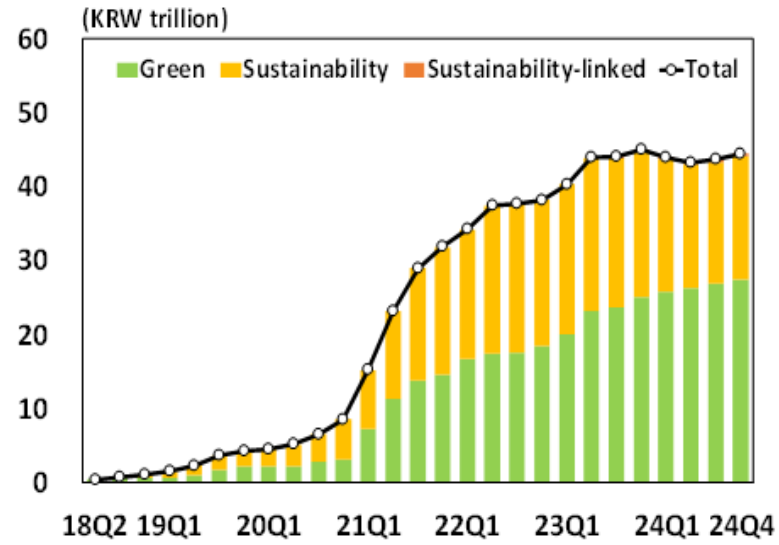


Source: KRX

• Issuance Statistics

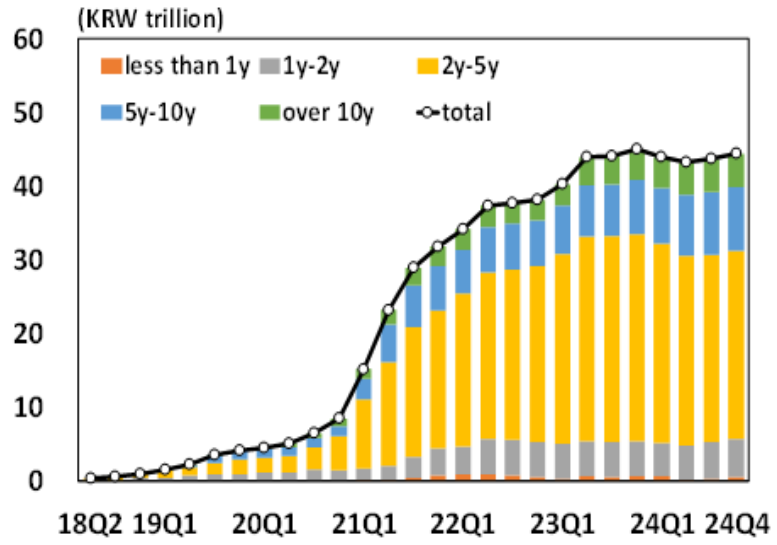
- **(Bond type)** Green>Sust.>Sust.-linked
- **(Maturity)** Long(98.9%)>Short

Issuance Trends by Bond Type



Source: KRX

Issuance Trends by Maturity



Source: KRX

- **(Currency) 100% KRW**
- **(Interest rate) Fixed(98.4%)>Variable**

• Issuance Statistics

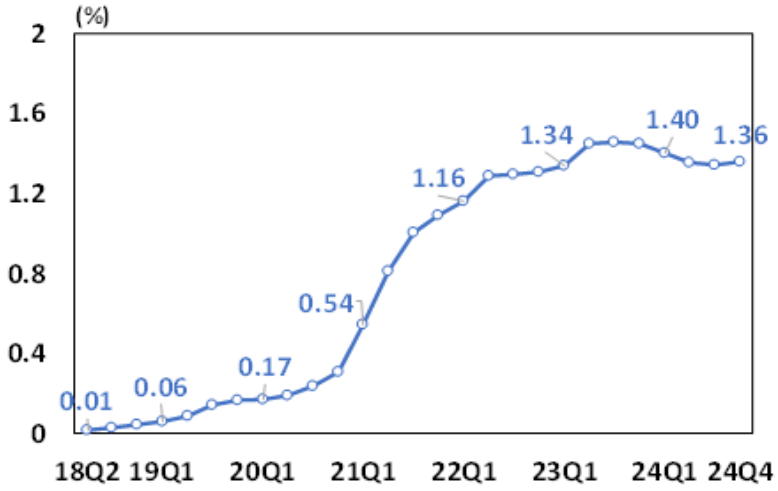
- As 1.36%* of Total Bonds

* Based on domestic issuances by residents.

- As 1.83% of Global Climate Finance Bonds**

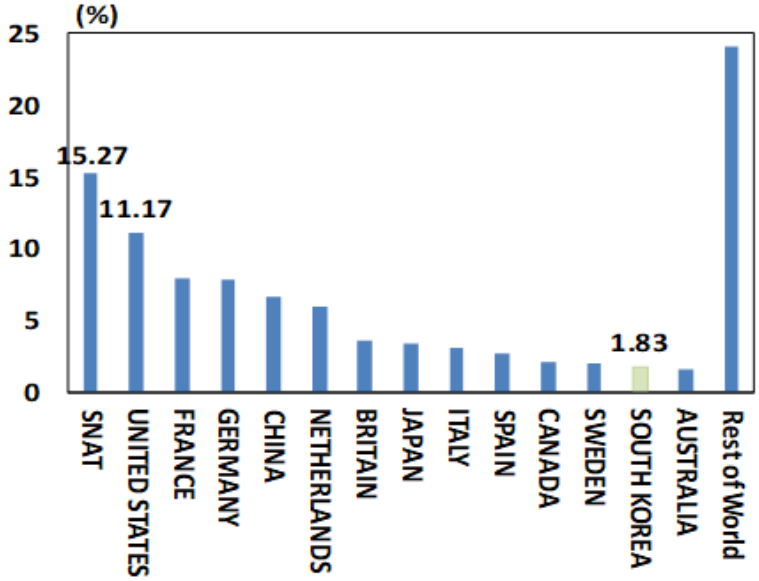
** Includes overseas issuances by residents. (KRW 68.1tn estimated.)

Share of Climate Finance Debt Securities in Total Bond Outstanding



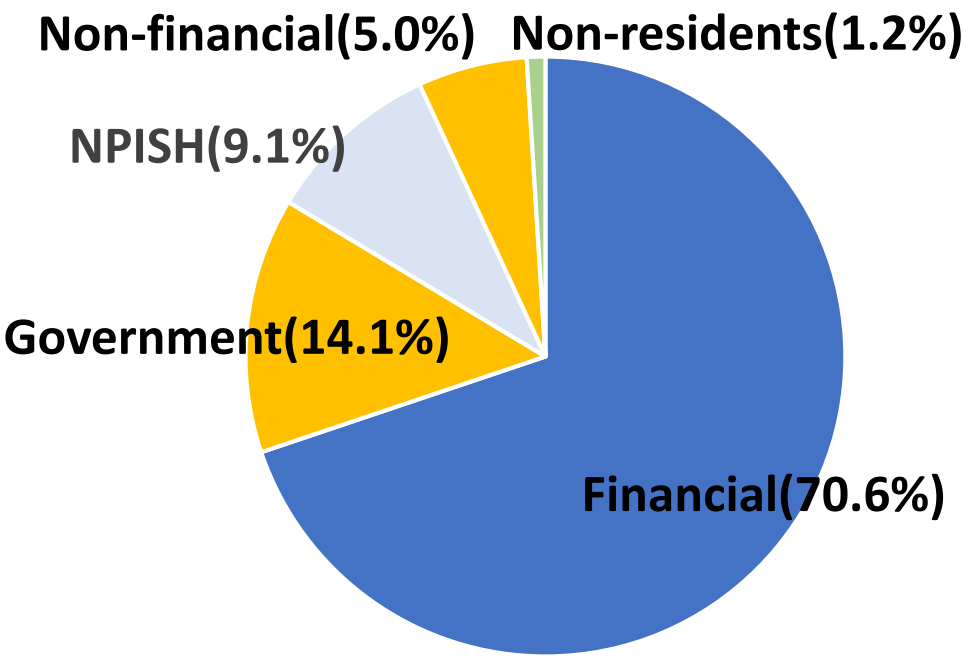
Source: KRX

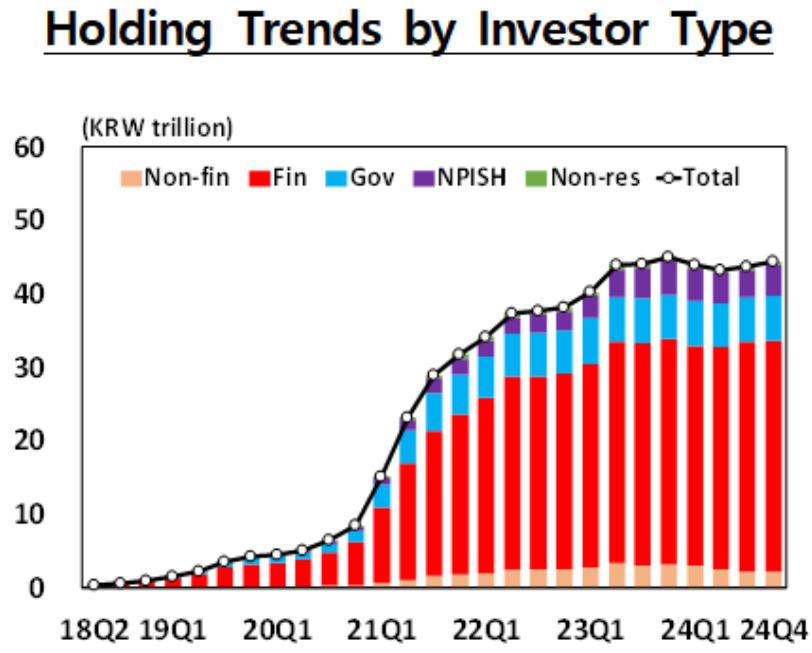
Global Market Share of Climate Finance Bond Issuance by Country



Note: 1) As of 14.01.2025
Source: Bloomberg

• Holding Statistics (As of end-2024)

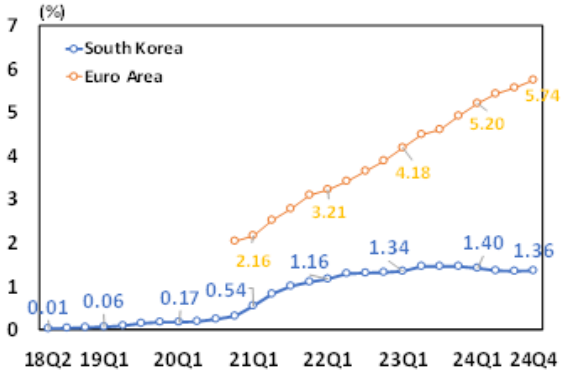




Source: KRX, KSD

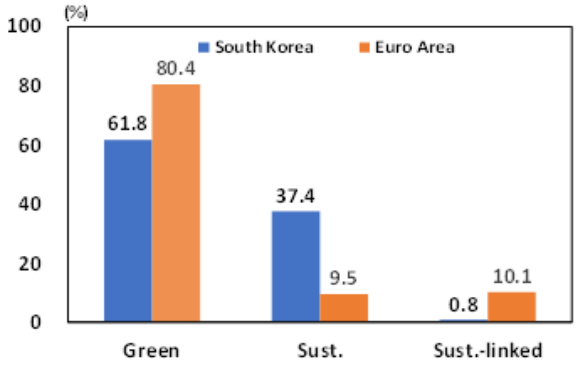
• International Comparison

Share of Climate Finance Debt Securities in Total Bond Outstanding



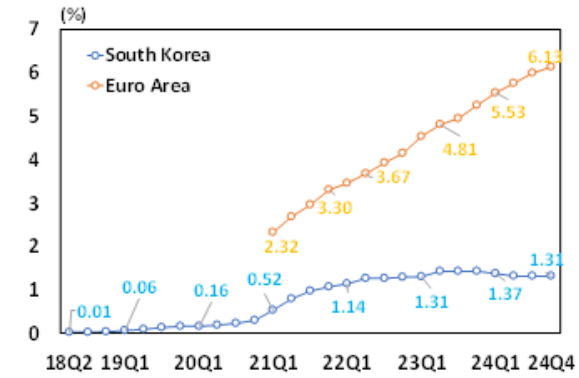
Source: KRX, ECB

Share of Issuance by Bond Type (As of end-2024)



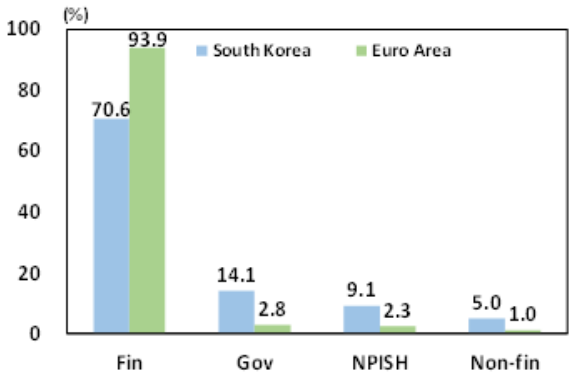
Source: KRX, ECB

Share of Climate Finance Debt Securities within Residents' Bond Holdings



Source: KRX, ECB

Share of Climate Finance Bond Holdings by Investor Type[1] (As of end-2024)



Note: 1) Excluding non-residents.
Source: KRX, ECB

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V Implications

1. Low Market Share Compared to Euro Area.

- Domestic share is 1.36% vs. 5.74% in the Euro Area.
- Korea's share of Global climate finance bond issuance(1.8%) is similar to GDP share(1.7%).

2. Limited Issuance by High-emission industries.

- Chemical and steel industries have minimal share.
- primarily issued by eco-friendly industries(e.g., EV financing, ESS, Renewable energy).

3. Limited Role of Government Sector.

- Government issuance volume(1.3%) is small.
- The role as a benchmark issuer remains limited.

Statistics for Climate Finance Debt Securities can serve as a foundational Dataset for central banks to design incentive schemes - such as central bank-backed interest subsidies - for institutions contributing to sustainable growth.

V Next Steps

☞ **Most core and advanced ambitions data can be compiled for residents' domestic issuances in line with the implementation timeline.**

- **Securing Additional Basic Data.**

  - Collect data on 1. bonds issued abroad by residents.

    And 2. bonds issued by non-residents acquired by residents.

→ **Review feasibility of using market data sources**(e.g., Bloomberg, Datastream)

- **Verification and Improvement of Statistics.**

  - Reflect finalized international guidelines in classification system.

  - Keep monitoring source data quality and prevent distortions in green bond statistics(e.g., green washing).

⇒ **Submit compilation results to BIS&ECB according to timeline.**

Thank you.

Any inquiries : dueoe@bok.or.kr

Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Bridging ESG data gaps: a global initiative integrating the LEI into the global energy ownership tracker

Anna Mowat,
Global Energy Monitor

Alexandre Kech,
Global Legal Entity Identifier Foundation

This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

Bridging ESG Data Gaps: A Global Initiative Integrating the LEI into the Global Energy Ownership Tracker

4 October 2025



GLEIF
Enabling global identity
Protecting digital trust

Global Energy Monitor

Agenda

1. **Who is Global Energy Monitor?**
2. **What is the Global Energy Ownership Tracker?**
3. **Who is GLEIF and what is the LEI?**
4. **Integrating LEIs with the Ownership Tracker**
5. **Opportunities from Data Interoperability**

GLEIF
Enabling global identity
Protecting digital trust

Global
Energy
Monitor

Background on GEM

GEM began in 2007 as a project to support the anti-coal movement in the US by developing freely shared data on a custom wiki platform. The organization now has ~90 staff in 13 countries.



GLEIF
Enabling global identity
Protecting digital trust

Global Energy Monitor

GEM has a large library of energy, heavy, and extractive industry trackers

GEM developed its "tracker" methodology for coal plants. It now has over 25 trackers covering coal, gas, oil, renewables, heavy industry, finance, and ownership.


Global Integrated Power Tracker


Global Energy Transition Tracker


Global Coal Plant Tracker


Global Coal Mine Tracker


Global Oil Infrastructure Tracker


Global Oil and Gas Extraction Tracker


Global Coal Project Finance Tracker


Global Coal Terminals Tracker


Global Oil and Gas Plant Tracker


Global Gas Infrastructure Tracker


Global Methane Emitters Tracker


Global Solar Power Tracker


Global Bioenergy Power Tracker


Global Geothermal Power Tracker


Global Hydropower Tracker


Global Wind Power Tracker


Global Nuclear Power Tracker


Global Steel Plant Tracker


Global Blast Furnace Tracker


Africa Energy Tracker


Global Energy Ownership Tracker


Private Equity Tracker


Portal Energético para América Latina


Asia Gas Tracker


Europe Gas Tracker

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Global Energy Monitor

The Global Energy Ownership Tracker covers ownership research for several asset classes

Long term aspiration is to cover ownership for all other trackers



Global Energy Ownership Tracker



Global Oil Infrastructure Tracker



Global Coal Mine Tracker



Global Gas Infrastructure Tracker



Global Cement and Concrete Tracker



Global Iron Ore Mine Tracker



Global Iron and Steel Plant Tracker



Global Integrated Power Tracker



Global Bioenergy Power Tracker



Global Coal Plant Tracker



Global Oil and Gas Plant Tracker

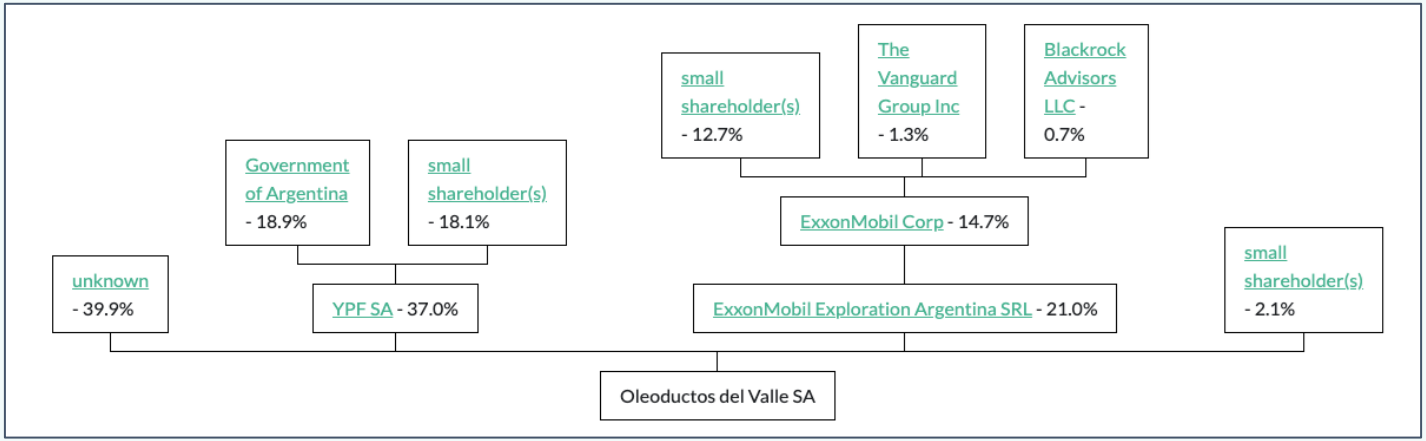
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We map each level of the chain from the direct owner up to the highest-level ultimate parents



Oldelval Oil Pipeline (Argentina)



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GEM publishes a network format of entities...

