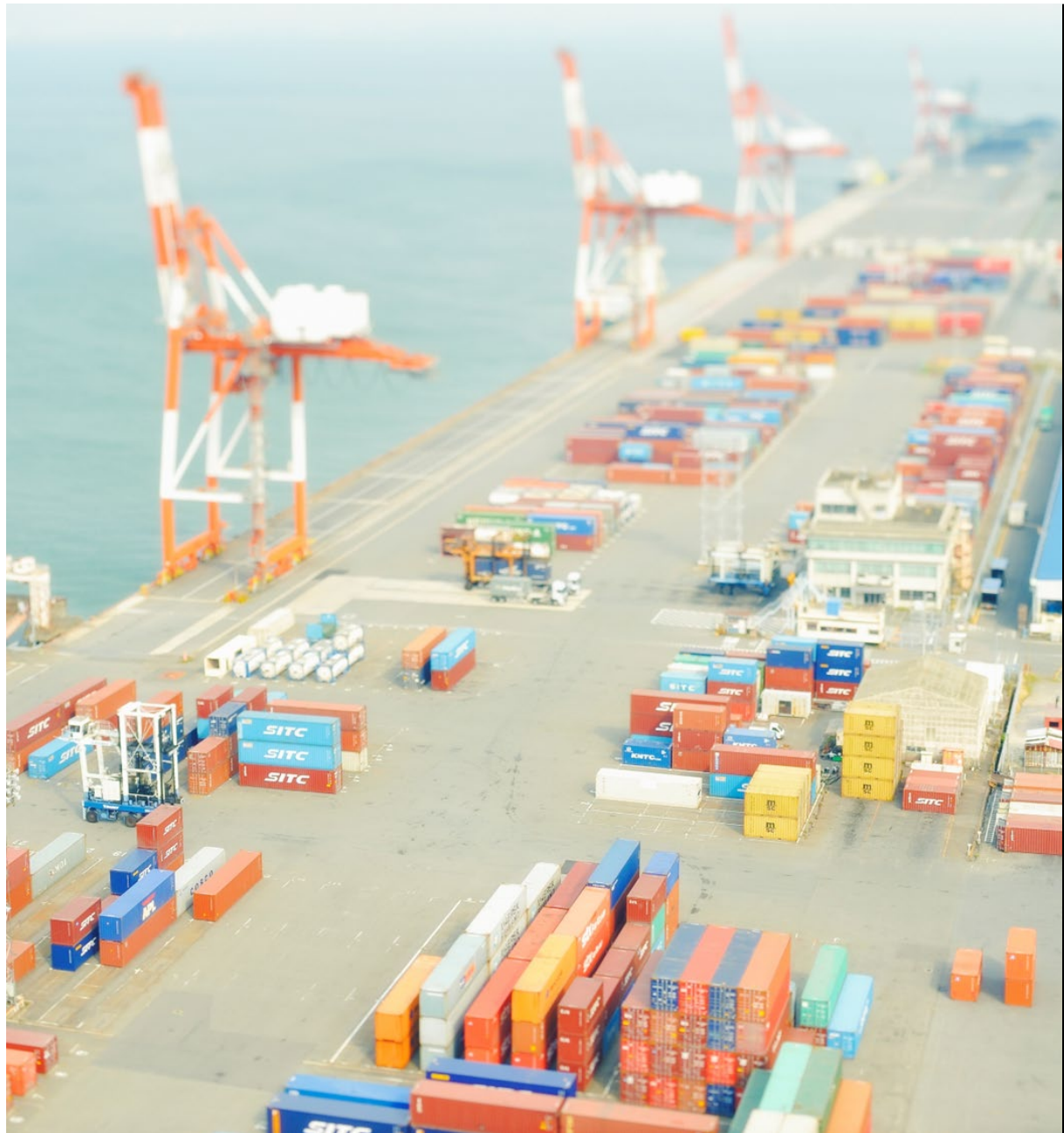




THE BLIND SPOTS OF AGGREGATE STATISTICS

Firm-Level Evidence on Corporate Debt

20 AUGUST 2026

ALEXANDRE SOUSA · ANA REIS · DANIEL PEIXEIRO



BANCO DE
PORTUGAL
EUROSISTEMA

THE AGGREGATE REALITY



Entities



Non-Financial Corporations (S.11)