A unique GEM Entity ID is assigned to each entity in our network.

GEM Entity ID	Full Name	Name Local	Name Other	Abbreviation	Entity Type	PubliclyListed	Home Page	Registration Country	Registration Subdivision	Headquarters Country	Headquarters Subdivision	Global Legal Entity Identifier Index
E100001014315	1832 Asset Management LP				legal entity	FALSE		Canada		Canada	Ontario	5493000GV3I1S3MMF497
E100001016594	1947 Trust				legal entity			Singapore		Singapore		
E100000120000	24 Hour Mining and Industry Co Ltd		24 Hour Mining & Indu		legal entity	FALSE		Myanmar		Myanmar		not found
E100001010786	24R Advisory Services Pvt Ltd				legal entity	FALSE		India		India		not found
E100000000393	27 municipal utilities and regional energy suppliers				legal entity			Germany				not found
E100002002888	3A Capital Services Ltd				legal entity			India		India		
E100001013982	3Bear Energy LLC				legal entity	FALSE		United States	Delaware	United States	Colorado	not found
E100001010780	3B Power Sdn Bhd				legal entity	FALSE		Malaysia		Malaysia		not found
E100000002360	3-Energoortalyk JSC	АО 3-Энергоорталык			legal entity	FALSE	https://ww	Kazakhstan		Kazakhstan		not found
E100000120001	3S Enerji ve Maden Üretim				legal entity							
E100001001188	4C Acquisition LLC				legal entity	FALSE		United States		United States		not found
E100000131204	4th Gen Fuels LLC				legal entity	FALSE		United States		United States	Kentucky	not found
E100000002168	8 Rivers Capital LLC				legal entity	FALSE	https://8ri	United States	Delaware	United States	North Carolina	not found
E100002003905	9404-5515 Québec Inc				legal entity	FALSE		Canada	Quebec	Canada	Quebec	not found
E100000131205	99 Thuwanon Co Ltd				legal entity	FALSE		Thailand		Thailand	Krung Thep Maha Nakh	not found
E100000120002	A1 Group Inc				legal entity	TRUE		United States		United States	California	not found
E100000000602	A2A SpA				legal entity	TRUE		Italy		Italy	Brescia	81560076E3944316DB24
E100000003925	A2A Airport Energy SpA		SEA Energia [former]		legal entity		https://a2a	Italy		Italy		8945009PO0HAVTAPVZ51
E100002003519	A2A Calore e Servizi SRL				legal entity	FALSE		Italy		Italy		not found
E100000002361	A2A Energiefuture SpA				legal entity	FALSE		Italy		Italy	Milano	not found
E100002016402	AAA Capital Management	АО "ААА УПРАВ	AAA Upravlenie Kapita		legal entity	FALSE	https://aaa	Russia		Russia		253400MD780G2CR8BM30

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Entity ownership connections…

Subject Entity ID	Subject Entity Name	Interested Party ID	Interested Party Name	% Share of Ownership	Data Source URL
E100000001789	Centrais Elétricas Barcarena	E100000001265	New Fortress Energy	100	https://www.globenewswire.com/news-release/2019/10/21/1932637/0/en/Golar-Power-awarded-PPA-for-605MW-LNG-to-Power-Project-in-Barcarena-Brazil.html,https://ir.newfortressenergy.com/node/7571/html,https://www.reuters.com/article/energia-gas-terminalgnl-idBRKBN2931E5-OBRBS
E100000001790	Companhia Energética de Minas G	E100001011531	State of Minas Gerais	17.04	https://ri.cemig.com.br/governanca-corporativa/composicao-acionaria
E100000001790	Companhia Energética de Minas G	E100001011532	FIA Dinamica Energia	15.9	https://ri.cemig.com.br/governanca-corporativa/composicao-acionaria
E100000001791	Canindé Energias	E100000003074	Gastrading Comercializadora de Energias		https://solucoes.receita.fazenda.gov.br/Servicos/cnpjreva/cnpjreva_Solicitacao.asp
E100000001792	Centrais Elétricas de Pernambuco	E100000001794	Eletricidade do Brasil		https://www.fitchratings.com/research/pt/infrastructure-project-finance/fitch-afirma-rating-aa-bra-da-1a-emissao-de-debentures-da-epesa-perspectiva-estavel-21-02-2018,https://ebrasilenergia.com.br/quem-somos/,https://repositorio.simplificpavarini.com.br/Banco%20de%20Arquivos/DebenturesRegistro/ELETRICIDADE%20DO%20BRASIL%20SA%20-%20EBRASIL%20-%202%20E%20-%201%20S/6%20-%20EGAS%20-%203%C2%AA%20AGE%20-%20Aprova%C3%A7%C3%A3o%20da%20CF%20+%20Poderes%20REGISTRADA%20(JUCEP%2030%2001%2018....PDF
E100000001794	Eletricidade do Brasil	E100001011475	DC Energia e Participações	100	https://contracts.justia.com/companies/new-fortress-energy-llc-6251/contract/249094/
E100000001798	Faixa Preta Investimentos	E100002000335	Mercurio Holding		https://solucoes.receita.fazenda.gov.br/Servicos/cnpjreva/cnpjreva_Solicitacao.asp
E100000001801	Grupo Neoenergia	E100000000975	Iberdrola	100	https://www.iberdrola.com/conocenos/sociedades-grupo,https://www.neoenergia.com/en-us/about-us/energy-future/Pages/our-history.aspx
E100000001803	Litos Energia	E100002000969	Mitsubishi Power		https://power.mhi.com/media/366921/download
E100000001804	Natural Energia Participações	E100000123261	natural person(s)		https://solucoes.receita.fazenda.gov.br/Servicos/cnpjreva/cnpjreva_Solicitacao.asp
E100000001804	Natural Energia Participações	E100002000591	Fox Energy Servicos de Energia		https://solucoes.receita.fazenda.gov.br/Servicos/cnpjreva/cnpjreva_Solicitacao.asp
E100000001804	Natural Energia Participações	E100002000592	Martins Empreendimentos, Engenharia e Participacoes		https://solucoes.receita.fazenda.gov.br/Servicos/cnpjreva/cnpjreva_Solicitacao.asp
E100000001804	Natural Energia Participações	E100002000593	Newlima		https://solucoes.receita.fazenda.gov.br/Servicos/cnpjreva/cnpjreva_Solicitacao.asp
E100000001806	Ponte Nova Energia	E100000123261	natural person(s)		
E100000001809	Prumo Logistica	E100000001086	Mubadala Investment Company	50	https://www.gna.com.br/a-gna/nossos-acionistas,https://www.prumologistica.com.br/en/prumo/,https://www.upstreamonline.com/energy-transition/prumo-signs-deal-for-offshore-wind-and-green-hydrogen-in-brazil-s-acu-port/2-1-1323504
E100000001809	Prumo Logistica	E100000001197	EIG Global Energy Partners	50	https://www.gna.com.br/a-gna/nossos-acionistas,https://www.prumologistica.com.br/en/prumo/,https://www.upstreamonline.com/energy-transition/prumo-signs-deal-for-offshore-wind-and-green-hydrogen-in-brazil-s-acu-port/2-1-1323504

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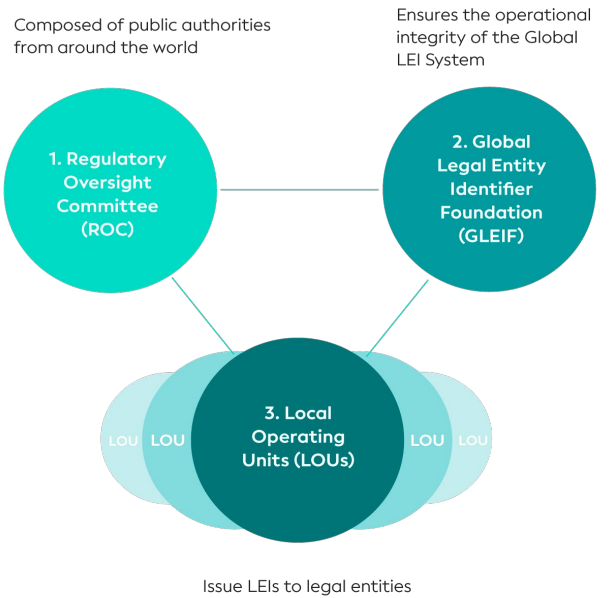
And a parent company-first format.

Parent GEM Entity ID	Parent	Project	Share	Ownership Path	Status	Capacity (MW)
E100000000339	Energetický a průmyslový holding AS	Kilroot power station GT5	100	Energetický a průmyslový holding AS -> EP UK Investments Ltd [100.0%] -> Kilroot power station GT5 [100.0%]	operating	340
E100000000339	Energetický a průmyslový holding AS	Fiume Santo power station GT1		Energetický a průmyslový holding AS -> EP Power Europe AS [100.0%] -> EP Produzione SpA [100.0%] -> Fiume Santo power station GT1 [unknown %]	mothballed	40
E100000000339	Energetický a průmyslový holding AS	Ballylumford power station B2	100	Energetický a průmyslový holding AS -> EP UK Investments Ltd [100.0%] -> Ballylumford power station B2 [100.0%]	operating	60
E100000000339	Energetický a průmyslový holding AS	Komorany power station K7	69	Energetický a průmyslový holding AS -> EP Infrastructure AS [69.0%] -> EP Energy AS [100.0%] -> United Energy AS [100.0%] -> Komorany power station K7	announced	35
E100000000339	Energetický a průmyslový holding AS	South Humber Bank power station 2	100	Energetický a průmyslový holding AS -> EP UK Investments Ltd [100.0%] -> South Humber Bank power station 2 [100.0%]	operating	580
E100000000339	Energetický a průmyslový holding AS	Tynagh power station GT1	80	Energetický a průmyslový holding AS -> EP UK Investments Ltd [100.0%] -> Tynagh Energy [80.0%] -> Tynagh power station GT1 [100.0%]	cancelled	299
E100000000339	Energetický a průmyslový holding AS	Provence power station ST1	100	Energetický a průmyslový holding AS -> Provence power station ST1 [100.0%]	operating	49
E100000000339	Energetický a průmyslový holding AS	Tavazzano power station 6	100	Energetický a průmyslový holding AS -> EP Power Europe AS [100.0%] -> EP Produzione SpA [100.0%] -> Tavazzano power station 6 [100.0%]	operating	385
E100000000339	Energetický a průmyslový holding AS	EP Energy Developments power station GT1	100	Energetický a průmyslový holding AS -> EP Energy Developments Ltd [100.0%] -> EP Energy Developments power station GT1 [100.0%]	pre-construction	350
E100000000339	Energetický a průmyslový holding AS	South Humber Bank power station 1	100	Energetický a průmyslový holding AS -> EP UK Investments Ltd [100.0%] -> South Humber Bank power station 1 [100.0%]	operating	810
E100000000339	Energetický a průmyslový holding AS	Enecogen power station U10		Energetický a průmyslový holding AS -> EP Netherlands BV [100.0%] -> Enecogen power station U10 [unknown %]	operating	435
E100000000339	Energetický a průmyslový holding AS	Enecogen power station U20		Energetický a průmyslový holding AS -> EP Netherlands BV [100.0%] -> Enecogen power station U20 [unknown %]	operating	435
E100000000339	Energetický a průmyslový holding AS	Tavazzano power station GT8	100	Energetický a průmyslový holding AS -> EP Power Europe AS [100.0%] -> EP Produzione SpA [100.0%] -> Tavazzano power station GT8 [100.0%]	retired	320
E100000000339	Energetický a průmyslový holding AS	Ballylumford power station C32	100	Energetický a průmyslový holding AS -> EP UK Investments Ltd [100.0%] -> Ballylumford power station C32 [100.0%]	operating	300
E100000000339	Energetický a průmyslový holding AS	Ostiglia power station OS5, timepoint 1	100	Energetický a průmyslový holding AS -> EP Power Europe AS [100.0%] -> EP Produzione SpA [100.0%] -> Ostiglia power station OS5, timepoint 1 [100.0%]	pre-construction	890

Who is the Global Legal Entity Identifier Foundation (GLEIF)?

- GLEIF is a not-for-profit Swiss foundation, founded by the Financial Stability Board (FSB)
- GLEIF is overseen by the Regulatory Oversight Committee (ROC) with
  - 70 regulators and
  - 19 observers
  - from 50 countries
- GLEIF Board has 18 independent directors
- 38 accredited partners for LEI issuing (LOUs) and growing
- > 3 million LEIs as of today, available as open data without IP or copyright protection

The Financial Stability Board (FSB) and the Group of Twenty (G20) have endorsed the LEI, Global LEI System and GLEIF.



Legal Entity Identifier (LEI) and Key Reference Data
Who is who? Who owns whom?

"Level 1"

LEI Code G5GSEF7VJP5I7OUK5573

(Primary) Legal Name	BARCLAYS BANK PLC
Registered At	Companies Register (Companies House) Companies Register (Companies House) England and Wales, United Kingdom of Great Britain and Northern Ireland RA000585
Registered As	01026167
Jurisdiction Of Formation	GB
General Category	GENERAL
Entity Legal Form	Public Limited Company (en) Cwmni Cyfyngedig Cyhoeddus (cy) B6ES
Entity Status	ACTIVE
Entity created at	1971-10-04 01:00:00+01:00
BIC Code	BARCGB22XXX
MIC Code	BPLC

- EntityID & Authoritative source, Mappings, Address information (…)

"Level 2": Parents, children & fund relationships

Parents — Published Relationship · Lapsed Relationship · Reporting Exception

BARCLAYS PLC (Direct Parent)

BARCLAYS PLC (Ultimate Parent)

Direct children (85) — Published Relationship · Lapsed Relationship

BARCLAYS BANK PLC

- 台灣巴克萊證券股份有限公司 (Direct)
- BARCLAYS OCIO SERVICES LIMITED (Direct)
- ISLE OF WIGHT HOME LOANS LIMITED (Direct)
- NORTHWHARF NOMINEES LIMITED (Direct)

Managed Funds (40) — Published Relationship · Lapsed Relationship

- INSIGNIA 80% PROTECTED EQUITY FUND (Managed Fund)
- SHILLER US SECTOR INDEX FUND (Managed Fund)
- BARCLAYS US EQUITY INTRADAY MOMENTUM FUND (Managed Fund)

Branches (3) — Published Relationship · Lapsed Relationship

- BARCLAYS BANK PLC PARIS BRANCH (Branch)
- Barclays Bank PLC (Branch)
- 英国巴克莱银行有限公司上海分行 (Branch)

- GLEIF API: https://api.gleif.org/docs
- LEI Search: https://search.gleif.org
- Golden Copy: https://www.gleif.org/en/lei-data/gleif-golden-copy

GEM already has LEIs integrated into its own data and is working to integrate GEM Entity IDs into GLEIF.

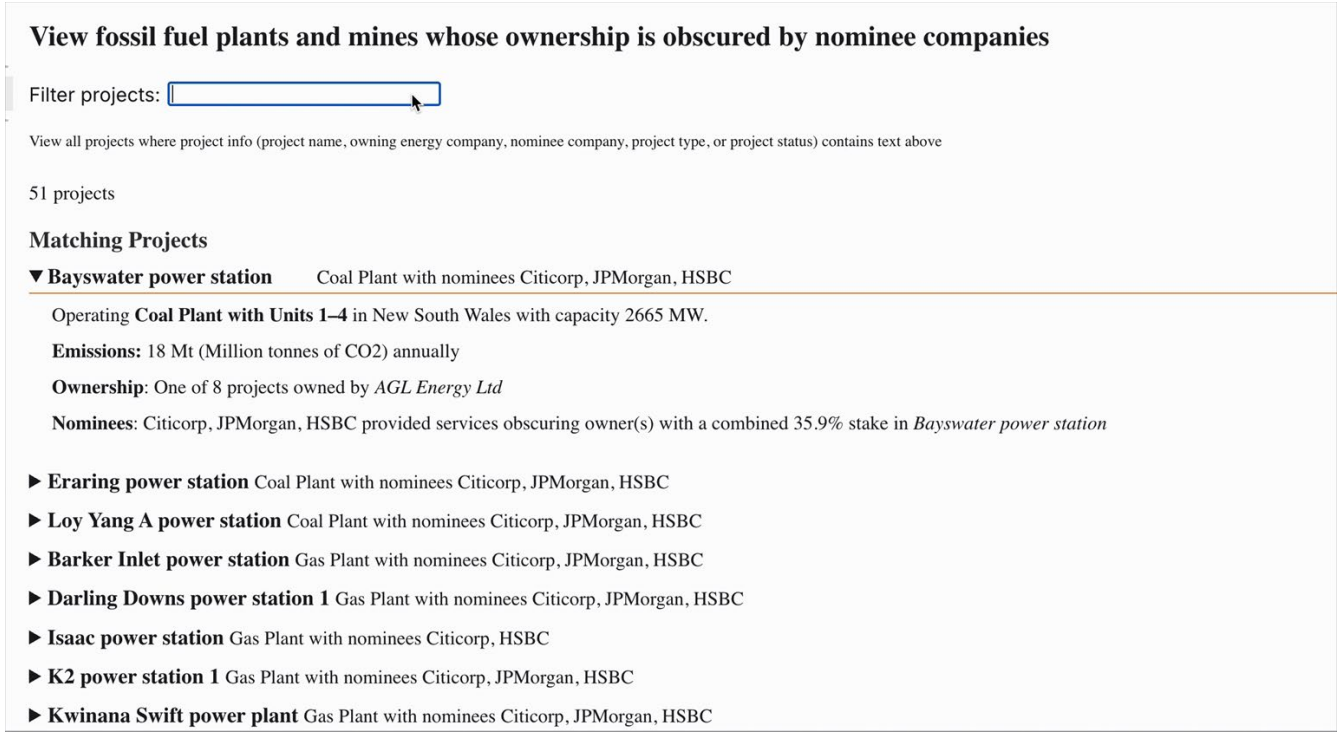
- GEM Entity ID to be added to GLEIF entity pages
- Crosswalk document will be published and available for download on the GLEIF website
    - Updated roughly once a month (or whenever a GEM asset tracker has a new release)
- Links to each relevant GLEIF entity pages embedded in GEM Ownership tracker dataset

GEM Entity ID	Full Name	Global Legal Entity Identifier Index
E100002005185	Akçansa Çimento Sanayi ve Ticaret AŞ	789000E4UZB42H2HX767
E100000002141	Akenerji Elektrik Üretim AŞ	7890006JO4YATIQAG941
E100001014067	Aker BP ASA	549300NFTY73920OYK69
E100001014068	Aker Capital ASA	5493004SEKKPH2GS1D50
E100001000634	Akfen Yenilenebilir Enerji AŞ	984500C9EC85457B3E55
E100001000635	Akkan Enerji ve Madencilik AŞ	894500OLC7T8S2AR9O59
E100001011231	Akkök Holding AŞ	789000NHYUUC7523GX39
E100002005195	Akmenes Cementas AB	549300PNKQ2BHZ2TI065
E100002003740	Akora Resources Ltd	213800G8DFDRQAASP451
E100000002409	Aksa Akrilik Kimya Sanayii AŞ	789000OKY3ICX0Y2NY41
E100000002411	Aksa Enerji Uretim AŞ	789000KQC5JTW1S3JG98
E100000000735	Akzo Nobel NV	724500XYIJUGXAA5QD70
E100000002418	Alabama Power Co	0RL818ELFOHP5JHOFU19
E100002016488	Alaska Permanent Fund Corp	DFKMC7AUPF2H39L1JO20

Opportunities from Data Interoperability

- **Asset-level Data**
- **Independent Verification of Financed Emissions**
    - GEM is the ownership data lead at the Climate TRACE coalition
- **Increased ownership data granularity**
    - All levels of ownership (subsidiaries, SPVs, etc.)
    - 5% threshold
    - Citations and most recent research date included

You can search from a company-first or an asset-first perspective



View fossil fuel plants and mines whose ownership is obscured by nominee companies

Filter projects:

View all projects where project info (project name, owning energy company, nominee company, project type, or project status) contains text above

51 projects

Matching Projects

▼ **Bayswater power station** Coal Plant with nominees Citicorp, JPMorgan, HSBC

Operating **Coal Plant with Units 1–4** in New South Wales with capacity 2665 MW.

Emissions: 18 Mt (Million tonnes of CO2) annually

Ownership: One of 8 projects owned by *AGL Energy Ltd*

Nominees: Citicorp, JPMorgan, HSBC provided services obscuring owner(s) with a combined 35.9% stake in *Bayswater power station*

▶ **Eraring power station** Coal Plant with nominees Citicorp, JPMorgan, HSBC

▶ **Loy Yang A power station** Coal Plant with nominees Citicorp, JPMorgan, HSBC

▶ **Barker Inlet power station** Gas Plant with nominees Citicorp, JPMorgan, HSBC

▶ **Darling Downs power station 1** Gas Plant with nominees Citicorp, JPMorgan, HSBC

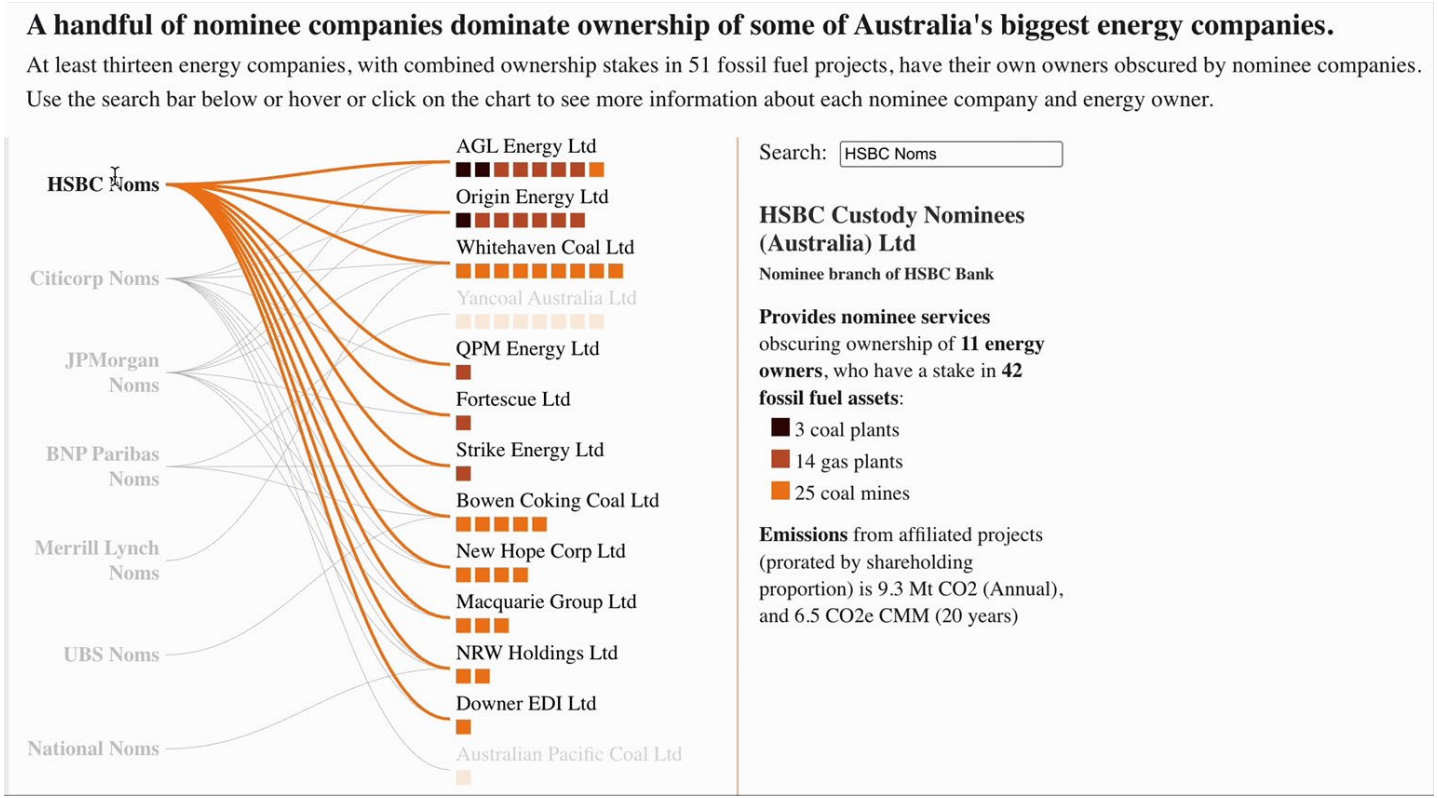
▶ **Isaac power station** Gas Plant with nominees Citicorp, HSBC

▶ **K2 power station 1** Gas Plant with nominees Citicorp, JPMorgan, HSBC

▶ **Kwinana Swift power plant** Gas Plant with nominees Citicorp, JPMorgan, HSBC

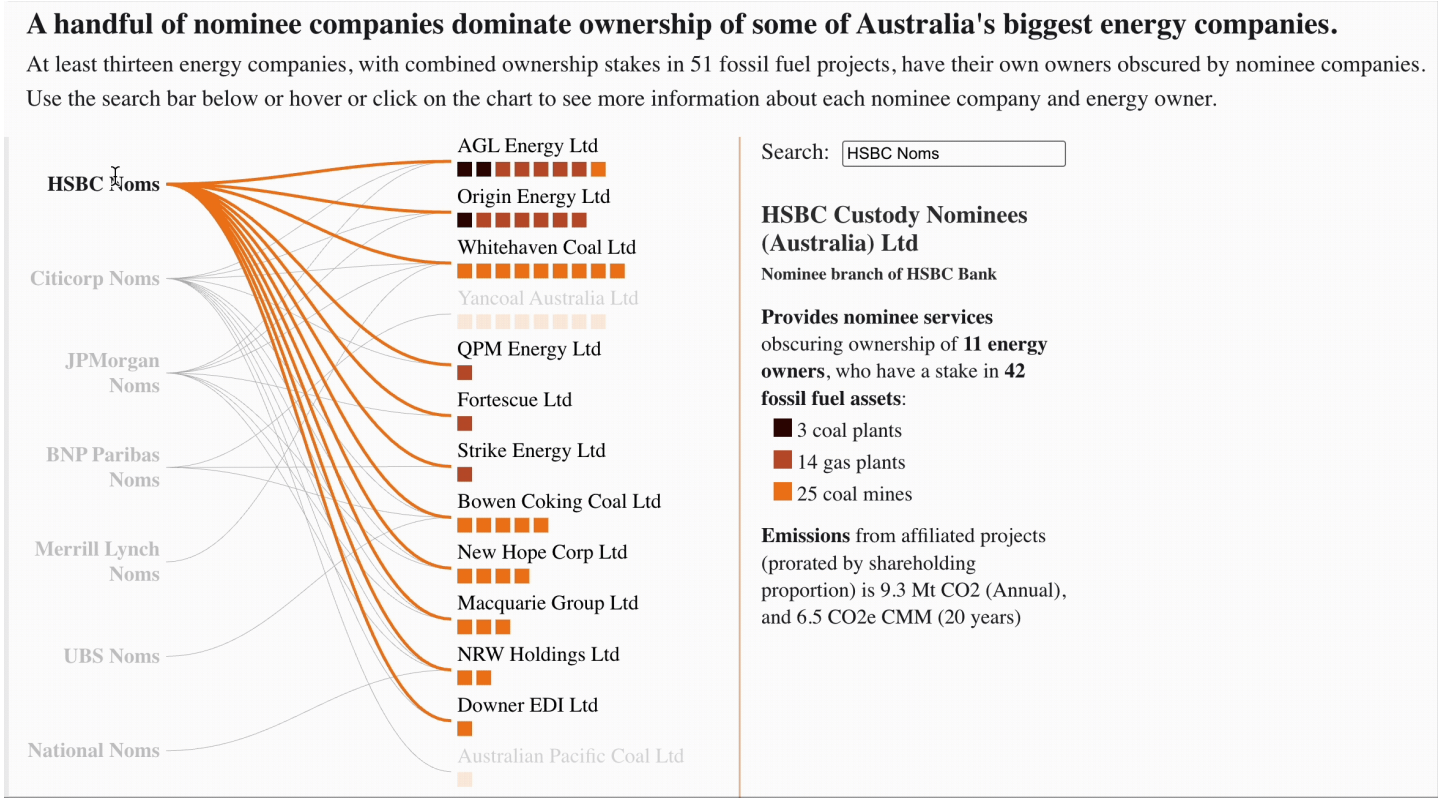
* Example from recent GEM report on Australian nominee companies

Emissions can be aggregated up from any asset to any parent



* Example from recent GEM report on Australian nominee companies

Emissions can be aggregated up from any asset to any parent



* Example from recent GEM report on Australian nominee companies

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Thank you

Climate TRACE Ownership Information: Global Energy Monitor Methodology for Ownership Data

Anna Mowat*, Gabriel Louis, and Maisie Bird
All authors affiliated with Global Energy Monitor and Climate TRACE
***Contact** Ownership Sector Lead: anna.mowat@globalenergymonitor.org

1. Introduction

As part of a collaboration with Climate TRACE, Global Energy Monitor (https://globalenergymonitor.org/), referred to as GEM, has contributed technical and ownership data sets for combustion power plants (i.e., burning coal, gas, oil, and/or bioenergy), steel plants, coal mines, iron ore mines, oil pipelines, natural gas liquids (NGL) pipelines, gas pipelines, concrete and cement plants, and small oil "teapot" refineries in China. GEM's technical data includes detailed information on the various assets such as plant capacity, location, and operating status. GEM's ownership data includes information on the project-level ownership for various projects and the interested party that owns the project-level owner. This information is described in more detail in our Methods section.

With the exception of the teapot refineries in China, GEM releases these data sets as stand-alone trackers, which are spreadsheets with project-level data:

- Global Coal Plant Tracker
    - The Global Coal Plant Tracker (GCPT) provides information on coal-fired power units around the world generating 30 megawatts and above. The tracker catalogs every operating coal-fired generating unit, every new unit proposed since 2010, and every unit retired since 2000.
- Global Oil and Gas Plant Tracker
    - The Global Oil and Gas Plant Tracker (GOGET) is a worldwide dataset of oil and gas-fired power plants. It includes units with capacities of 50 megawatts or more (20 megawatts or more in the European Union and the United Kingdom). The tracker catalogs every oil and gas power plant at this capacity threshold of any status, including operating, announced, pre-construction, construction, shelved, canceled, mothballed, or retired.
- Global Bioenergy Power Tracker
    - The Global Bioenergy Power Tracker (GBPT) is a worldwide dataset of utility-scale bioenergy power facilities. It includes bioenergy units with capacities of 30 megawatts or more. The tracker includes every bioenergy unit at the 30

megawatt capacity threshold for operating, announced, pre-construction, and in construction power station units.

- Global Coal Mine Tracker
    - The Global Coal Mine Tracker (GCMT) is a worldwide dataset of coal mines and proposed projects. The tracker provides asset-level details on ownership structure, development stage and status, coal type, production, workforce size, reserves and resources, methane emissions, geolocation, and over 30 other categories.
- Global Steel Plant Tracker
    - The Global Steel Plant Tracker (GSPT) provides information on global crude iron and steel production plants and includes every plant currently operating with a capacity of five hundred thousand tons per year or more of crude iron or steel.
- Global Oil Infrastructure Tracker
    - The Global Oil Infrastructure Tracker (GOIT) is an information resource on crude oil and natural gas liquids (NGL) transmission pipeline projects and their development. Currently, GOIT attempts to include all global crude oil and NGL transmission pipelines of any status, though availability on this infrastructure varies across countries and regions, and some are researched more completely than others.
- Global Gas Infrastructure Tracker
    - The Global Gas Infrastructure Tracker (GGIT) is an information resource on natural gas transmission pipeline projects and liquefied natural gas (LNG) import and export terminals. Currently, GGIT aims to include all LNG terminals regardless of threshold, as well as all global gas transmission pipelines over predetermined size thresholds.
- Global Cement and Concrete Tracker
    - The Global Cement and Concrete Tracker (GCCT) will provide information on global integrated and grinding plants including all plants that have been proposed or under construction since 2018 and retired or mothballed since 2021. The GCCT will provide asset-level data on ownership, operating status, annual clinker and cement capacity, and production methods including relevant green cement technology. Its first release is currently scheduled for July 2025.
- Global Iron Ore Mine Tracker
    - The Global Iron Ore Mines Tracker (GIOMT) provides information on global iron ore mines, and includes all operating, proposed, shelved, retired or mothballed mines since 2023. The GIOMT provides asset-level data on ownership structure, development stage and operating status, annual production since 2022, and design capacity for each mine.
- Global Cement and Concrete Tracker
    - The Global Cement and Concrete Tracker (GCCT) provides information on global integrated and grinding plants, including all plants that have been proposed

or under construction since 2018 and retired or mothballed since 2021. The GCCT provides asset-level data on location, ownership, operating status, annual clinker and cement capacity, and production methods including relevant green cement technology.

The data GEM contributed on China's small oil refineries is released by Climate TRACE as part of the Fossil Fuel Operations sector, in the subsector Oil Refining.

GEM has enhanced, updated, and expanded the ownership data in the trackers above. In revamping this data, we have organized the data following Open Ownership's Beneficial Ownership Data Standard, or BODS (Open Ownership, 2024; https://www.openownership.org/en/topics/beneficial-ownership-data-standard/). We adopted BODS because it is considered the only widely used standard for organizing data on ownership structures. The data has been enhanced by adding missing ownership data, bringing other ownership data up to date, making the ownership data consistent across the trackers listed above, and adding additional details on entities, as described below.