Instruments



Debt Securities



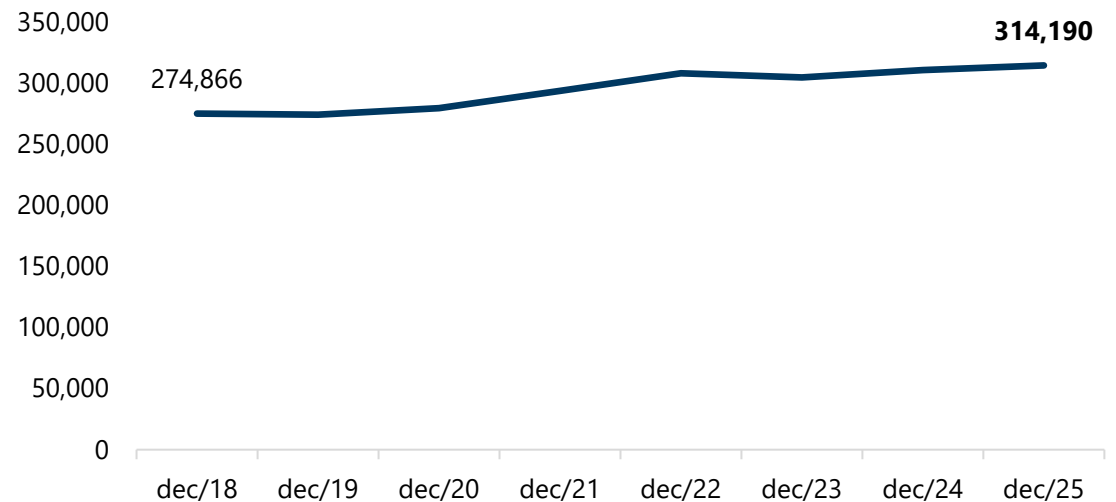
Loans



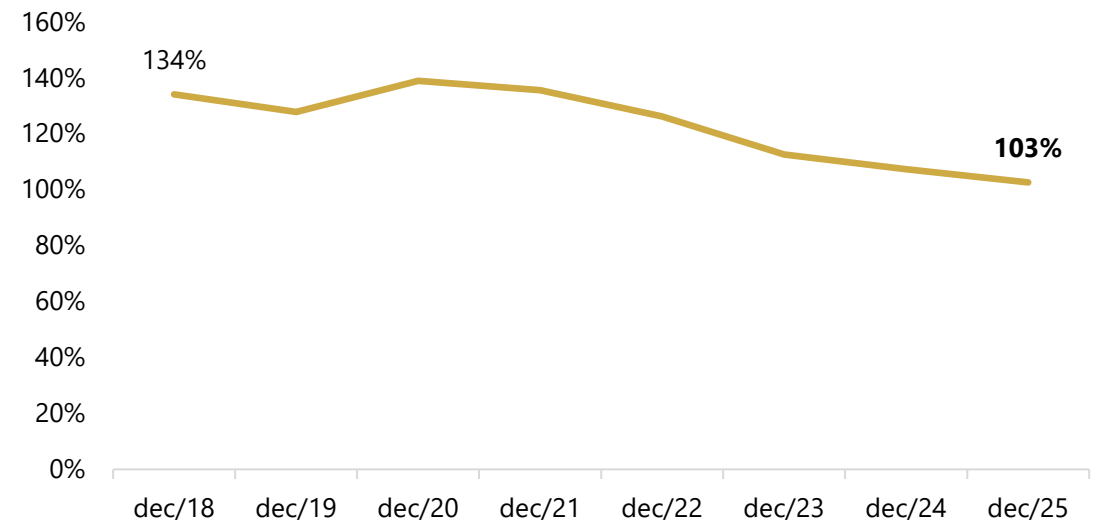
Trade Credits



Total Indebtedness | M€



Total Indebtedness | % GDP



FROM AGGREGATE DATA TO MICRODATA



Can we uncover the details behind the aggregates?

Sources with monthly granular data

Granular source

Debt securities

Security-by-security
database

Loans from the resident financial sector

Portuguese CCR

Loans from non-residents

External Statistics

Risk

In-House Credit
Assessment System

Firm characterization

Internal Entity
Register

Sources without monthly granular data

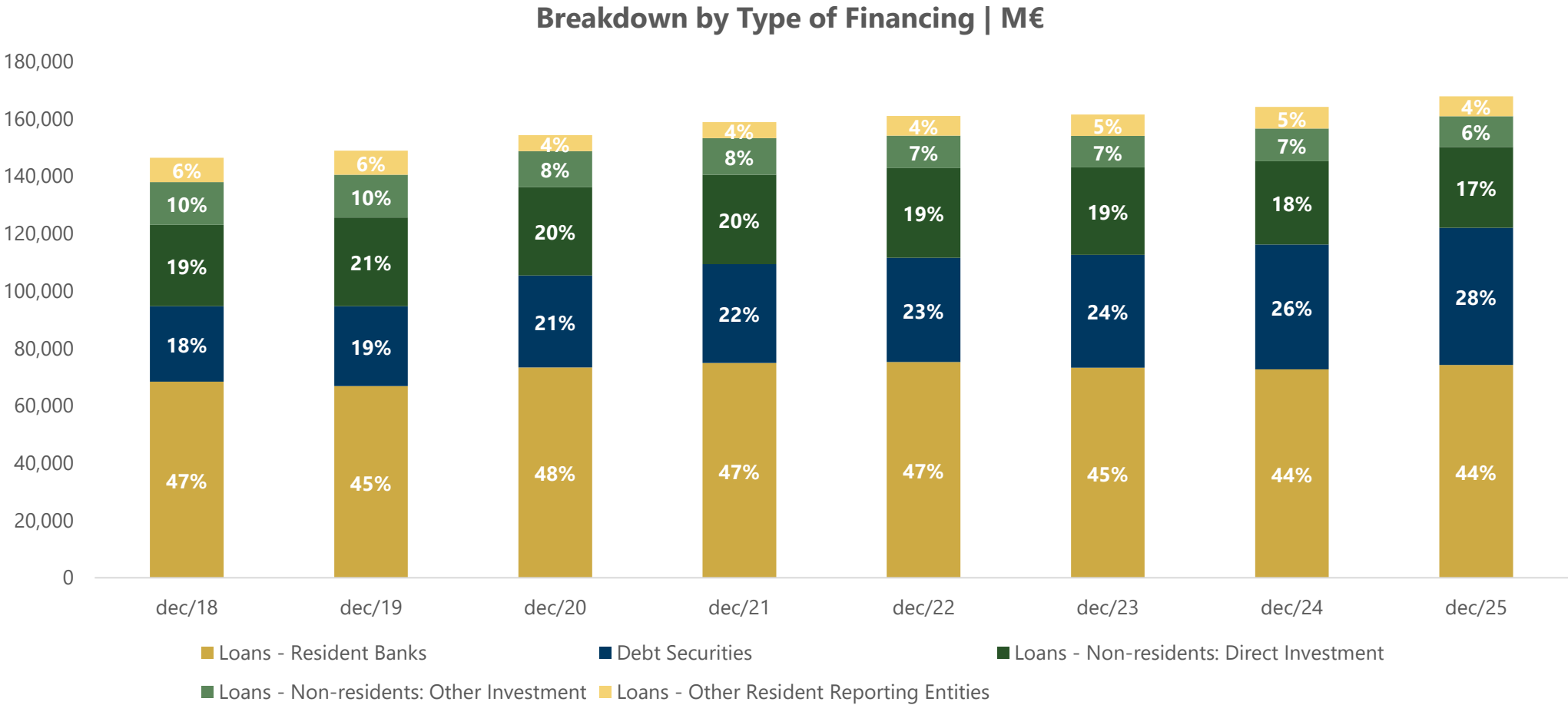
**Loans from residents outside the
CCR scope**

Trade credits

NON-FINANCIAL CORPORATIONS' INDEBTEDNESS



Between 2018 and 2025, **indebtedness grew**, with **debt securities** rising from €26bn to €48bn and from 18% to 28% of the total. **Loans from resident banks** remained the largest funding source, though their share decreased from 47% to 44%.