GEM also preprocesses entity names received from other Climate TRACE coalition members before integrating them into the Global Energy Monitor (GEM) PostgreSQL database and assigning entities unique GEM Entity IDs. The preprocessing ensures consistent and accurate matching of entities across datasets, facilitating reliable data ingestion and analysis.

2. Methods

The terminology used here conforms with BODS whenever relevant. Accordingly, by "entities," we are referring to companies, governments, government agencies, and other bodies that are involved in ownership.

GEM's ownership data is stored in a custom PostgreSQL database, which allows for representation of hierarchical relationships between various entities involved in ownership of projects, such as power plants, pipelines, or coal mines. Other sources may refer to our term "projects" as "assets"; we consider the two terms to be equivalent.

Each piece of GEM's ownership data pertains to one of two types of relationships:

- Immediate owners of projects: GEM records each entity that directly owns a project (such as a power plant) and the percentage that entity holds in the project's ownership structure when available.
- Higher-level ownership: GEM additionally records the entities that own the immediate owners of projects, including the higher-level entities' percent share when available. We

trace ownership structures up to the highest level owner(s) identifiable in open sources. These highest level owners include:

- Publicly traded companies,
- The highest privately held entity in any given ownership branch,
- State bodies or governments, and
- Actual persons (not a company), who we refer to as "natural person(s)"

Each project's ownership tree thereby includes immediate, intermediate, and ultimate ownership, as applicable.

As in BODS, the GEM database refers to a lower-level entity as the "subject" and the higher-level entity as the "interested party."

In addition, the database stores various attributes of the entities, as described below. This additional data helps to provide unambiguous identification of the entities and can also enable certain types of analyses.

2.1 Types of Entities

In the database, each entity is assigned a type, as either a legal entity, state, state body, anonymous entity, natural person, unknown entity, or arrangement, following the definitions in BODS.

2.1.1 Legal Entity

As defined by BODS, a legal entity is an organization created with a memorandum of incorporation or similar registration documents, and which is registered by a government. There are many types of legal entities, including Corporation, Limited Liability Company, and Company Limited. For GEM's ownership work, we define "legal entity" in line with BODS terminology.

In addition, in GEM's database, we differentiate privately owned and publicly traded companies (also known as a publicly held company, publicly listed company, or listed company). This is in line with BODS schema for marking publicly listed companies. Another reason we differentiate is because in some jurisdictions, such as the United States (U.S.), public companies are required to publish audited financial statements and information on beneficial ownership over 5% (Securities and Exchange Commission, 2023). Identifying public companies is also useful for guiding research, since publicly traded companies tend to disclose ownership information in their annual reports or in filings made with the stock exchange on which they are traded.

2.1.2 State

The entity type "state" refers to national, subnational, and local governments. In BODS terminology, it is a country, nation, or community with legal sovereignty within a territory. In GEM's dataset, we follow a convention for naming states:

- National governments: "Government of X."
- State/regional governments: "State of X" or "Province of X" (for example), depending on the name of the type of country subdivision.
- City governments: "City of X" or "Municipality of X."
    - U.S. Cities: follow the same pattern as well as adding the state where the city is located in parentheses.
        - For example, "City of Chicago (Illinois)" for the city government in Chicago, Illinois, United States.

2.1.3 State Body

In BODS terminology, "state body" refers to a core administrative or legislative body within a state's apparatus. For example, these could be ministries or government agencies. State bodies are entered in GEM's dataset as distinct from the state (the government) to make the ownership data as specific as possible.

When labeling state bodies in our dataset, we use the official name of the government agency or ministry as the entity name. In cases where ministry or government agency names are similar to government agency names in other countries, we enter the country name in parentheses at the end of the entity name—for example, "Ministry of Energy (Iraq)."

2.1.4 Arrangement

For other cases of ownership that do not fit into any of the categories above, we have applied a general category "arrangement," based on advice from Open Ownership's staff. We apply the category of "arrangement" to entities that meet the following criteria:

- Joint ventures that are not registered in a government business registry
- Other entities, such as trusts, universities, and certain general partnerships, that are not registered in a business registry and are found to hold ownership in a project or subject
- Business groups that are described in online sources as holding ownership of a project or subject but for which a principal registered legal entity (i.e., a parent or holding company) could not be identified in online sources and no other information regarding the ownership of the asset or subject is available

2.2 Sources and Datasets employed

The availability of data on ownership varies widely between countries, and GEM relies on the most authoritative open data that is available at the time of this work. This includes diverse sources, such as state business registries, government data sets, company reports, news articles,

stock exchanges, and other sources. On GEM.wiki, GEM publishes data for each project (e.g., power plant) which shows the ownership data as well as the data sources whenever available.

Examples of the government data sets that GEM uses to compile ownership data include Form EIA-860, which is a United States government agency electricity dataset from the U.S. Energy Information Administration (EIA, 2023). Additionally, GEM gathers ownership data from various company reports, such as annual reports and financial statements, which may identify the subsidiaries of a company and/or the projects owned by a company. In some cases, GEM obtained ownership information from news articles from accredited sources (such as Reuters, Bloomberg, and S&P Global), and press releases from company websites.

2.3 Entity Data Structure

For each entity, GEM stores data in the following data fields, as available and as relevant:

- **Entity Type:** The options follow the definitions in BODS, as described above, with the most common types being:
    - Legal entity
    - State
    - State Body
    - Arrangement
- **Legal Entity Type:** This field is used only when the "Entity Type" is a "Legal entity." The entries are standardized in their abbreviated forms; for example, a Limited Liability Company is standardized as "LLC."
- **Entity Status:** This field is used if the entity is dissolved or amalgamated.
- **Publicly Listed:** This indicates whether a company is "listed," that is, it has stock listed on a public stock exchange. (Such companies are also referred to as publicly traded or publicly held.) This option is available only for the entity type "legal entity."
- **Abbreviation**: The abbreviation of the entity name (if any), based on its primary name. This can be an acronym or other shortening of the name.
- **Name local**: The name of the company in the local language (e.g., for a Chinese company, the name in Chinese).
- **Name other**: Multiple names can be added, in English and/or other languages. When an entity was previously referred to by another name, we enter former names with "[former]" appended at the end. For example, "Anergi International Ltd" has the entry "Applied Energy Services [former]."
- **Registration Jurisdiction—Country & Subdivision.** For legal entities registered with a federal business registry, the country is listed. For legal entities registered with a provincial or state registry only, the subnational division is additionally listed.
- **Headquarters Jurisdiction—Country & Subdivision.** The location of the headquarters can be listed by country and by subdivision, as available.

- **Organization Identifiers:** This indicates an ID for an entity and is most commonly available only for legal entities. The ID systems currently in use in GEM's data set are listed below, with the short identifiers in parentheses as assigned by org-id.guide.
    - Global Legal Entity Identifier Index (XI-LEI)
    - Refinitiv PermID (XI-PID)
    - UK Companies House (GB-COH)
    - China's Unified Social Credit Identifier (CN-USCI)
    - China's State Administration for Industry and Commerce (CN-SAIC)
    - IDs assigned by the US Energy Information Administration, as published in Form EIA-860, for entities that own power-generating projects
    - S&P Capital IQ - SPCIQ: Can be found on companies pages in your S&P IQ account
    - India's Corporate Identification Number (Ministry of Corporate Affairs) (IN-CIN)
    - Russia's Uniform State Register of Legal Entities of Russian Federation (RU-INN)
    - Brazil's National Registry of Legal Entities (Federal Revenue Service) (BR-CNPJ)

Figure 1 shows a subset of tables in GEM's relational database that pertain to data on entities, with the data fields for each. For more information about the database structure, please contact the methodology authors at GEM.

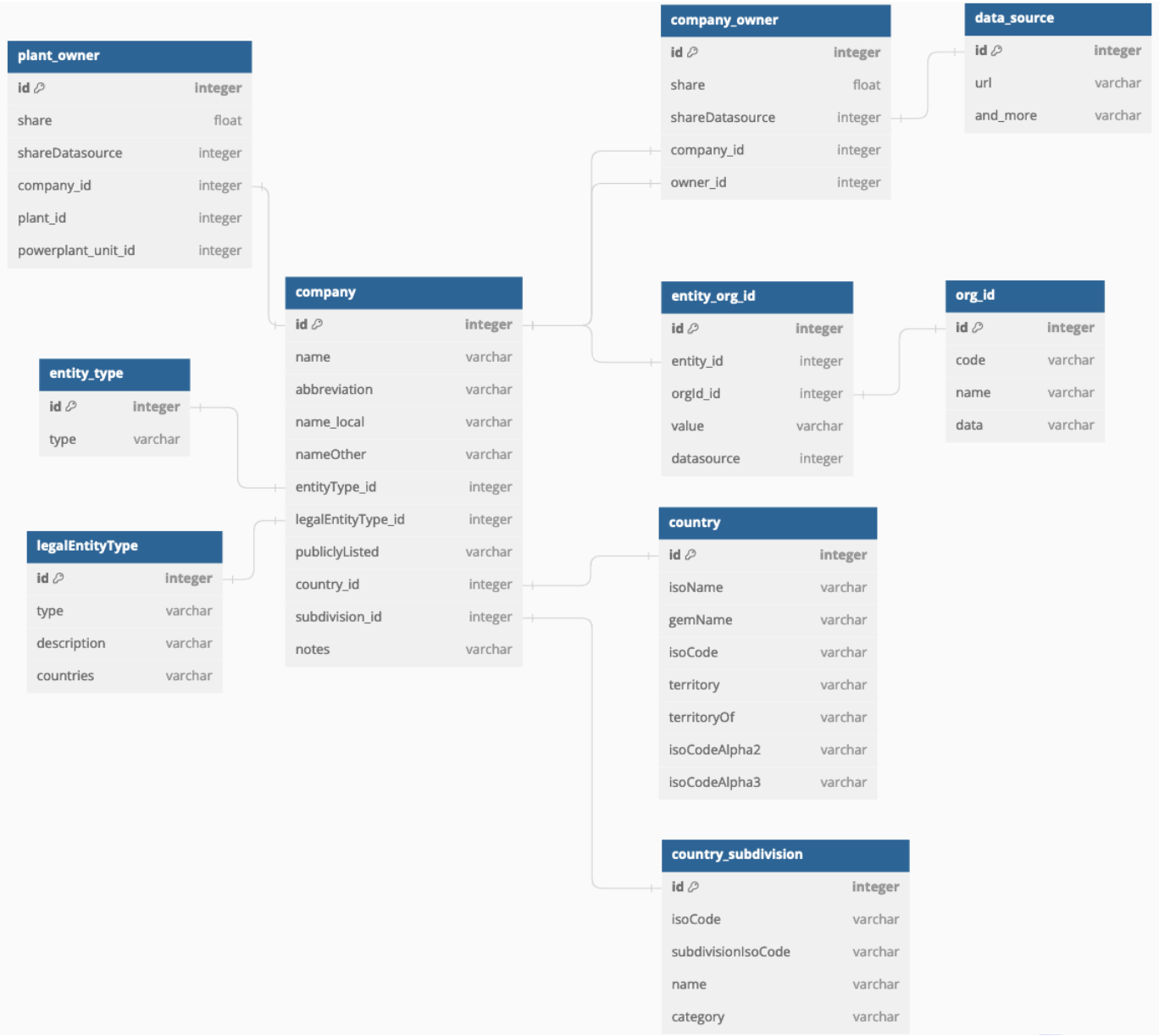


Figure 1 Diagram of a subset of tables in GEM's relational database, containing data on entities.

3. Research Practices

3.1 Assigning owners

When adding new entities to our database, GEM identifies the immediate owner reported for each project in GEM's trackers, and compares it against GEM's database of entities to avoid duplicating entities under different names.

To ensure that GEM does not create duplicate entities for entities, GEM relies on the collection of various information including: company name in English, company name in local language,

company abbreviation, entity type, legal entity type, publicly listed status, previous company names, location of registration and/or headquarters, and several organization identifiers such as the Legal Entity Identifier (LEI) issued by the Global Legal Entity Identifier Foundation (GLEIF), the Refinitiv Permanent Identifier (PermID), and national registration numbers. These identifiers and other information about the entities help GEM identify when one entity is being referred to in different ways.

The owners reported in authoritative data sources may not always be the immediate owner of a project. Many projects' immediate owner is a special purpose vehicle (SPV), a type of company that is often set up to own one particular project (such as a power plant).

However, GEM's focus is on tracing ownership "upward" to the level of ultimate parent entities (as defined below), in order to show how ownership aggregates. GEM does not trace ownership "downward" to identify any lower-level owner that may be below the owner reported for a particular project.

3.2 Ownership trees

Starting from the immediate owners of projects (as reported by our sources), GEM researchers add additional data as available on the higher-level interested parties of these starting subject entities. This terminology follows BODS, in which each relationship between two entities has a lower-level "subject" and a higher-level "interested party."

In the GEM database, the levels of ownership for an entity are displayed in an ownership tree. The ownership tree of an entity provides a visual representation of the different levels of ownership for a given entity.

An example is shown in Figure 2 in the following section for the ownership of JERA Co Inc., a Japanese power generation company.

3.3 Parents

To aggregate data at a high-level, GEM has created a particular definition for the ultimate parent entities, referred to below as simply the "parent(s)." Within each ownership tree (or tree branch), GEM defines a parent following the rules described below:

- The lowest-level publicly listed company, if any.
- If there are no publicly listed companies, then the highest-level state-owned enterprise, if any. That is, the parent is not assigned to a state or state body if there is a lower-level legal entity.
- If there are no listed companies or state-owned enterprises, then the ultimate parent is assigned to the highest-level privately owned company. Natural persons are not assigned as parents, as long as there is available data on lower-level entities. In certain cases, in

which the highest-level owners are general investors, such as major banks, then we define the parent as the highest-level energy company in that tree or tree branch.

- One exception is for the case of China, in which certain entities are designated as central enterprises by the central government. The State-owned Assets Supervision and Administration Commission of the State Council (SASAC) has named 98 companies as central enterprises (SASAC, 2023). The Ministry of Finance has named an additional 27 companies as central enterprises (MOF, 2021). If an ownership tree (or tree branch) reaches one of these designated central enterprises, then that central enterprise is listed as the ultimate parent for that tree branch.

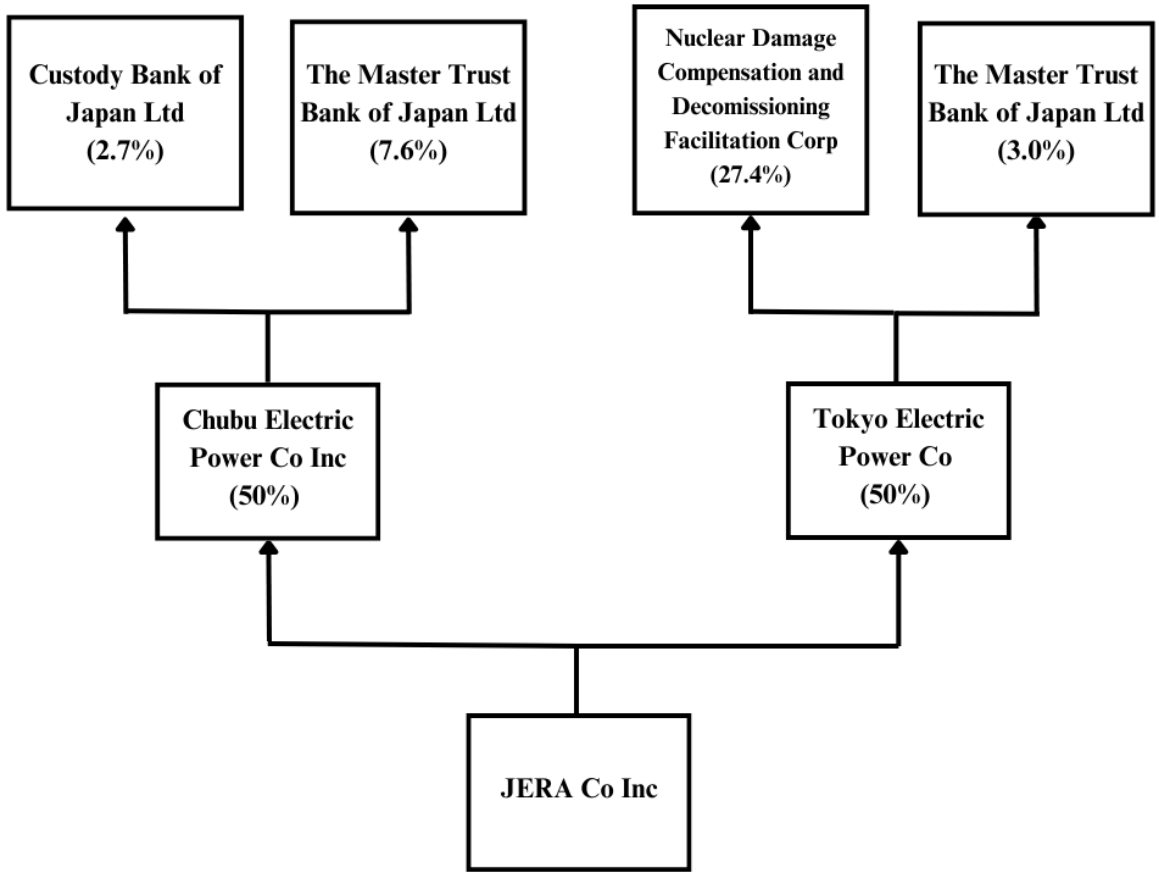


Figure 2 Ownership Tree of the first two ownership levels above JERA Co Inc, starting from the bottom to the top of the figure. The higher-level owners display the next level of ownership and the percent of indirect ownership of JERA Co Inc. This figure is paired down since GEM's full ownership tree for JERA has 5 layers of ownership and 17 unique entities holding direct or indirect ownership. The remaining interested party ownership for Chubu Electric and Tokyo Electric is attributed to small shareholders and natural persons.

In the example ownership tree shown in Figure 2 for JERA Co Inc, the immediate interested parties are Chubu Electric Power Co Inc and Tokyo Electric Power Co Inc, which each hold 50% of JERA Co Inc. The next level of ownership displays the interested parties of these two entities. The Master Trust Bank of Japan Ltd and Custody Bank of Japan Ltd are the interested parties in the subject Chubu Electric Power Co Inc, and thus have indirect ownership of JERA Co Inc. The same can be said for Nuclear Damage Compensation and Decommissioning Facilitation Corp and The Master Trust Bank of Japan Ltd, which are the interested parties of the subject Tokyo Electric Power Co, and thus have indirect ownership of JERA Co Inc. However, Chubu Electric Power Co Inc and Tokyo Electric Power Co are both publicly listed companies, and therefore, following GEM's definition of parents, each of them is defined as a parent of JERA Co Inc., each owning 50% of JERA Co Inc.

In tracing ownership trees upward from the reported owners, GEM stores data on all entities involved as long as they own at least 5% of a project or a subject entity. We have decided to track ownership of at least 5% to follow the practice of the US Securities and Exchange Commission (SEC), which requires individuals or entities with at least 5% beneficial ownership in a public company to file this through a Schedule 13D form. By storing data on ownership of at least 5%, GEM is providing a nearly comprehensive view of ownership, going beyond the entities that have controlling interests in a project or a subject entity.

GEM's parent designations do occasionally list states or state bodies if there weren't any lower-level entities in a given ownership tree (or tree branch). An example of this is Bharat Aluminium Co Ltd (see the description in Figure 3).

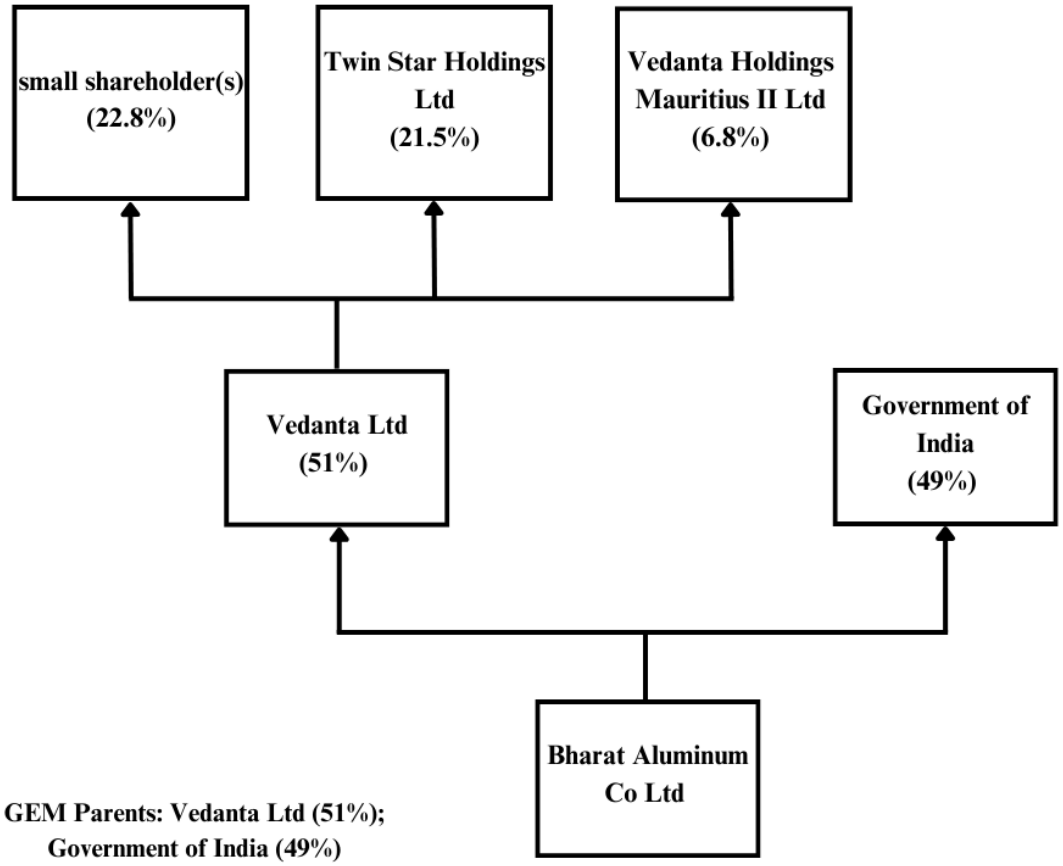


Figure 3 Ownership Tree of the first two ownership levels above Bharat Aluminum Co Ltd, starting from the bottom and to the top. The percent value refers to the entity's direct or indirect ownership of Bharat Aluminum Co Ltd. For assigning the parents of Bharat Aluminium Co Ltd, the Government of India is listed as one of the parents, because there isn't any other legal entity to report as the parent on that branch of the ownership tree. This figure is paired down since GEM's full ownership tree for Bharat Aluminum Co Ltd has 7 layers of ownership and 9 unique entities holding direct or indirect ownership.

Similarly, if the lowest-level owner in a particular ownership tree is a natural person, then a designation for "natural person(s)" in general is reported, rather than listing names of individual natural persons.

3.4 Mergers and acquisitions

Mergers and acquisitions fall into the three following scenarios:

1. Acquisition (change in ownership): the entity's legal status did not change; its name may or may not have changed, but it is still registered as its own legal entity. It is not dissolved or amalgamated.

In the case of a corporate acquisition, we have labeled the company that is the acquirer as the interested party and the acquired company as the subject (following the BODS terminology for relationships between entities).

2. Amalgamation: the entity has been amalgamated into another entity and is therefore no longer active.

When a company has been amalgamated into another, the company's previous legal identity becomes defunct, and it is no longer active. In this case, we label the companies entity status as "amalgamated" and link its subject companies to the entity that it amalgamated into.

3. Merger: the entity has merged with another entity and the entities combined their identities (e.g., ExxonMobil).

In the case of a merger between companies, if one company survives and the other does not, we have mapped the subjects of the acquired company to the acquiring company and labeled the acquired companies entity status as "amalgamated". We also update the name of the acquiring entity to its new name.

For example, in the ExxonMobil merger in 1998, Exxon was technically the acquirer, while the Mobil name was retained as a brand name within the combined company. Therefore, Mobil Corp. was amalgamated into Exxon Corp., and Exxon Corp. became renamed as ExxonMobil Corp.

4. GEM Ownership data provided to Climate TRACE

In total for 2025, GEM contributed 27,737 unique entities to the Climate TRACE database, an increase from last year's total - 19,588 entities - a ~30% increase The immediate and parent ownership to source-level emissions for the following sectors:

- Coal plant sector - 8,309 entities
- Gas plant sector - 8,810 entities
- Bioenergy plant sector - 4,149 entities
- Coal mine sector - 6,653 entities
- Iron Ore mine sector - 988 entities
- Steel plant sector - 2,250 entities
- Oil, Gas, and NGL pipeline sector - 2,314 entities
- Cement and Concrete sector - 3,189 entities

For a breakdown of ownership by asset count see the Summary of Asset Count by Operating Status 24 Oct 2025.csv. Note that some counts may be unit level and some are plant level. Legal Entity Identifiers, PermIDs, and UK Companies House ID are included in the summary sheet for better data interoperability.

Some entities repeat across sectors, so the sum of the individual sectors is greater than the total 27,737 entities.

Refer to each sector's methodology on the Climate TRACE GitHub repository to understand how these assets were incorporated into each respective sector.

5. Preprocessing Entity Names for Climate TRACE Data Integration into the Global Energy Monitor Database

This section outlines the standardized process used to preprocess entity names received from other Climate TRACE coalition members before integrating them into the Global Energy Monitor (GEM) PostgreSQL database. The preprocessing ensures consistent and accurate matching of entities across datasets, facilitating reliable data ingestion and analysis.

This preprocessing pipeline ensures that entity names from Climate TRACE coalition members are systematically cleaned, normalized, and matched against the Global Energy Monitor database. By combining geolocation enrichment, exact and fuzzy matching, and manual review, the process maintains high data integrity and supports scalable ingestion workflows.

- The Global Energy Monitor database maintains a comprehensive set of energy-related entities.
- Preprocessing is implemented via a Python notebook named `database_preprocessing`, hosted in the `ClimateTRACE_ownership` GitHub repository found in the GEM GitHub.
- This approach is modular and adaptable for other teams or projects ingesting data into the GEM database.

Preprocessing Workflow

5.1. Data Acquisition

- Receive CSV files containing entity data from Climate TRACE data engineers at WattTime.
- These files include a `location` column specifying point locations related to the asset the entity owns.

5.2. Location Normalization

- Extract all unique locations from the `location` column.

- Use the Python `geopy` library with the Nominatim geocoding service to resolve each unique location to its corresponding state and country.
- Append the resolved state and country information back into the dataframe, enriching the location data.
- Note: Efforts are ongoing to encourage teams to include state or country information directly in parentheses within city names for improved accuracy.

5.3. Immediate Owner Name Standardization

- Filter for media owners whose names start with "City of".
- Apply targeted transformations to standardize these names for consistency.
- GEM uses the standardized city name approach of “City of Jacksonville (Florida)” to avoid user confusion.

5.4. Entity Data Retrieval from GEM

- Query the GEM PostgreSQL database to pull the current list of entities.
- Create two temporary columns for matching purposes:
    - Temporary full name: Concatenation of the entity's name and legal entity type, cleaned by removing spaces, converting to lowercase, and replacing ampersands (`&`) with "and".
    - Temporary name: Similar cleaning applied to the name column alone (without legal entity type).

5.5. Exact Matching

- Perform two exact merges between the preprocessed immediate owner names from the Climate TRACE data and the GEM entities:
    - Match against the temporary full name.
    - Match against the temporary name.
- Transfer the GEM entity IDs into the Climate TRACE dataframe for matched rows.

5.6. Fuzzy Matching for Unmatched Entities

- Identify rows in the Climate TRACE data without matched GEM entity IDs.
- Apply a fuzzy matching algorithm using **Levenshtein distance** to compare unmatched immediate owner names against GEM entity names.
- Levenshtein distance is preferred for its effectiveness with short strings (1-2 words).
- Filter matches with a similarity score ≥ 0.9 (on a 0 to 1 scale).
- Manually review these high-confidence matches.

- Use a running dictionary (crosswalk) to map alternate names to the correct GEM entity IDs.

5.7. Handling New Entities

- Entities that do not match after fuzzy matching are sent to GEM data engineers.
- GEM engineers add these new entities directly into the GEM PostgreSQL database.
- This process generates new entity IDs for previously unmatched entities, enabling future matches.

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The Global Energy Ownership Tracker provides information on the chain of ownership for various energy projects. The data maps each level of the chain from the direct owner (as in, the lowest-level identified owner in the chain of ownership) up to their highest-level ultimate parents (e.g., corporations, investment firms, and governments). Ownership links are reported with the percentage of ownership, including owners that have controlling interest as well as those with minority, non-controlling interests (if over a threshold of 5% ownership).

This asset ownership data set covers nine of GEM's trackers:

- The Global Coal Plant Tracker
- The Global Oil and Gas Plant Tracker
- The Global Coal Mine Tracker
- The Global Iron & Steel Tracker
- The Global Bioenergy Plant Tracker
- The Global Iron Ore Mines Tracker
- Natural Gas Transmission pipelines from the Global Gas Infrastructure Tracker
- Crude oil and natural gas liquid transmission pipelines from the Global Oil Infrastructure Tracker
- Global Cement and Concrete Tracker

Details about how each tracker identifies their assets and what methodologies they follow can be found on each of their respective pages of the GEM website linked above.

The Global Energy Ownership Tracker is updated after each new release of these underlying trackers. The most recent release of this data was in September 2025 and contains ownership data for Coal Plants, Oil and Gas Plants, Bioenergy Plants, Iron and Steel Plants, Coal Mines, Iron Ore Mines, Cement and Concrete Plants, and Natural Gas Pipelines.

To learn about the various components of each GEM tracker, read About GEM's Trackers. To receive notifications from this project, please sign up for our mailing list. If you have questions about this project, please contact the Project Manager, Anna Mowat.

Irving Fisher Committee on
Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Strengthening the adoption of data and metadata standards: the African Development Bank's efforts in enhancing statistical infrastructure for sustainable development across Africa

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This contribution was prepared for the seminar. The views expressed in this publication are those of the authors and do not necessarily represent the official views of the Committee, its members, or the BIS.

Abstract

Reliable, timely, and comparable data is essential for evidence-based policymaking and for monitoring progress toward sustainable development goals. Yet many African countries continue to face challenges in harmonizing data production, dissemination, and use due to fragmented statistical systems and uneven adoption of international data and metadata standards.

Through the Africa Information Highway (AIH) initiative, the African Development Bank (AfDB) is supporting countries modernize their statistical infrastructure by promoting SDMX-based interoperability, standardized metadata practices, and integrated data-sharing ecosystems. The rollout of national and regional SDMX-native Open Data Platforms (ODP 2.0) has significantly improved the way national statistical offices, central banks, ministries, manage, disseminate and exchange data.

Drawing on concrete examples from recent technical assistance and capacity-building programs, this paper highlights how standards-driven modernization contributes to improved data quality, transparency, comparability, and policy coordination. It also reflects on strategic priorities that are shaping the next phase of digital transformation across African statistical systems.

Keywords: Data standards; SDMX; Metadata; Statistical modernization; Africa Information Highway; Open Data.

JEL classification: C80; C82; O55

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1. Introduction

High-quality, timely, and interoperable data is increasingly recognized as a strategic asset for development planning, macroeconomic management, and monitoring progress toward global and regional agendas. African countries, however, continue to operate in fragmented data environments with limited standardization, resulting in inefficiencies, duplication, and inconsistent data flows.

The African Development Bank (AfDB), through the Africa Information Highway (AIH), has undertaken a systematic effort to strengthen data governance and promote the adoption of international data and metadata standards across the continent. The initiative's central objective is to create a unified Pan-African data ecosystem where institutions can produce and exchange data seamlessly and reliably.

2. The Africa Information Highway (AIH): Objectives and architecture

2.1 Context and vision

The AIH was launched in 2012 to modernize data dissemination infrastructures and promote transparency across African countries. It provides open and centralized access to key official statistics for governments, researchers, private sector actors, and the public.

2.2 Core components of AIH

The Africa Information Highway (AIH) is built on a set of integrated and mutually reinforcing components designed to modernize data ecosystems across African countries. Each component addresses a specific dimension of data production, governance, interoperability, and dissemination. Together, they form a coherent architecture that supports the digital transformation of statistical systems and enables institutions to meet the growing demand for high-quality, timely, and comparable data.

- *Open Data Platforms (ODP)***:** public good portals enabling open access to harmonized datasets.
- *Data Innovation***:** use of emerging technologies, big data to complement official statistics and enhance data-driven decision-making.
- *Data and metadata standards***:** ensuring interoperability, discoverability, quality assurance, and consistency across institutions.

3. The role of data and metadata standards

3.1 Why metadata matters

Metadata is a foundational element of modern data ecosystems. It provides the essential contextual information—definitions, classifications, sources, units of measure, methodologies, and quality dimensions—that allows data to be correctly understood, interpreted, and reused. Without metadata, datasets become isolated, ambiguous, and difficult to integrate, leading to inconsistencies and loss of trust among users.

In national statistical systems, metadata plays a critical role in ensuring transparency, comparability, and accountability. It documents how data was collected, processed, and validated, helping policymakers, researchers, and partners evaluate the reliability and limitations of the information they use. For institutions managing multi-source data flows, standardized metadata is indispensable for harmonization and interoperability across government systems.

Metadata is even more important in today's environment of advanced analytics and artificial intelligence. AI and machine-learning workflows require clear, structured, and machine-readable metadata to function effectively. High-quality metadata enables:

- *Accurate feature engineering, by providing semantic meaning and relationships between variables;*
- *Automated data discovery and integration, essential for large-scale AI pipelines;*
- *Improved model performance, as metadata-driven validation reduces noise and inconsistencies;*
- *Responsible AI, by documenting data provenance, quality constraints, and potential biases;*
- *Scalability, allowing AI systems to process heterogeneous datasets from different institutions using common standards.*

Standardized metadata also ensures that datasets can be published, consumed, and reused through APIs, dashboards, or SDMX-native systems without requiring manual intervention or complex transformations. This makes metadata a critical enabler of AI-ready data ecosystems, where institutions can quickly leverage modern analytical tools to generate insights, develop predictive models, and support evidence-based decision-making.

3.2 SDMX as a unifying standard

SDMX (Statistical Data and Metadata eXchange) has become the global reference standard for structuring, documenting, and exchanging statistical data. It provides a comprehensive framework that integrates data modelling, metadata documentation, automated reporting, and machine-to-machine exchange. For institutions that manage complex data flows, such as central banks, statistical offices, and ministries of finance, SDMX offers a unified language that ensures consistency across indicators, domains, and countries.

The adoption of SDMX across Africa plays a transformative role in strengthening statistical infrastructure. First, it improves data quality and internal coherence by enforcing standardized classifications, definitions, and validation rules. This helps ensure that macroeconomic indicators, financial series, and social statistics follow comparable structures across time and across institutions.

Second, SDMX acts as a powerful enabler of comparability and harmonization. African countries frequently report data to multiple regional and global partners, often using different formats. SDMX streamlines this process by aligning national data structures with international statistical standards, thereby reducing duplication, inconsistencies, and reporting burdens.

Third, SDMX supports automation and efficiency. Machine-readable structures allow institutions to automate data ingestion, transformation, validation, and dissemination. For central banks, this means faster compilation of monetary, financial, and external sector statistics, as well as more efficient transmission of data to regional bodies, the IMF, the AfDB, or other partners. Automation also reduces operational risks associated with manual data processing.