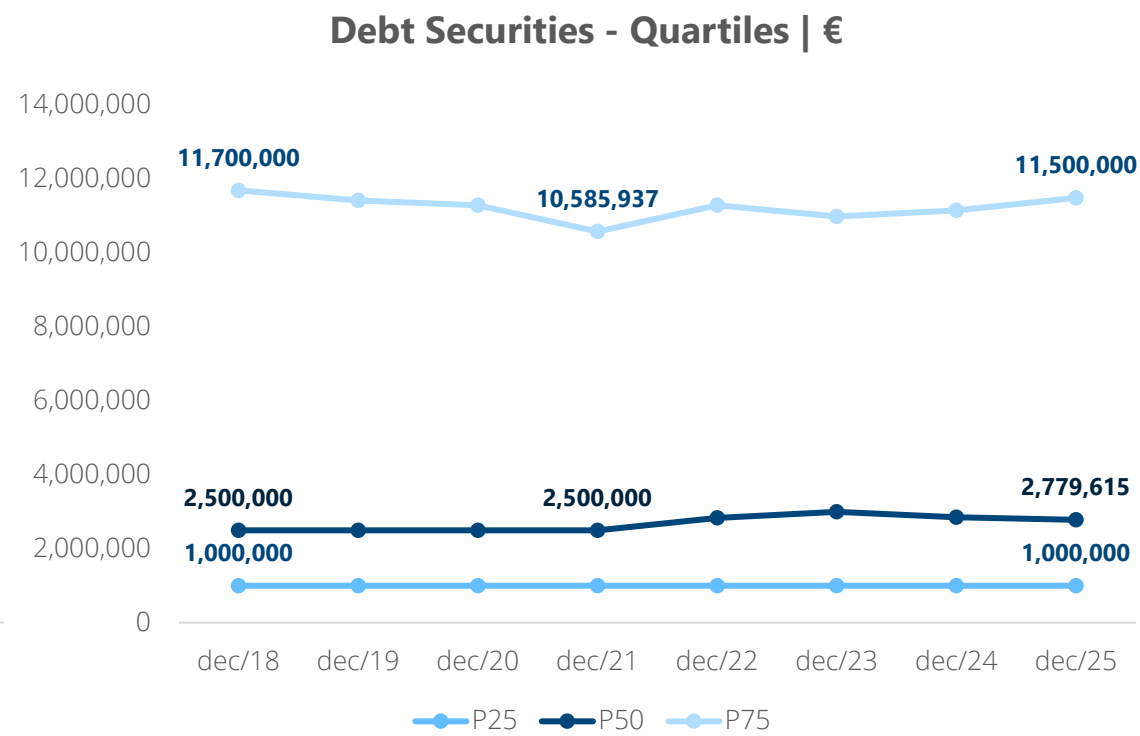
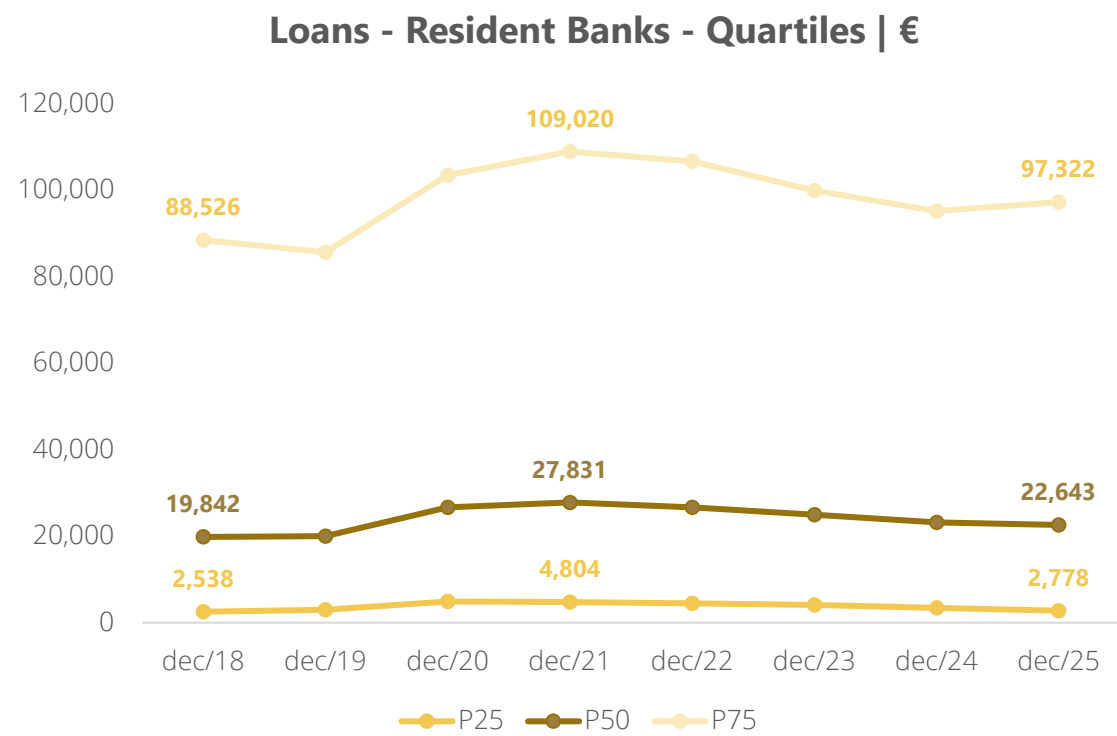


Source: Granular Debt Dataset

NON-FINANCIAL CORPORATIONS' INDEBTEDNESS | Distribution



The median **amount of loans from resident banks increased during the pandemic**, peaking at €27.8k in December 2021. The median **amount of debt securities issued remained broadly stable**, rising from €2.5M to €2.7M between 2018 and 2025.