Fourth, SDMX enables multi-source integration. Many African countries operate in fragmented data environments, where information is dispersed across ministries, agencies, and administrative systems.

With SDMX, heterogeneous datasets can be combined into unified, interoperable data flows—facilitating cross-sector analysis, early-warning systems, sustainability indicators, and SDG monitoring.

Fifth, SDMX enhances data governance and transparency. Its metadata-rich structure documents data lineage, methodologies, units of measure, and update cycles. This is particularly critical in areas such as sustainability data, climate finance, and financial stability, where clear metadata is essential for both national oversight and international comparability.

Finally, SDMX provides the technical foundation for AI-ready and digital-first data ecosystems. By ensuring structured, standardized, and machine-interpretable datasets, SDMX facilitates the deployment of advanced analytics, automated dashboards, and AI-driven insights. In a context where countries are beginning to adopt AI tools for forecasting, anomaly detection, and policy simulations, SDMX ensures that underlying data streams are reliable, interoperable, and scalable.

4. ODP 2.0: A multi-purpose SDMX platform

4.1 Technical architecture

ODP 2.0 represents the next generation of the Africa Information Highway's statistical technology stack. It is a modular, open-source, and SDMX-native platform designed to modernize the way African institutions manage, exchange, and disseminate data. Built around international best practices, ODP 2.0 consolidates data governance, data processing, visualization, and interoperability into a single integrated environment, enabling institutions to operate with greater efficiency, transparency, and automation.

The platform's modular architecture allows countries to adopt components progressively, depending on their institutional needs, technical capacity, and data maturity. Because ODP 2.0 is fully open-source, countries benefit from continuous improvements from the global SDMX community, reduced vendor dependency, and long-term sustainability.

ODP 2.0 offers several key capabilities that directly support statistical modernization:

- *Unified data management and dissemination:* ODP 2.0 consolidates data from multiple domains — macroeconomic, social, financial, or sustainability indicators — into a single SDMX-native repository. This unified structure reduces fragmentation, improves internal consistency, and makes it easier for users to access and compare data across sectors. Central banks and statistical offices can publish official time series, maintain revisions histories, and provide public or restricted access based on governance rules.
- *Automated synchronization between national, regional, and international databases:* The platform enables machine-to-machine synchronization with regional and global partners such as the AfDB, IMF, and specialized agencies. Countries can automatically supply updated datasets to regional institutions, reducing manual reporting burdens and ensuring that regional databases reflect the latest national data. This automation is essential for sustainability indicators, macroeconomic reporting frameworks, and cross-country comparability.
- *Standardized APIs for seamless system integration*: ODP 2.0 provides a suite of SDMX-compliant APIs that allow external systems—national data warehouses, administrative systems, geoportals, or central bank statistical platforms—to connect and exchange data seamlessly. These APIs ensure interoperability across heterogeneous environments and support real-time or scheduled data flows. For central banks, standardized APIs facilitate integration with monetary and financial statistics systems, dashboards, and analytical tools.

- *Advanced visualization and exploration capabilities*: The platform includes built-in visualization modules for interactive charts, tables, dashboards, and thematic analysis. Users—from policymakers to researchers—can explore data directly within the platform without requiring additional tools. Visualization capabilities are especially valuable for sustainability and climate indicators, where trends, disparities, and regional patterns benefit from graphical representation. These tools also enhance transparency and support public communication.

Together, these features enable ODP 2.0 to serve as a comprehensive, future-ready data platform that supports SDMX modeling, strengthens governance, and facilitates evidence-based decision-making. It is a cornerstone of AfDB's efforts to harmonize data infrastructure across Africa and equip countries with the tools needed to participate effectively in regional and global statistical ecosystems.

4.2 Concrete benefits for countries

The deployment of ODP 2.0 delivers a series of tangible and high-value benefits for national institutions seeking to modernize their statistical and data-exchange systems. By providing a unified, SDMX-native infrastructure, the platform helps overcome long-standing challenges related to fragmentation, inefficiency, and inconsistencies across government data systems. Several concrete benefits have already emerged across countries adopting or preparing to adopt ODP 2.0:

- *Automated data retrieval and reporting*: ODP 2.0 significantly reduces reliance on manual processes by enabling automatic ingestion, validation, and dissemination of data. Machine-to-machine synchronization ensures that updates from central banks, statistical offices, and administrative systems are seamlessly reflected in national and regional databases. This automation enhances timeliness, minimizes human error, and strengthens the reliability of high-frequency and macro-financial indicators. In contexts where reporting obligations to regional and international organizations are considerable, automation allows countries to meet deadlines more consistently while reallocating human resources toward analysis rather than data processing.
- *Interoperability across ministries and institutions*: One of the most persistent challenges in African data ecosystems is institutional fragmentation, where ministries, agencies, and central banks use incompatible systems and formats. ODP 2.0 addresses this by providing a harmonized SDMX-based environment that facilitates structured data exchange across sectors. Standardized APIs and metadata frameworks enable ministries of finance, central banks, revenue authorities, planning commissions, and national statistical offices to collaborate more effectively. This interoperability supports whole-of-government approaches to policy design, such as integrated macroeconomic frameworks, fiscal risk analysis, and sustainability reporting.
- *Efficient integration of multiple formats and sources*: African countries increasingly rely on diverse data sources—administrative records, surveys, geospatial data, financial market information, registries, and sustainability metrics. ODP 2.0 can integrate these heterogeneous sources into a unified SDMX-native structure, eliminating the costly and error-prone process of manually converting or reconciling different formats. This capability is especially relevant for compiling climate-related statistics, environmental data, and new structural indicators that rely on multiple systems. Improved integration strengthens analytical coherence and allows policymakers to build more comprehensive, multidimensional assessments.
- *A unified access point for policymakers*: ODP 2.0 consolidates key national datasets in a single, coherent platform, ensuring that policymakers, analysts, and researchers do not need to navigate multiple portals or request information from different institutions. This unified access point improves transparency, enhances user experience, and supports evidence-based decision-

making by providing consistent, up-to-date, and well-documented information. Advanced visualization modules within the platform also allow decision-makers to explore trends, compare regions, and generate customized analytical outputs without requiring technical expertise.

Taken together, these benefits demonstrate how ODP 2.0 serves as a strategic enabler of statistical modernization, allowing countries to build resilient, interoperable, and AI-ready data ecosystems. The platform not only simplifies current workflows but also prepares institutions for future innovations in automation, advanced analytics, and digital transformation.

5. Technical assistance for SDMX implementation

5.1 Recent engagements

The AfDB, working closely with its partners has intensified its support to different institutions across African countries (National Statistics Offices (NSO), Central Banks, etc.) to modernize their data architecture in line with international standards. This collaboration reflects a growing recognition from counties that robust, interoperable, and SDMX-native systems are essential for timely macroeconomic surveillance, financial stability analysis, and efficient reporting to regional and global organizations. Through the deployment of ODP 2.0, the AfDB is helping countries transition from fragmented, manual processes to streamlined, automated, and metadata-driven data workflows.

5.2 Lessons from the technical assistance

The projects undertaken with NSO, central banks and other institutions reveal several critical lessons that shape the path forward for SDMX-driven modernization in Africa. These insights underscore that the transition to interoperable, standards-based data ecosystems is as much an institutional endeavor as it is a technical one.

- *Strong governance frameworks are essential for SDMX adoption*: Experience shows that SDMX implementation cannot succeed without clear, formalized governance structures. Institutions that established data governance committees, defined ownership of datasets, and adopted standard operating procedures progressed significantly faster than those relying on ad-hoc arrangements. Governance frameworks ensure alignment between departments, promote compliance with SDMX standards, and guarantee continuity when staff change. They also provide the mandate needed to harmonize legacy systems and to enforce rules around metadata creation, quality assurance, and revision policies.
- *Institutional coordination accelerates harmonization*: SDMX adoption forces institutions to break down silos. Projects progressed faster in institutions where IT departments, statistical units, and dissemination departments worked jointly on SDMX modeling, system mapping, and governance reforms.
- *Capacity building is a prerequisite for sustainability*: Even when modern platforms such as ODP 2.0 are deployed, their long-term success depends on the skills and institutional knowledge of the teams maintaining them. Without continuous capacity building, institutions risk reverting to manual processes or failing to maintain SDMX registries and metadata repositories. The Bank's regional workshops for Francophone and Anglophone countries directly respond to this need by establishing a sustained learning environment.

6. Capacity building and regional cooperation

Building sustainable and interoperable statistical systems requires more than the deployment of technical platforms. It demands a long-term investment in human capital, institutional collaboration, and peer learning mechanisms that enable countries to transition from fragmented data environments to modern, standards-based ecosystems. Recognizing this need, the African Development Bank has placed capacity building and regional cooperation at the center of its modernization agenda.

To support countries in adopting SDMX and ODP 2.0, the AfDB is organizing regular regional workshops as part of a broader program to harmonize data practices across the continent. Example are provided below:

- *Francophone countries (Tunis, June 2025)* – This workshop delivered intensive training on SDMX data modelling, metadata management, and the processes required to migrate national open data platforms to ODP 2.0. The sessions included hands-on exercises on designing Data Structure Definitions (DSDs), developing mapping tables for legacy systems, and implementing automated data flows. Particular emphasis was placed on aligning macroeconomic, social, and administrative datasets with international standards to strengthen both internal consistency and cross-country comparability. The workshop also fostered collaboration among francophone national statistical offices, central banks, and line ministries.
- *Anglophone countries (Addis Ababa, July 2025)* – The Anglophone workshop focused on advanced SDMX modelling, system integration, interoperability frameworks, and the governance structures required to sustain modernization efforts. Participants worked on real-world use cases related to central banking statistics, sustainability indicators, and automated reporting to regional and international partners. The training also highlighted best practices in cross-departmental coordination, data quality assurance, and the use of SDMX APIs to automate internal workflows. The workshop served as a hub for peer-to-peer exchange among Anglophone countries undertaking similar modernization efforts.

7. Strategic priorities for the future

As African countries continue modernizing their statistical systems, the next phase of the Africa Information Highway initiative will focus on consolidating achievements and ensuring long-term sustainability. Advancing interoperability, strengthening data governance, and embracing emerging technologies will be essential for building resilient data ecosystems capable of supporting evidence-based policymaking, financial stability, and sustainable development.

7.1 Deepening adoption of SDMX and standards

While substantial progress has been made among national statistical offices, the next frontier involves extending SDMX adoption across a broader institutional ecosystem—including line ministries, central banks, revenue authorities, planning agencies, and regional economic communities. Expanding coverage is critical to harmonizing data produced by different government entities and reducing inconsistencies that often arise from parallel reporting systems.

Deepening adoption will also require countries to integrate SDMX principles into their internal data architectures, ensuring that new administrative systems, survey processes, and financial reporting tools are built on standards-compliant foundations. This will not only accelerate automation but also support multi-source integration of economic, social, and environmental data, an essential requirement for sustainability frameworks and global reporting obligations.

7.2 Strengthening governance and data quality frameworks

Sustaining modernization requires robust governance systems that clarify roles, ensure compliance with standards, and promote consistent application of methodologies. The future focus will include developing national data governance frameworks that embed SDMX and metadata management into institutional processes and regulatory guidelines.

A key priority is the implementation of metadata-driven quality reporting systems. By leveraging standardized quality frameworks and automated validation pipelines, institutions will be able to detect anomalies, track revisions, ensure definitional consistency, and reduce manual interventions. This is especially important for high-frequency and sustainability-related data, where timeliness and accuracy are essential for monitoring vulnerabilities, assessing climate-related risks, and informing monetary and fiscal policies.

Improved governance also strengthens cooperation between data producers and enhances transparency for users, thereby reinforcing public confidence in official statistics.

7.3 Integrating emerging technologies

The modernization of Africa's statistical systems will increasingly rely on emerging technologies capable of improving efficiency, scalability, and analytical depth. Artificial intelligence (AI), machine learning, advanced analytics, and new generations of AI systems, such as Large Language Models (LLMs) and Agentic AI, offer unprecedented opportunities to enhance the value of data systems built on SDMX and ODP 2.0.

AI-enabled tools can assist with automated classification, predictive modeling, anomaly detection, and early-warning systems for macro-financial stability and sustainability risks. When combined with standardized, machine-readable metadata, AI systems can integrate multi-domain datasets—economic, administrative, geospatial, climate-related, or environmental—to generate richer insights and support scenario-based policy analysis.

Emerging applications of LLMs provide additional capabilities highly relevant to statistical offices and central banks. LLMs can:

- interpret complex metadata and generate structured descriptions aligned with SDMX standards.
- support automated documentation of methods and data lineage.
- provide natural language interfaces for querying ODP 2.0 databases and SDMX APIs.
- summarize large volumes of statistical or administrative information for decision-makers.
- assist in harmonizing definitions and detecting inconsistencies across national and regional datasets.

Similarly, the expansion of APIs and interoperable digital services will enable real-time data exchange between institutions, improve the timeliness of statistical releases, and support the creation of

advanced dashboards tailored to policymakers' needs. These technologies enhance institutional resilience by reducing reliance on manual processes, improving auditability, and ensuring continuity during periods of operational disruption.

When anchored in robust SDMX and metadata foundations, these innovations—AI, LLMs, Agentic AI, and real-time API-driven services, will allow African countries to transition from traditional reporting systems toward fully digital, automated, and AI-ready statistical ecosystems. This transformation is essential for supporting evidence-based policy, financial stability assessments, climate risk monitoring, and long-term sustainable development across the continent.

8. Conclusion

The modernization of statistical systems across Africa is entering a decisive phase, shaped by the adoption of international data and metadata standards and supported by strong institutional partnerships. The African Development Bank's leadership, particularly through the Africa Information Highway initiative, has played a pivotal role in laying the foundations for harmonized, interoperable, and sustainable data ecosystems. By promoting SDMX as a unifying standard and deploying ODP 2.0 as a modern dissemination and data sharing platform, the Bank has enabled countries to improve data quality, comparability, and transparency while reducing reporting burdens.

Experiences from different institutions such as NSO and central banks demonstrate that modernization efforts are most effective when supported by well-defined governance frameworks, strong inter-institutional coordination, and continuous capacity building. These elements ensure that SDMX adoption is not merely a technical upgrade but a structural shift toward better-organized, metadata-driven, and standards-aligned data management practices. The regional training programs and the emerging Pan-African Data Sharing Community further illustrate the importance of collective learning and peer support in sustaining modernization across the continent.

Looking ahead, the integration of emerging technologies—AI, machine learning, LLMs, Agentic AI, offers significant opportunities to enhance the analytical capabilities and operational efficiency of statistical systems. When anchored in robust SDMX and metadata foundations, these innovations can support predictive analytics, real-time data integration, climate and sustainability reporting, and advanced macro-financial surveillance.

Consolidating these achievements will require continued investment in capacity building, alignment with global standards, and strengthened collaboration among national, regional, and international institutions. By maintaining this momentum, African countries will be well positioned to transition toward fully digital, automated, and AI-ready statistical ecosystems that support effective policymaking, financial stability, and sustainable development across the continent.

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Strengthening the adoption of data and metadata standards

The African Development Bank's efforts in enhancing statistical infrastructure for sustainable development across Africa

Momar KOUTA

Senior Statistical Information Systems Officer

AIH: Context & Objectives

July 2012

AfDB



Facilitating public access to official statistics

Unlock the power of data for everyone.

Using international standards

Guarantee trusted, high-quality, and comparable statistics.

Enhancing data openness and transparency

Build trust through open and transparent data sharing.

Empowering official statistics ecosystem

Boost the capacity and impact of data-driven institutions.

AIH: Components

Data Innovation

Drives creative data solutions to boost informed decision making in Africa



Open Data Platforms

Provide centralized access to a wide range of data resources for the public and policymakers



SDMX

Promote the use international data and metadata standard



Data & Metadata Standards: Facilitating data sharing and interoperability for evidence-based policy



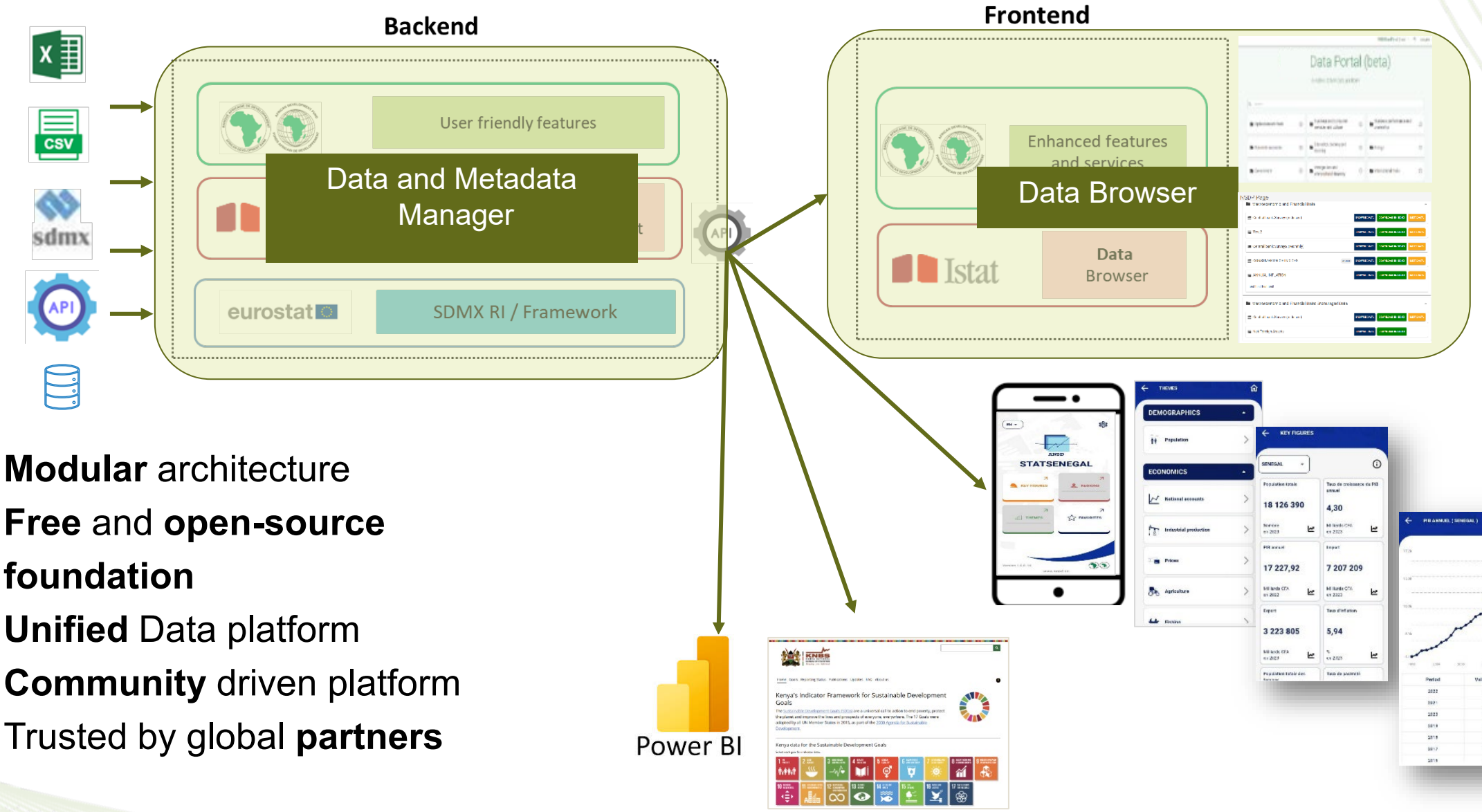
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Why Metadata Matters

- **Discoverability and reuse**: Makes data easy to find (catalogs, tags, indexes).
- **Trust & quality**: Ensures reliability by documenting source and context.
- **Interoperability**: Standardized descriptions enable data sharing across systems.
- **Governance**: Tracks ownership, rights, and compliance with policies.
- **Innovation**: Powers analytics, AI, and dashboards for decision-making.



ODP 2.0: SDMX Multi-Purpose Data Platform

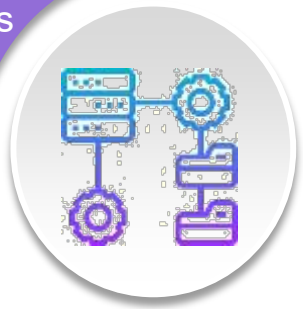


- **Modular** architecture
- **Free** and **open-source foundation**
- **Unified** Data platform
- **Community** driven platform
- Trusted by global **partners**

SDMX Native Platforms – Key Benefits

Seamless data **sharing**

- Seamless data exchange
- Automated synchronization
- Interoperability across systems
- Efficient data reporting



Improved **collection**

- Integration with multiple Data sources and formats
- Automated data Retrieval



Enhanced **accessibility**

- Unified Access Point (Data hub)
- Seamless connectivity and multi systems integration
- Data exploration and visualization
- Standardized & open data formats + metadata



ODP 2.0 in Action: Technical assistance to Central Banks and revenue services







- In collaboration with the IMF, technical assistance has been provided to the Bank of Botswana, where data modeling is already well advanced for ODP2.0 implementation.
- Discussions are under way with the Bank of Mauritius regarding the implementation of ODP2(potential joint support AfDB & IMF).
- Technical assistance is also ongoing with both the South African Reserve Bank and the South African Revenue Service.

SDMX Native Platforms – Mobile application

Google Play



SDMX ODP 2.0: Capacity building

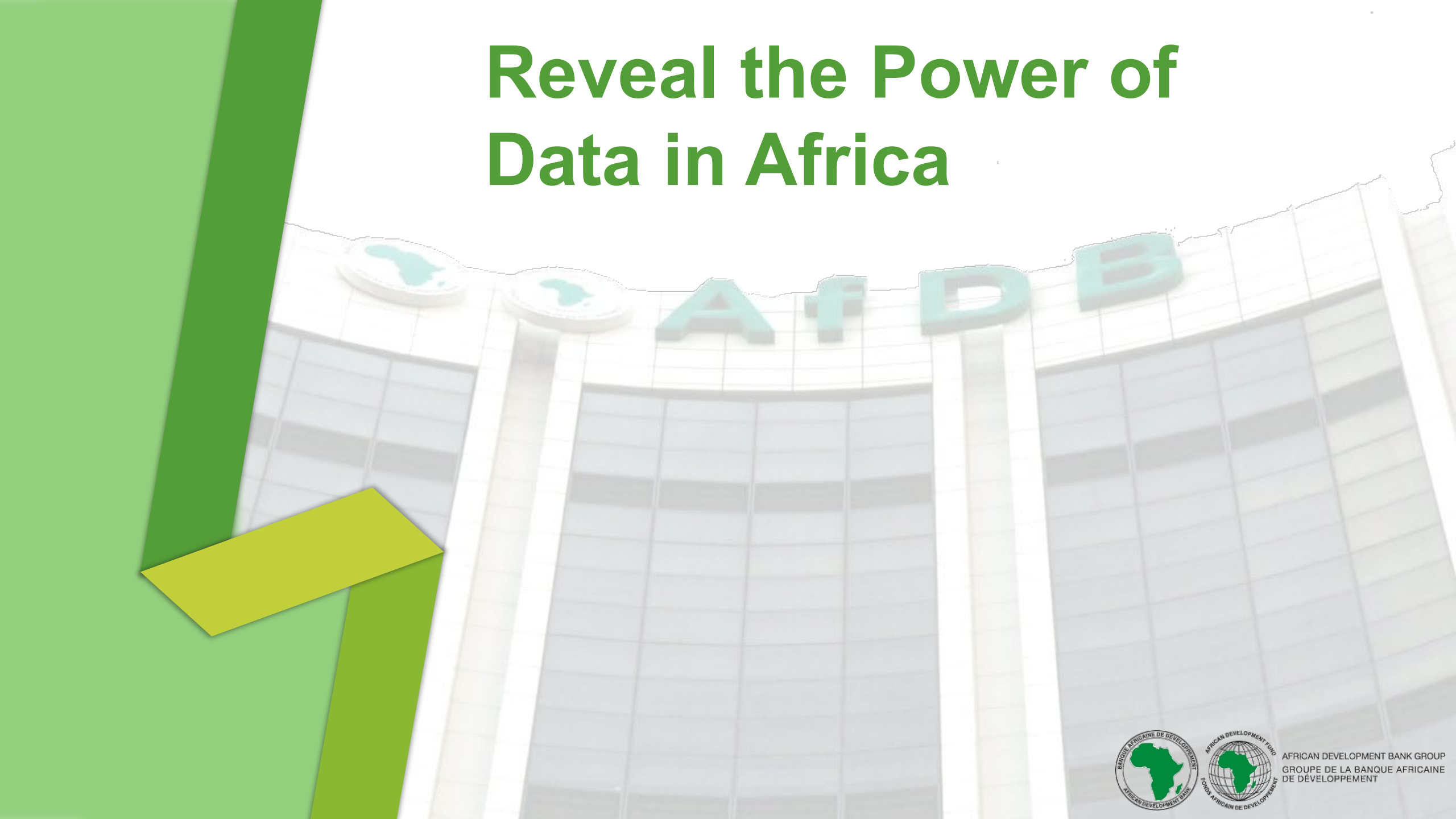
Regional workshop to help Francophone countries modernize statistical systems with SDMX and ODP 2.0 (June 23 to 27, 2025, Tunis)



Regional workshop supporting Anglophone countries in data modeling for ODP 2.0 migration (July 21 to 25, 2025, Addis Ababa)



Reveal the Power of Data in Africa



AFRICAN DEVELOPMENT BANK GROUP
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Irving Fisher Committee on Central Bank Statistics

BIS

IFC Satellite Seminar on "Sustainability data issues and central banks' experience"

4 October 2025

Boosting climate data accessibility for financial decision-making

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Boosting climate data accessibility for financial decision-making

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Abstract

The escalating impacts of climate change pose extraordinary challenges to the global financial system, underscoring the urgent need for financial institutions, regulators and policymakers to access reliable, comprehensive climate data for robust risk management and strategic planning. In light of this pressing requirement, the Network for Greening the Financial System (NGFS) and its partners have created the NGFS Data Directory 2.0 – marking a substantial advancement over the directory's initial 2022 release. Built from the ground up, the NGFS Data Directory 2.0 reflects a thoughtful redesign driven by lessons learned since the release of the original version. Through an intensive process involving design thinking workshops and continuous dialogue with prospective users, the development team has engineered a versatile, user-focused platform that addresses prior shortcomings while embedding innovative features to ensure easier access and more effective use of climate data within the financial sector. This document offers a comprehensive overview of the development process behind the NGFS Data Directory 2.0 – covering stages from initial ideation, collaborative design sessions, iterative prototyping with the NGFS Expert Network on Data, to agile implementation and a successful soft launch at COP29 in November 2024. It highlights how adopting a user-centred approach and fostering collaborative development have resulted in a platform tailored to meet the complex needs of the financial community in navigating climate-related risks.

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1. Introduction

The financial sector increasingly recognises the imperative to embed climate-related risks into risk management frameworks, investment strategies and regulatory compliance (Huang et al (2018), Nefzi et al (2025)). Central to these efforts is access to accurate, comprehensive climate data. However, significant challenges remain in data accessibility, consistency, quality and comparability across diverse sources (Fareed et al (2025)). The NGFS Data Directory 2.0 addresses these challenges by providing a centralised, user-friendly platform designed for efficient climate data discovery and sharing (Hoffmann et al (2025)). This initiative received strategic support from the Bank for International Settlements Innovation Hub (BISIH), the Monetary Authority of Singapore (MAS) and the Bank of France, whose collaborative efforts have been instrumental in the development of the directory. Building on the foundation of its predecessor, the enhanced platform aims to serve as a trusted, comprehensive reference tailored specifically to the needs of the financial sector.

The primary objectives of the NGFS Data Directory 2.0 project are to:

- enhance search and browsing functionalities to improve data discoverability
- significantly elevate the user experience through intuitive design and navigation
- implement well-governed content management systems to ensure data quality
- facilitate user-driven content updates via collaborative features
- enable data providers to upload data in bulk through the platform
- empower contributors to rate, comment and add contextual information on data and metrics.

This report offers a detailed analysis of how these objectives were systematically pursued and achieved through a user-centred development process. It explores the rationale underpinning the initiative, the methodological approach adopted and the key features that distinguish this iteration from the original directory. Additionally, the report discusses the broader implications for climate risk management within the financial sector and outlines future pathways for ongoing enhancement and adaptation.

2. NGFS Data Directory – version 1

2.1 Addressing data gaps through a centralised data repository

The inception of the NGFS Data Directory was driven by recognition that significant gaps in climate-related data posed substantial barriers to effective climate risk management within the financial sector (Grisey (2022)). Developed by the NGFS Workstream on Bridging Data Gaps, this directory was formally introduced alongside the publication of the *Final report on bridging data gaps* in 2022, representing a tangible step towards mitigating these challenges (NGFS (2021, 2022)). The primary aim of the original Data Directory was to establish a comprehensive repository of climate-related data sources and metrics pertinent to a broad spectrum of financial institutions and regulatory bodies. By systematically cataloguing available data, the directory enhanced transparency regarding existing resources, facilitated access and identified areas where data deficiencies persisted. This effort aligns with the NGFS's overarching mission to advance environment and climate risk management within the financial sector and to mobilise mainstream financial flows towards a sustainable economy – bolstering the financial system's capacity to manage climate risks and channel capital into green and low-carbon investments.

The initiative achieved noteworthy success in aggregating climate data and compiling an extensive inventory that included 329 unique metrics and methodology combinations, 1,262 raw data

items, 748 data source links and 514 identified data gaps. This comprehensive compilation provided vital insights into the climate data landscape and served as a valuable reference for stakeholders seeking to embed climate considerations into their operational frameworks. By systematically classifying climate data sources and highlighting key gaps, the directory contributed significantly to the collective understanding of climate data availability and needs. It underscored both the diversity of existing data sources and the critical areas requiring further development. This dual focus laid the foundation for ongoing efforts to improve data accessibility, quality and relevance.

2.2 Challenges and opportunities for enhancement

Despite its considerable contributions, the original NGFS Data Directory had several limitations that affected its efficacy and sustainability (Grisey (2022), Hoffmann et al (2025)). User feedback and internal assessments identified key challenges, informing the development of subsequent iterations:

- A primary concern was the static nature of the directory. In a rapidly evolving field characterised by continual methodological advancements, new data sources and emerging metrics, the absence of mechanisms for regular updates rendered the directory increasingly outdated. This diminished its reliability and utility as a comprehensive reference tool for those seeking the most current climate data.
- User experience constraints limited the directory's impact. Many users reported difficulties navigating the platform, citing unclear information hierarchies and an unintuitive interface design. The lack of advanced search functionalities hindered efficient data retrieval, causing frustration and discouraging sustained engagement. These usability issues disproportionately affected users with limited prior familiarity with climate data sources.
- The directory's limited mechanisms for community engagement hindered its capacity to evolve organically. The absence of features enabling user contributions, feedback or collaborative interactions prevented the platform from benefiting from collective expertise and real-time updates. This constraint placed the maintenance burden solely on the NGFS, posing sustainability challenges.
- Operational hurdles also played a significant role. The lack of formal processes or dedicated resources for content management led to gradual obsolescence. Without clear governance structures or sustainable funding, maintaining the directory's relevance proved increasingly difficult.
- Finally, awareness and visibility issues curtailed its reach. Many potential users remained unaware of the directory's existence or uncertain about how to leverage its resources effectively, limiting its overall impact as a public good. Without active promotion and community engagement, it remained underutilised.

These challenges underscored the necessity for a more dynamic, user-centric and collaborative platform – one capable of addressing these shortcomings. The insights gained from the initial iteration have been instrumental in shaping the NGFS Data Directory 2.0, with a focus on enhancing usability, fostering community involvement, ensuring sustainability and expanding visibility to better serve the evolving needs of stakeholders.

3. Design thinking workshop series

3.1 Mapping out the desired user journeys

To ensure that the NGFS Data Directory 2.0 effectively addresses user requirements and surpasses the limitations of its predecessor, the NGFS adopted a rigorous, user-centric design thinking methodology. In collaboration with the BISIH Singapore Centre, the NGFS Secretariat organised a series of workshops aimed at eliciting comprehensive insights from key stakeholders and prospective users (BIS (forthcoming)). The design process started with the engagement of an external consultancy to facilitate four workshops between September and December 2023. These sessions were strategically sequenced to enable iterative refinement, progressing from exploring the initial concept to prioritising features in detail. The inaugural workshop, held on 29 September 2023, convened a core project team comprising representatives from the NGFS Secretariat, BISIH Singapore Centre, MAS and the Bank of France. This foundational session centred on aligning the team's understanding of project objectives, establishing clear success metrics and identifying potential challenges. Collaborative deliberations culminated in a shared vision for the directory as a trusted, comprehensive and dynamically updated reference platform for climate-related data – fostering community contributions and serving as a valuable public resource.

Subsequent workshops, on 18 and 31 October 2023, expanded stakeholder engagement to include potential users from the public and private sectors. Workshop 2 primarily involved members of the NGFS Expert Network on Data, while Workshop 3 targeted financial institutions, including banks, insurers and asset managers. These sessions explored participants' experiences with the original directory, their information needs and expectations for an enhanced platform. Notably, while awareness of the directory was widespread, active use was limited among many participants, underscoring the need for greater visibility and an improved user experience.

Across both stakeholder groups, despite varying familiarity levels, consensus emerged around key expectations for Data Directory 2.0. Participants noted the importance of comprehensive coverage, emphasising the inclusion of diverse data sources and metrics. They highlighted the imperative for current and real-time information, reflecting the evolving nature of climate data. Additionally, they expressed a strong preference for a community-driven, crowd-sourced content management approach, facilitating collective contributions to the directory's growth and accuracy. All participants identified ease of use, characterised by intuitive navigation and efficient search functions, as a priority.

The final workshop (Workshop 4), on 7 December 2023, brought the core team together to synthesise insights from previous engagements and prioritise development features. Facilitators presented a consolidated list of potential functionalities derived from stakeholder input, which the team systematically evaluated based on user value, technical feasibility and resource considerations. This rigorous assessment culminated in the selection of high-priority features that would underpin the initial release of the NGFS Data Directory 2.0.

Through this comprehensive series of workshops, the project team garnered critical insights into user needs and expectations. The process unveiled a clear demand for a dynamic, collaborative platform capable of serving as a central, authoritative repository for climate-related data within the financial sector. By engaging a diverse array of stakeholders early in development, the NGFS ensured that the directory's design remains genuinely user-centric, directly addressing the specific challenges and preferences of its intended audience.

3.2 Creating a wireframe

Following the design thinking workshops, the project team systematically translated the collected requirements and insights into a detailed wireframe for the NGFS Data Directory 2.0 (BIS (forthcoming)). This wireframe outlined the user interface, information architecture and core functionalities of the

envisioned platform. The creation of this tangible prototype enabled iterative refinement of the concept and facilitated targeted stakeholder feedback before initiating technical development.

The wireframe development process started with a comprehensive analysis of the prioritised features identified during Workshop 4. These features were organised into logical clusters aligned with key aspects of the user experience, including account management, content discovery, data interaction and administrative controls. For each cluster, the team delineated specific user flows, screen layouts and interaction paradigms, ensuring a cohesive, intuitive and user-centric interface.