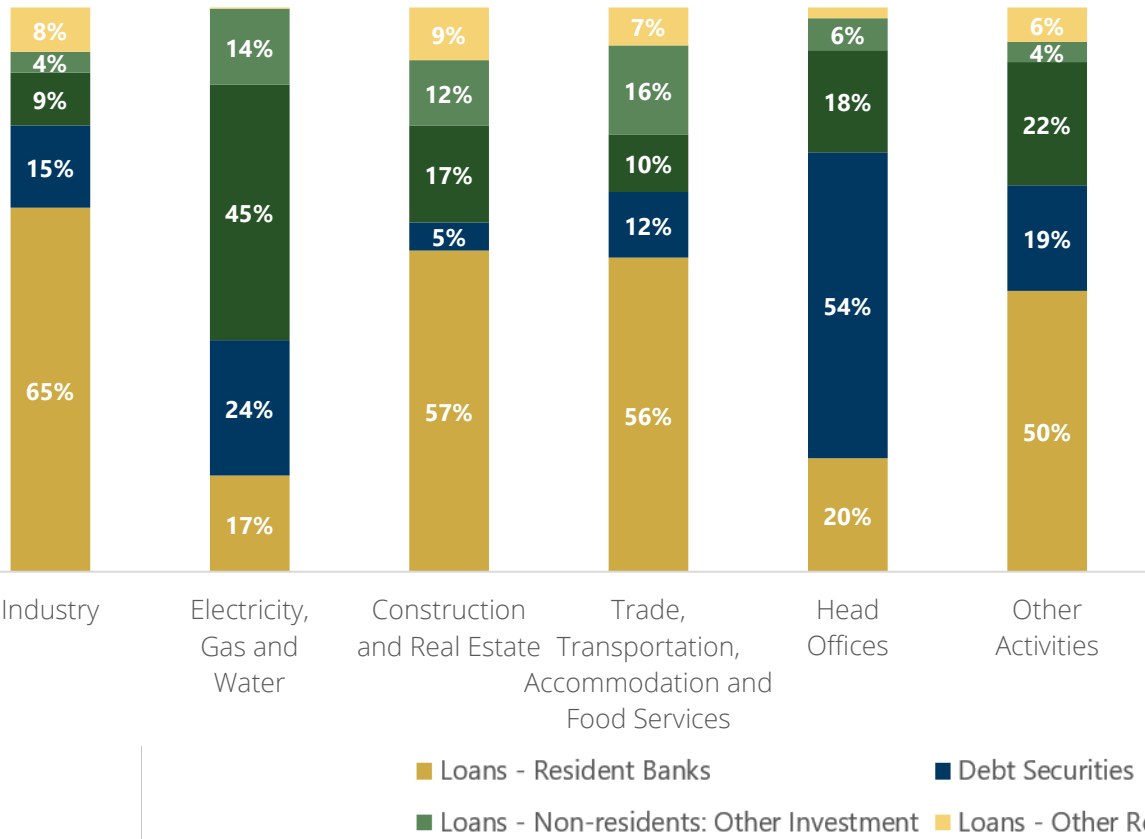
Source: Granular Debt Dataset

NON-FINANCIAL CORPORATIONS' INDEBTEDNESS | By NACE

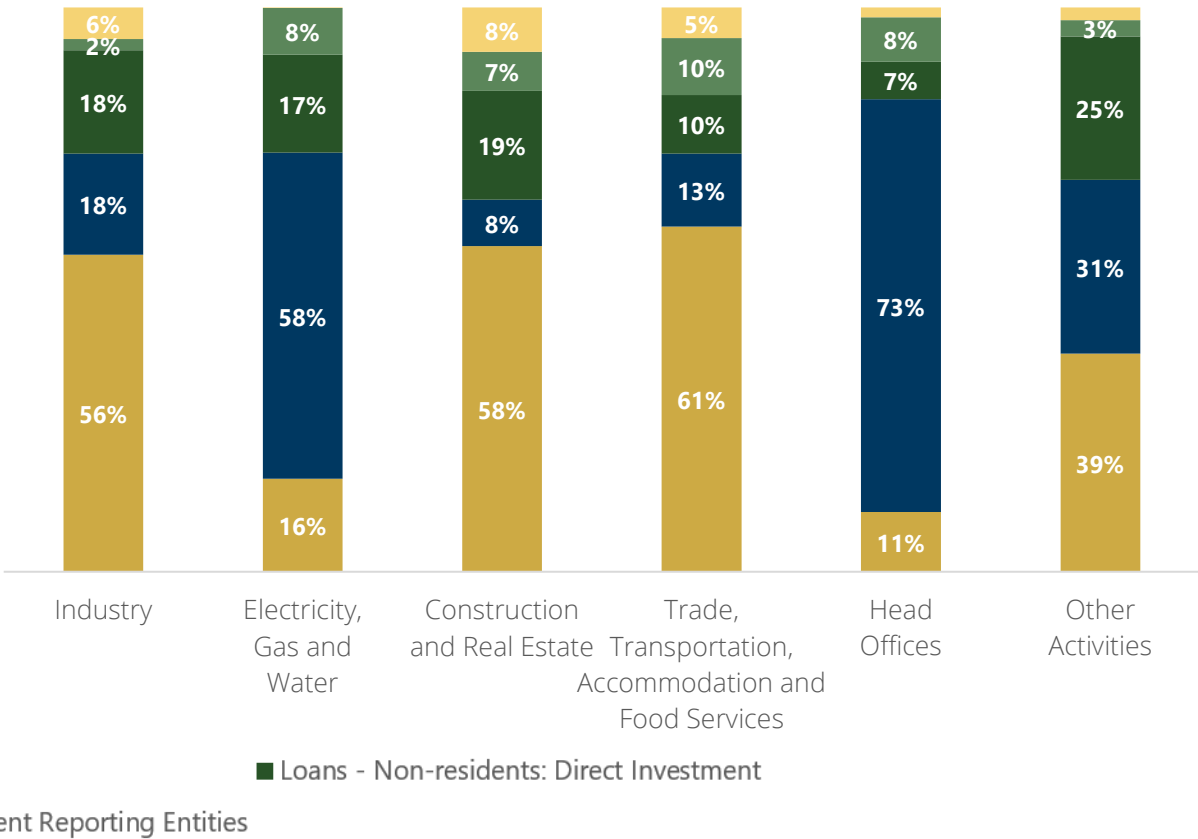


The **Electricity, Gas and Water sector** and **Head Offices** stand out for their **lower reliance on loans from resident banks**. Between 2018 and 2025, **the share of debt securities increased across all sectors**.

Breakdown by Type of Financing | Dec 2018 | %



Breakdown by Type of Financing | Dec 2025 | %

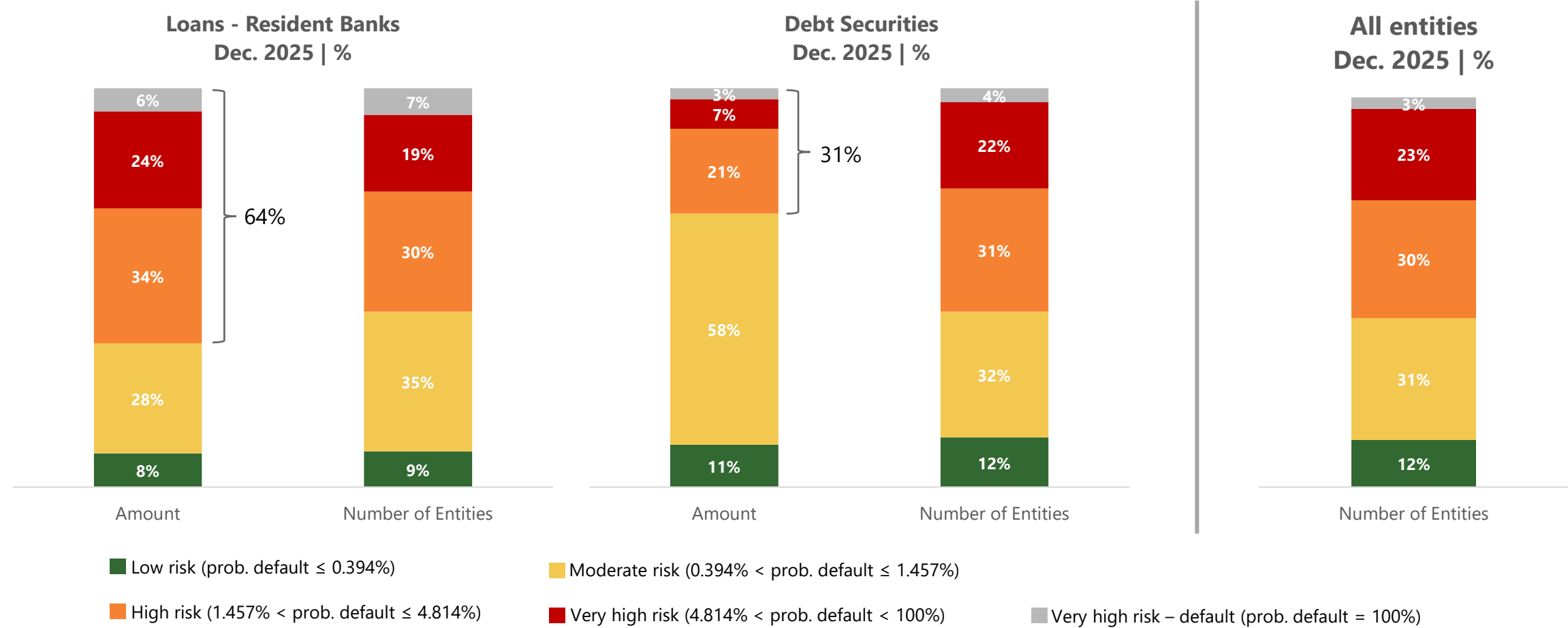


Source: Granular Debt Dataset

NON-FINANCIAL CORPORATIONS' INDEBTEDNESS | Risk



64% of loans from resident banks are owed by firms classified as high or very high risk, compared with 31% for debt securities.



Source: Granular Debt Dataset

KEY TAKEAWAYS



Microdata allows us to explore the distribution, coverage and breakdowns of corporate indebtedness across multiple new dimensions, such as size, sector and risk.



Companies of **different sizes, sectors of activity and risk levels** have **distinct financing patterns**. Financing through **debt securities** is concentrated in a **small number of firms**.



The database can **support further analysis**, including linking **borrowing costs across instruments** and assessing whether they affect **financing choices**.



EUROPEAN CENTRAL BANK

EUROSYSTEM

Holdings of euro area government debt: leveraging on Eurosystem data sources

IFC 13th biennial conference



20-21 August 2026
Basel

Benjamin Fuilu (benjamin.fuilu@ecb.europa.eu)
Gonçalo Amado (goncalo.amado@ecb.europa.eu)

European Central Bank

Motivation

- The holding composition of government debt has **important financial and economic policy implications and results from many and complex drivers**
- Special case for the **Euro Area aggregate government debt**: built on a single and centralised monetary and on many decentralised fiscal policies
- A rich literature points to:
 - Combination of sources: *Arslanalp and Tsuda (2014)*, *Dembiermont, C. (2015)*, *Fang et al. (2023)*
 - Trends in euro area government bonds ownership:
 - By banks and non-domestic sectors: *Afonso et al. (2024)*, *Bosetti et al. (2025)*, *Buch, C. (2026)*
 - By households: *Pavot J. et al. (2021)*, *Ferrara F. et al. (2024)*
 - Impact of geopolitical events: *Beck et al. (2025)*
- However, **Maastricht debt structure (government debt at face value by counterpart sector and instrument) is not available with a quarterly frequency!**

Leveraging on Eurosystem data sources

Main goal: develop a quarterly methodology that integrates various data sources while being **consistent with the Maastricht debt concept**.

Selected scope...

Financial instruments:

F_j

- Maastricht debt instruments: **other deposits**, **debt securities**, and **loans**
- **Consolidation** of transactions within government sector

Holding sectors coverage:

S_i

- Domestic:
 - NFCs
 - central bank
 - other MFIs
 - non money market investment funds
 - other financial institutions
 - insurance corporations
 - pension funds
 - Households and NPISH
- Non-resident aggregated
 → *Post aggregation of domestic sectors and of total economy (both consolidated)*

... and data sources.