Furthermore, the wireframe presented distinct user journeys tailored to the three primary user archetypes identified during the workshops. For guest users – members of the general public – the wireframe depicted a streamlined browsing interface facilitating access to publicly available content without registration barriers. For registered or accredited users – such as representatives from central banks, financial institutions and recognised organisations – it showcased enhanced functionalities, including content contribution, commenting and rating systems. For administrative users, the wireframe outlined comprehensive management dashboards supporting content moderation, user verification and overall platform oversight.

To validate and refine the design, the team engaged in a feedback cycle. Early wireframe drafts were shared with select stakeholders from the workshop series, who provided insights on usability, clarity and feature integration. This feedback was incorporated into successive versions, ensuring the evolving design more closely aligned with user needs and expectations. Throughout the development process, particular attention was paid to addressing the limitations of the original data directory. The information architecture was crafted to promote intuitive navigation through clear categorisation and contextual guidance. Advanced search and filtering functionalities were prominently incorporated to facilitate efficient content retrieval. Additionally, collaborative features – such as content contribution and feedback mechanisms – were seamlessly integrated to foster community engagement, with validation protocols to uphold content quality.

The finalised wireframe served as a comprehensive blueprint for the NGFS Data Directory 2.0, visualising a platform designed to surpass its predecessor's limitations while delivering increased value and usability. This meticulous design phase laid a robust foundation for subsequent development, ensuring that the technical implementation would accurately embody user requirements and project objectives.

4. Developing NGFS Data Directory 2.0

4.1 Methodology and approach

Building on insights gleaned from design thinking workshops and creating the wireframe, the development phase translated conceptual frameworks into a fully functional platform that not only addressed the limitations of the original directory but also introduced pioneering features to enhance usability and performance. A defining characteristic of the NGFS Data Directory 2.0 development process was its unwavering adherence to user-centred design principles. The project team adopted an agile methodology, implementing the Scrum framework with one-week sprint cycles. This iterative approach facilitated continuous refinement and real-time validation, ensuring responsiveness to emerging requirements and user feedback while maintaining steady progress towards strategic objectives.

The foundational insights derived from the design thinking workshops established clear user requirements and prioritised essential features. Recognising that prototypes and theoretical models alone could not guarantee an optimal user experience, the team engaged the NGFS Expert Network on Data early and throughout the development lifecycle. This proactive engagement proved instrumental in refining the platform's usability and functionality. Early involvement of the Expert Network allowed

potential users to interact with prototypes at various development stages, providing invaluable real-world feedback on navigation, information architecture and feature integration. Such iterative testing enabled the team to identify and resolve usability challenges proactively, preventing issues from becoming embedded in the final product and significantly enhancing overall user-friendliness and effectiveness.

Multiple prototype iterations were conducted based on this feedback:

- Initial prototypes were showcased to the Expert Network, eliciting critical insights into navigation complexities, ambiguous terminology and search inefficiencies.
- Systematic refinements followed, addressing these concerns through successive prototypes, progressively aligning the platform with user expectations.

This cycle of testing and refinement transformed the platform from a technically robust but potentially cumbersome interface into an intuitive, user-centric resource that aligns closely with actual workflows and user needs. By embedding usability considerations at every stage, the development team ensured that NGFS Data Directory 2.0 not only offers advanced features but also presents them in a manner that maximises accessibility and utility across its diverse user base.

4.2 Technical implementation

The technical development of the NGFS Data Directory 2.0 centred on establishing a resilient and scalable infrastructure to underpin the platform's capabilities and future expansion. The development team – consisting of the project partners and an IT vendor – delivered a first version within a condensed time frame of 3.5 months, aligning with the COP29 soft launch scheduled for November 2024. This milestone was achieved through the implementation of robust continuous integration/continuous delivery (CI/CD) pipelines and cloud-based infrastructure, ensuring the platform's reliability, scalability and optimal performance. Development activities progressed concurrently across multiple streams, with dedicated teams working on user interface/user experience (UI/UX) design as well as on application programming interface (API) development and backend integration using a headless Strapi content management system (CMS). This parallel approach facilitated specialised focus, enabling the refinement of both the front-end user interface and the underlying data architecture to meet high standards of usability and robustness.

Key technical components of the implementation included:

- Responsive design: The platform was engineered to operate seamlessly across a diverse range of devices and screen sizes, ensuring broad accessibility and user engagement.
- Headless CMS integration: Strapi is a flexible, API-driven content management system, providing a clear separation between content and presentation layers, thereby enhancing content management agility and scalability.
- Automated CI/CD pipelines: The team established sophisticated GitHub Actions workflows to automate the integration, testing and deployment processes, fostering a reliable and efficient development cycle with rapid iteration capabilities.
- Comprehensive documentation: With Confluence as a centralised knowledge repository, detailed documentation covering architectural decisions, implementation specifics and operational procedures was maintained to facilitate knowledge transfer, onboarding and sustainable maintenance.

To ensure a data-enriched experience from launch, the team preloaded critical data sets, enabling immediate and meaningful user interaction. These seed data supported both the COP29 showcase and the platform's transition to production, delivering a seamless experience with demonstrable end-to-end data flows and operational readiness.

4.3 COP29 soft launch

The development of the NGFS Data Directory 2.0 culminated in a strategic soft launch at the NGFS Finance Day Event during COP29 in Baku, Azerbaijan, in November 2024. This prominent international platform provided global exposure for the initiative, introducing it to key stakeholders within the climate finance community at a critical juncture. The soft launch effectively demonstrated the platform's comprehensive user journey – from discovering climate data and metrics to uploading data via the website. The project team showcased the platform's enhanced functionalities and collaborative features to an audience comprising international financial authorities, climate experts and prospective users. This presentation at COP29 underscored how the NGFS Data Directory 2.0 addresses the limitations of its predecessor. By aligning the platform's unveiling with this high-profile climate event, the project team maximised visibility and positioned the directory as a vital component of the global climate finance infrastructure.

Subsequent to the soft launch, the platform entered a structured user acceptance testing (UAT) phase, ending with its first UAT production release in December 2024. This phased approach facilitated ongoing refinement based on initial user feedback while maintaining momentum towards full deployment.

5. NGFS Data Directory 2.0 – a growing resource for climate risk data

5.1 Key features and innovations

The NGFS Data Directory 2.0 introduces a suite of advanced enhancements and innovative features that elevate it from a static archive to a dynamic, collaborative ecosystem. These developments directly address the limitations identified in the original directory and align with the strategic priorities defined during the design thinking workshops.

User-centric interface design

The platform boasts an intuitive navigation framework that seamlessly guides users through the discovery process, with clearly delineated pathways tailored to diverse information needs and user profiles. Its responsive architecture ensures optimal accessibility across a broad spectrum of devices – including desktops, tablets and smartphones – facilitating access to climate data anytime, anywhere. Complementary educational resources, such as interactive tutorials and contextual help features, empower users to navigate the directory efficiently and leverage its functionalities fully, thereby reducing entry barriers and enhancing the overall user experience.

Advanced search and discovery capabilities

Significantly surpassing its predecessor, the directory now incorporates sophisticated semantic search technology that allows users to retrieve relevant information through natural language queries, removing the need for precise keyword input or specialised search syntax. Augmented with comprehensive filtering options – based on criteria such as data availability, geographic scope, sector relevance and data provider – this search function substantially accelerates the data discovery process. These enhancements enable users to swiftly locate specific data sets within the directory's extensive repository, thereby optimising research efficiency.

Collaborative, community-oriented framework

Inspired by successful collaborative platforms like Wikipedia, the directory fosters a participatory environment where authorised users can contribute, update and refine content. Accredited contributors

– primarily representatives from central banks, financial institutions and recognised organisations – can submit new data points, suggest modifications and add contextual information. This collective approach harnesses the expertise and insights of the user community to ensure that the directory remains current, comprehensive and responsive to evolving information needs.

Content quality assurance mechanisms

To uphold high standards of accuracy and reliability, the directory employs a structured validation workflow. Contributions undergo a rigorous review process prior to publication, ensuring consistency with established standards and maintaining the platform's credibility as a trusted reference. Designed for efficiency and transparency, this workflow includes clear criteria for approval and constructive feedback, balancing the benefits of crowd-sourced content with the imperative for quality assurance.

Enhanced user interaction features

Interactive features, such as rating systems, enable users to assess the quality and utility of data sources, thereby guiding fellow users and motivating data providers to uphold high standards. Comment and discussion functionalities foster active knowledge exchange, transforming the directory into a vibrant community of practice. These engagement tools elevate the platform from a passive repository to an active forum for dialogue and collaboration, amplifying its overall value.

Seamless data provider integration

For contributors, the directory facilitates streamlined data submission processes, including bulk upload functionalities for large data sets and multiple entries. API integration capabilities enable data providers to push core data directly into the platform, minimising manual input and ensuring timely updates. Clear guidelines and templated submission procedures simplify onboarding, while adherence to existing standards reduces redundancy and enhances interoperability.

Collectively, these features forge a platform that is more accessible, dynamic and valuable than its predecessor. By addressing the specific challenges identified in the original directory and embedding innovative approaches to collaboration and content management, the NGFS Data Directory 2.0 will be an indispensable resource for climate-related data within the financial sector.

5.2 Success criteria and metrics

The success of the NGFS Data Directory 2.0 will be evaluated against clearly defined criteria across several dimensions.

Data quality

- Completeness: assessing whether the directory encompasses all data sets essential to users.
- Consistency: ensuring data are uniformly formatted and structured throughout the directory to facilitate seamless integration and analysis.
- Timeliness: monitoring the frequency and recency of data updates to maintain relevance and accuracy.

Usage metrics

- User adoption: tracking the number of active users and analysing trends to determine growth over time.
- Frequency of engagement: measuring how often users access and interact with the directory and its data sets.

- User satisfaction: collecting feedback via surveys and usability assessments to gauge whether the directory effectively meets user needs.
- Search effectiveness: monitoring the proportion of searches where users quickly locate pertinent data – ie the success rate.

Together, these metrics establish a comprehensive framework for evaluating the directory's performance and identifying opportunities for enhancement. Regular monitoring of these indicators will enable the team to ensure that the platform continuously aligns with user requirements and delivers sustained value to the financial community.

6. Outlook and future directions

The completion of the NGFS Data Directory 2.0 development and its subsequent soft launch at COP29 mark pivotal milestones in the platform's evolution. These achievements also herald the onset of a new strategic phase, characterised by ongoing refinement and expansion. Several critical dimensions will shape the directory's future trajectory and influence within the climate data ecosystem. The directory is currently in a comprehensive pilot testing phase. This period is instrumental in garnering nuanced insights into user interactions, detecting residual issues and informing targeted improvements. Feedback collected during this phase will be systematically integrated into subsequent iterations, ensuring that the platform remains responsive to user needs and evolving expectations.

While the platform launched with a curated selection of foundational data sets, sustained growth in both scope and depth is imperative to ensure its utility. This will be achieved through strategic initiatives aimed at addressing identified data gaps, alongside fostering organic contributions from the user community. Particular emphasis will be placed on emerging areas such as transition risk metrics, adaptation indicators and biodiversity-related data, thereby positioning the directory at the vanguard of climate data innovation.

These initiatives underscore a commitment to transforming the NGFS Data Directory 2.0 into a dynamic, adaptive resource that evolves in tandem with the rapidly changing climate finance landscape. Continuous improvement will expand its functionalities, enhance user engagement and reinforce its role as a vital tool for stakeholders navigating climate-related risks and opportunities.

The directory introduces several pioneering features – advanced search functionalities, collaborative content contributions and integrated quality assurance mechanisms – that directly address the limitations of the original platform. These enhancements facilitate superior climate data discovery, sharing and validation, thereby empowering financial institutions, regulators and other stakeholders to better understand and manage climate-related risks. Following the COP29 soft launch, the directory is poised to serve as a vital public resource, underpinning climate risk management and promoting the transition towards a greener financial system. Through ongoing refinement, targeted content expansion and active community engagement, the NGFS Data Directory 2.0 will adapt to emerging challenges and opportunities within the evolving landscape of climate finance, delivering sustained value to its expanding user base.

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NGFS Data Directory 2.0: a new era of climate data accessibility

Léopold Gosset, climate risk specialist, NGFS Secretariat

NGFS
Central Banks and Supervisors
Network for Greening the Financial System

NGFS: Foster awareness of climate information

- In 2022, the NGFS released the **Data Directory 1.0,** a catalogue of climate-related metrics (~1,200) and datasets (~750).
- In 2024 and early 2025, the NGFS developed the **NGFS Data Directory 2.0:** a **collaborative website** where information can be **crowdsourced** and **curated** by a **community of users.**
- The NGFS now aims to make the DD 2.0 available as a **public good** to **unlock the full potential of the wealth of already existing climate data** and **further bridge gaps**.

BANQUE DE FRANCE
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BIS Innovation Hub

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Data Directory 2.0: a user-centered development process

1

Design thinking workshop series

- Initial exploration
- Stakeholder engagement with private & public sector
- Synthesis & prioritization of development features

2

Agile wireframe creation & website development

- logical clusters for wireframe creation
- Sprint cycles for development
- Iterative feedback with workshop participants

3

Soft launch & pilot testing phase

- Soft launch at COP29
- User Acceptance Testing phase

Data Directory 2.0: a new era of climate data accessibility

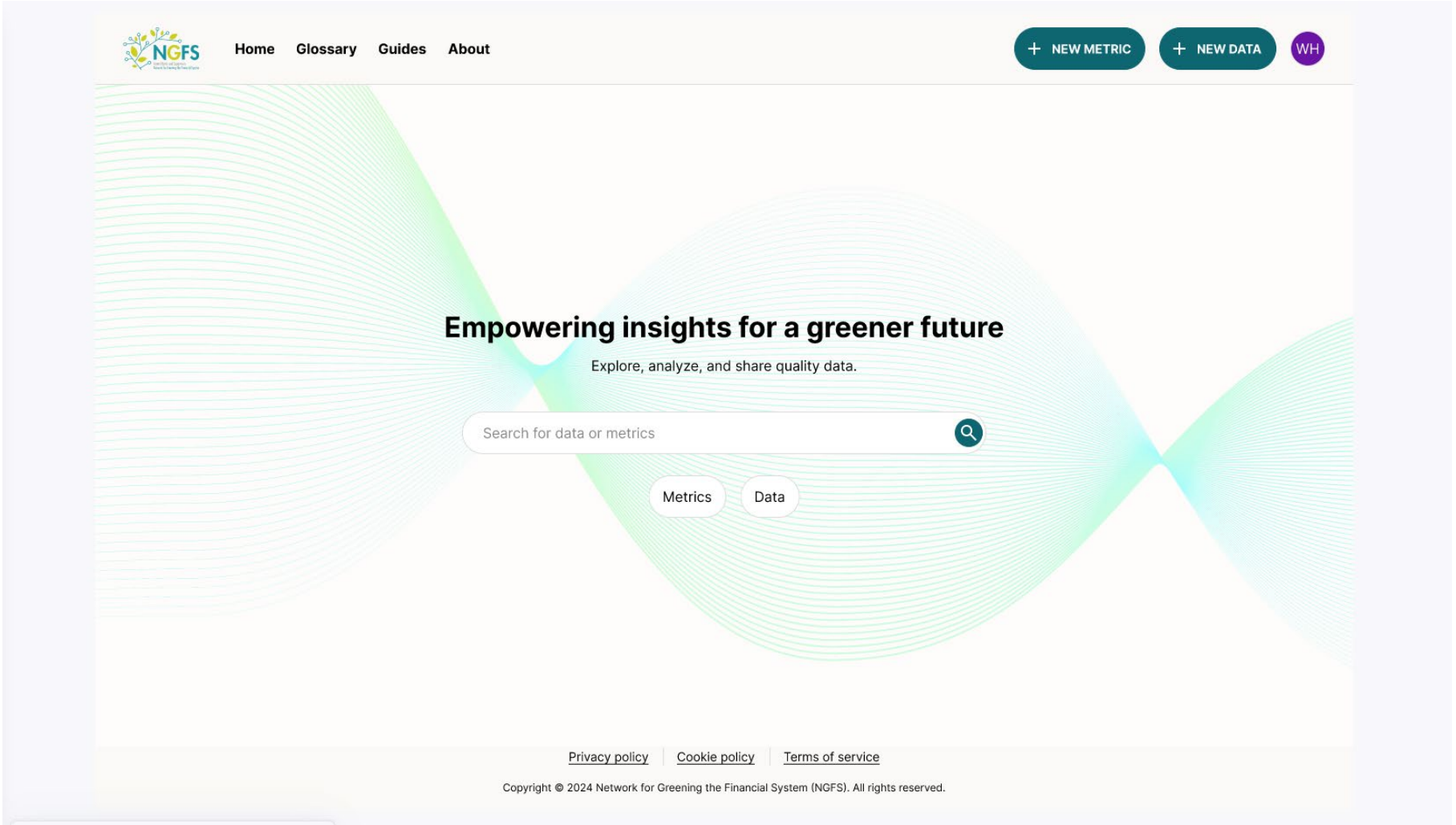
- **User-centric design** to enhance **usability** and hence **effectiveness :** different user journeys
- **Advanced search** and **analytics**
- **Web analytics** tools

- Building on the expert contribution of **NGFS members, finance practitioners, data providers, non-profit initiatives, academics** etc.



- **Contributive website** (e.g. wiki) : add info, ratings, comments
- Information **crowdsourced** from the community of users, while maintaining **credibility and reliability** (content management system)
- **Enhanced data integration**: partners (bulk) uploading information on their climate resources

Sneak-peek of the Data Directory 2.0



Link to demo video

Our solution is you!

- **Bringing the community together:** the DD 2.0 is open to **any interested participant.** Knowledge doesn't add, it multiplies!
- **Partnering with content providers:** core information can be **bulk uploaded**
- Need for **supporting partners** in hosting the website.

Thank you for your attention!

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