Government Finance Statistics (GFS)

T_{27}
 T_{28}

- ESA Transmission Programme Tables 27&28
- Aggregated data (total economy) with quarterly frequency
- Table 28 (Quarterly Maastricht debt) contains data at face value and is being **used as a target for data consistency**

Debtor side

Quarterly Financial Accounts (QFA)

QFA

- Sector by sector “who-to-whom” data available, but at standard valuation (nominal and market)

Creditor side

Securities Holdings Statistics (SHS)

SHS

- Only for debt securities, granular data available at face and market value

Leveraging on Eurosystem data sources

Main goal: develop a quarterly methodology that integrates various data sources while being **consistent with the Maastricht debt concept**.

Applied method...

For deposits and loans: *in proportion to the weight in QFA!*

→ For all sectors, **applying weight on QFA w-t-w tables** to Quarterly Maastricht debt aggregated figures

$$T28_{Si,Fj} = QFA_{Si,Fj} \times \left(\frac{T28_{S0,Fj}}{\sum_i QFA_{Si,Fj}} \right)$$

For debt securities: *sector specific face-to-market ratio!*

→ **Domestic** sectors holdings calculated from w-t-w outstanding amounts from QFA (market) **converted to face value** using a face-to-market ratio from SHS

$$T28_{Si,Fj} = QFA_{Si,Fj} \times \left(\frac{T27_{S0,Fj}}{QFA_{S0,Fj}} \right) \times \left(\frac{SHS_{face(Si,Fj)}}{SHS_{mrkt(Si,Fj)}} \right)$$

→ **Foreign** holdings calculated as **residual** for consistency with Quarterly Maastricht debt.

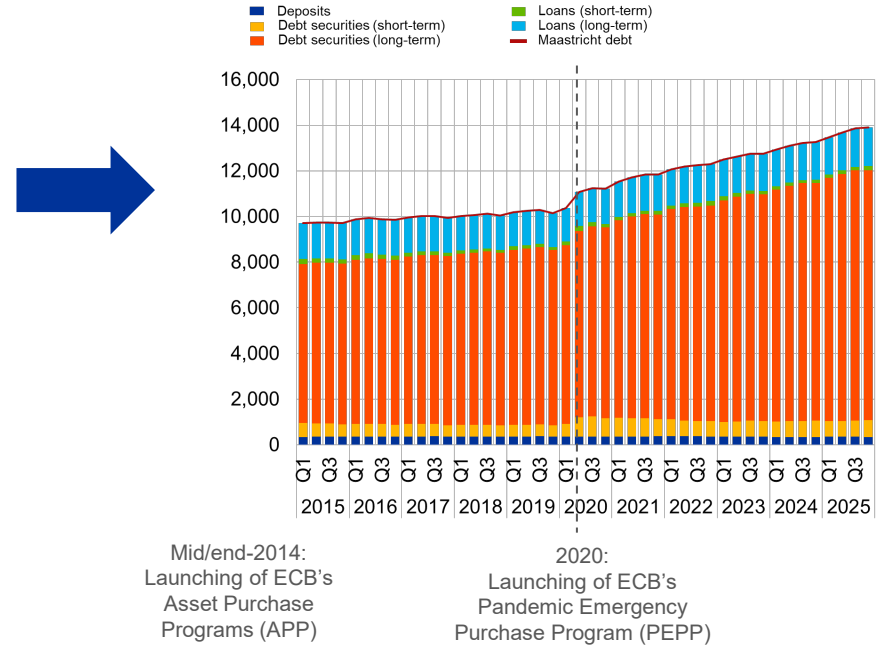
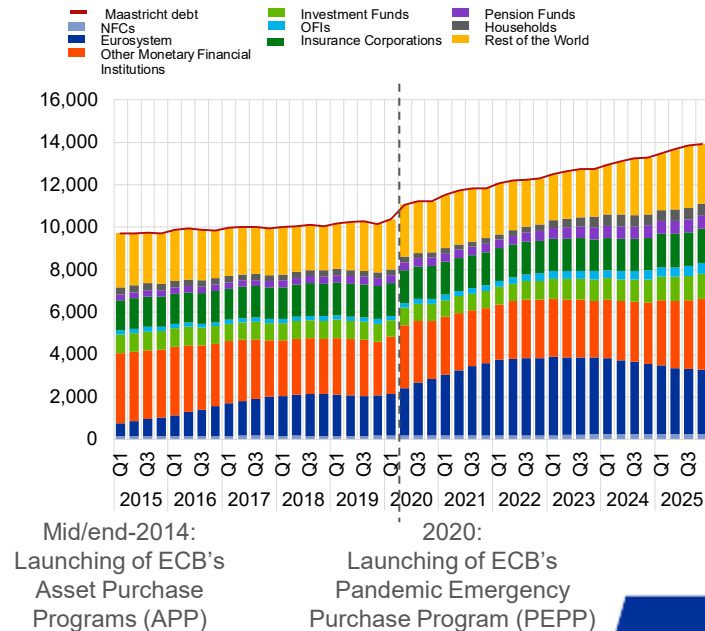
$$T28_{S2,Fj} = T28_{S0,Fj} - \sum_{Si \neq S2} T28_{Si,Fj}$$

Stylized facts (1/3)

Asset purchase programs as main influence for the debt holding structures

Debt securities cover a large majority of the Euro Area government debt (79% in end-2025)

Additional drivers can be captured in our study: the weight of loans and deposits shares (funds provided by EU institutions) remains significant



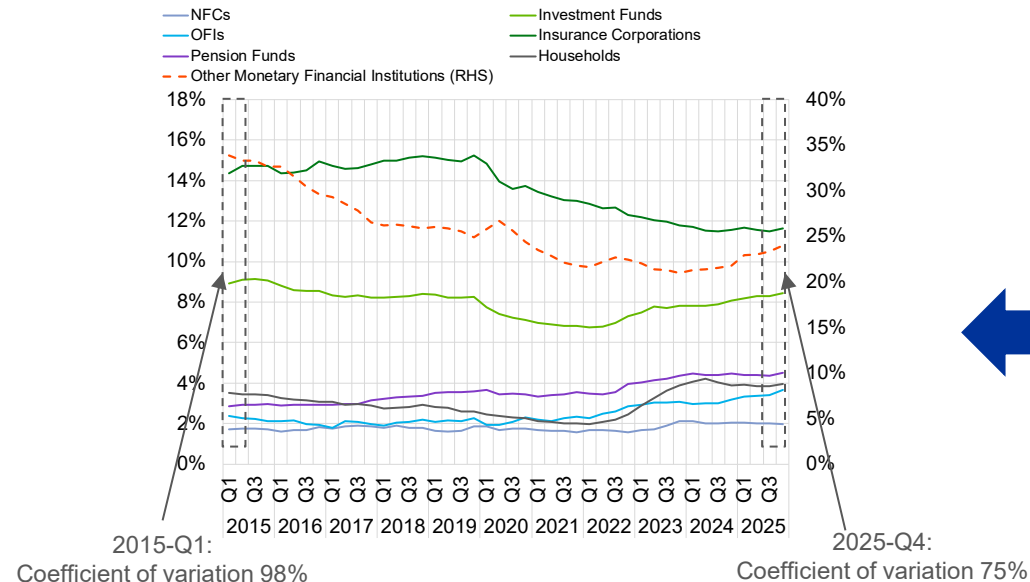
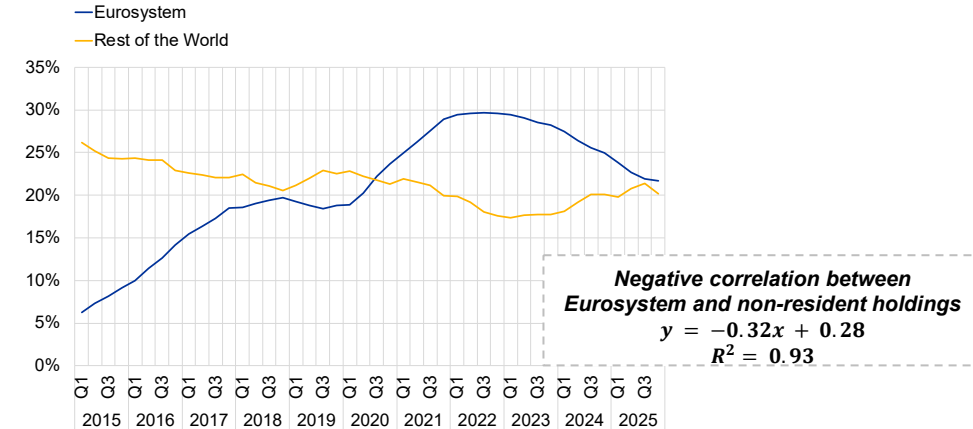
Over the past decade, significant influence of the Eurosystem's holdings of debt securities issued by Euro Area governments on the debt holding structure – resulting from the asset purchase programs (APP)

Stylized facts (2/3)

More diversification and new sectors gaining weight as holders of government debt

Eurosystem balance sheet expansion with several asset purchase programs such as APP and PEPP (peak mid-2022).

Rebalancing of foreign investors' portfolios towards more attractive investments



Recent pickup of Households holdings (several retails programs in euro area countries).

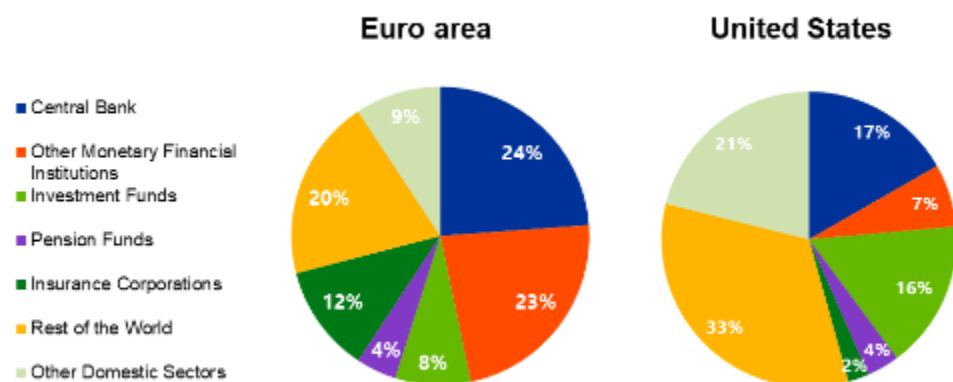
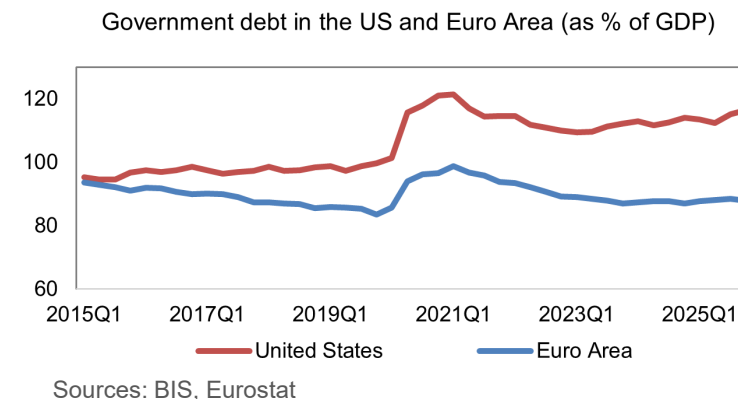
Still observed decline of banks' holdings following the 2008-12 crisis

Recently, lower degree of concentration (higher degree of dispersion)

Stylized facts (3/3)

Euro Area and US government debt trends are similar, with different structures

Euro area and United States government debt **have exhibited similar trends over the latest decade**, although the Euro area shows an *in fine* relative decrease of the debt compared to the US



(percentage of the government debt)

Sources: Peter G. Peterson Foundation (2026), ECB, Eurostat, authors' computation



However, with **different holding structures**:

- ✓ Higher share of foreign holdings for US government debt illustrating the dollar's global role
- ✓ US Households with more prominent role, especially for municipal bonds (MSRB, 2022)
- ✓ Euro area higher share of insurance corporations and banks' holdings resulting from lower corporate bond market in the EA (OECD, 2026) and different legislations (Corradin et al. 2025)
- ✓ Recent higher dispersion at the level of the holding sector.

Conclusion and way forward

❑ What has been achieved...

Closer zoom with higher frequency into the dynamics of euro area debt allocation across various institutional actors, especially shedding light on:

- ✓ Impact of the asset purchase programs on the debt holding structure
- ✓ Inverse relationship between Eurosystem and foreign holdings – *also visible in QFA statistics*
- ✓ Increased involvement of households and other traditionally less active sectors
- ✓ A ground Euro area economy comparison with other large and developed economies

Keeping the consistency with Maastricht debt figures, it therefore *fills a current data gap in macroeconomic statistics*

❑ ... and what could be next?

- ✓ Expanding the instrument breakdowns scope (e.g. green bonds; crypto-assets issuances)
- ✓ examining closer some specific sectors dynamics (e.g. households), especially **combining the data on indirect holdings** of those sectors via investment funds
- ✓ Further fine-tuning for the **calculation method**, especially the residual compilation of RoW holdings
- ✓ **Benchmarking with other data collections** e.g. external statistics, to show the geography of foreign holdings

The ECB, together with national central banks, is currently working on *how to implement such dataset as regular statistical output*

Using ML on Indonesia's From - Whom -to- Whom Financial Accounts as a Financial Surveillance Tool to Detect Unusual Behavior

13th Biennial IFC Conference · BIS, Basel · 20 –21 August 2026

The views expressed in this presentation are those of the authors and do not necessarily reflect those of Bank Indonesia.

Dini Sulliaty · Macroprudential, Monetary & Market Surveillance

Dept. Oktefvia Aruda Lisjana · Statistics Department

Bank Indonesia

From a Periodic Report to an Active Surveillance Tool

The gap

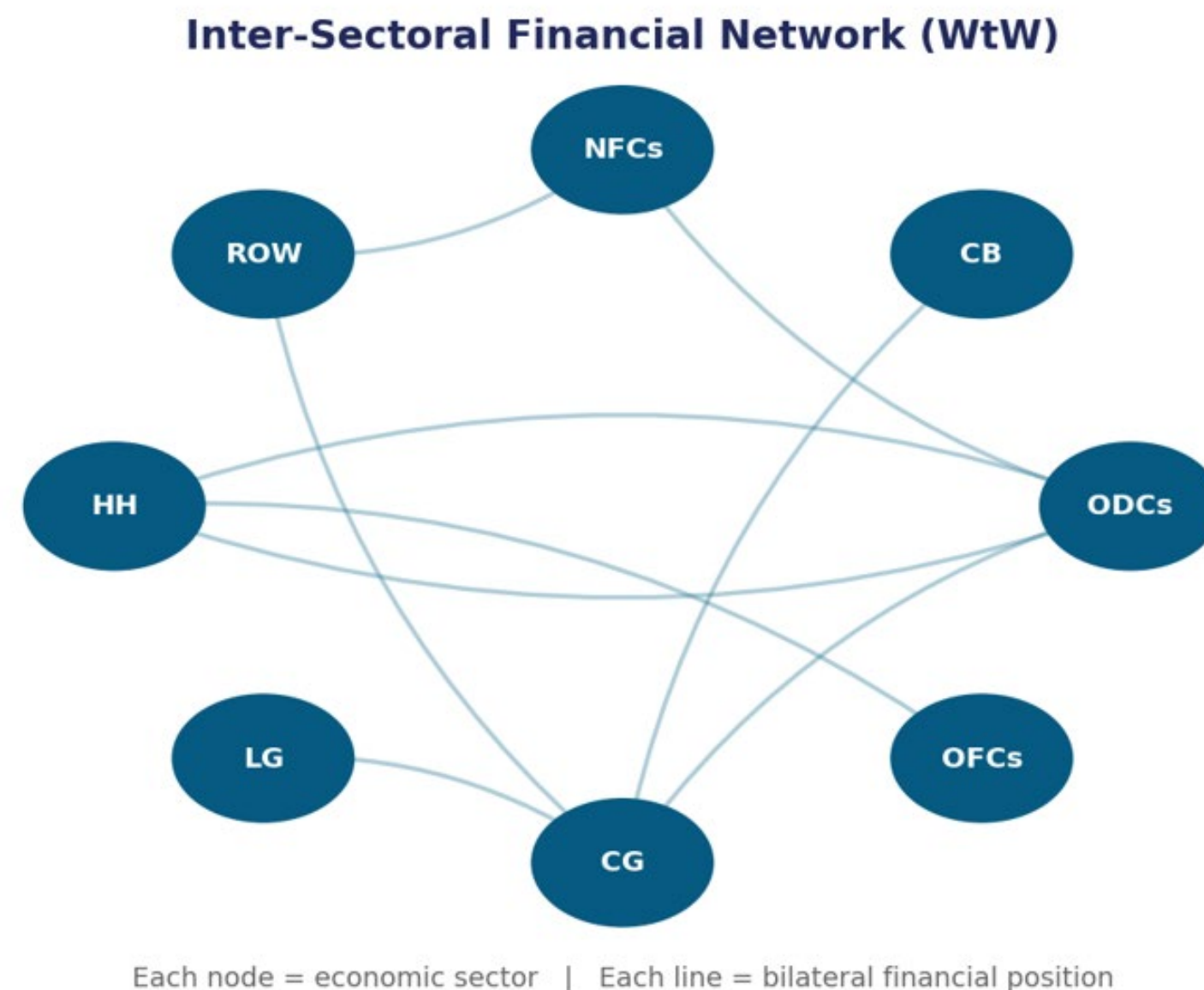
FABSI records who finances whom across every sector —a rich network. But it is reviewed periodically and manually, so unusual shifts can go unnoticed.

Our approach

A machine -learning model scans the matrix each quarter, flags the sectoral links that deviate most from their history, and presents them for analyst review.

Not a black box

It prioritises where judgement should go —it does not replace the analyst.



The financial system as a network of inter -sectoral positions

Data and Method

BASELINE

Rolling Z-score

Counts matrix cells breaching $\pm 2\sigma$ from their rolling norm. Simple, transparent, per-cell.

MAIN MODEL

Isolation Forest

Multivariate scan of all sectoral links at once. Isolates quarters that sit apart from the rest.

ROBUSTNESS

Autoencoder

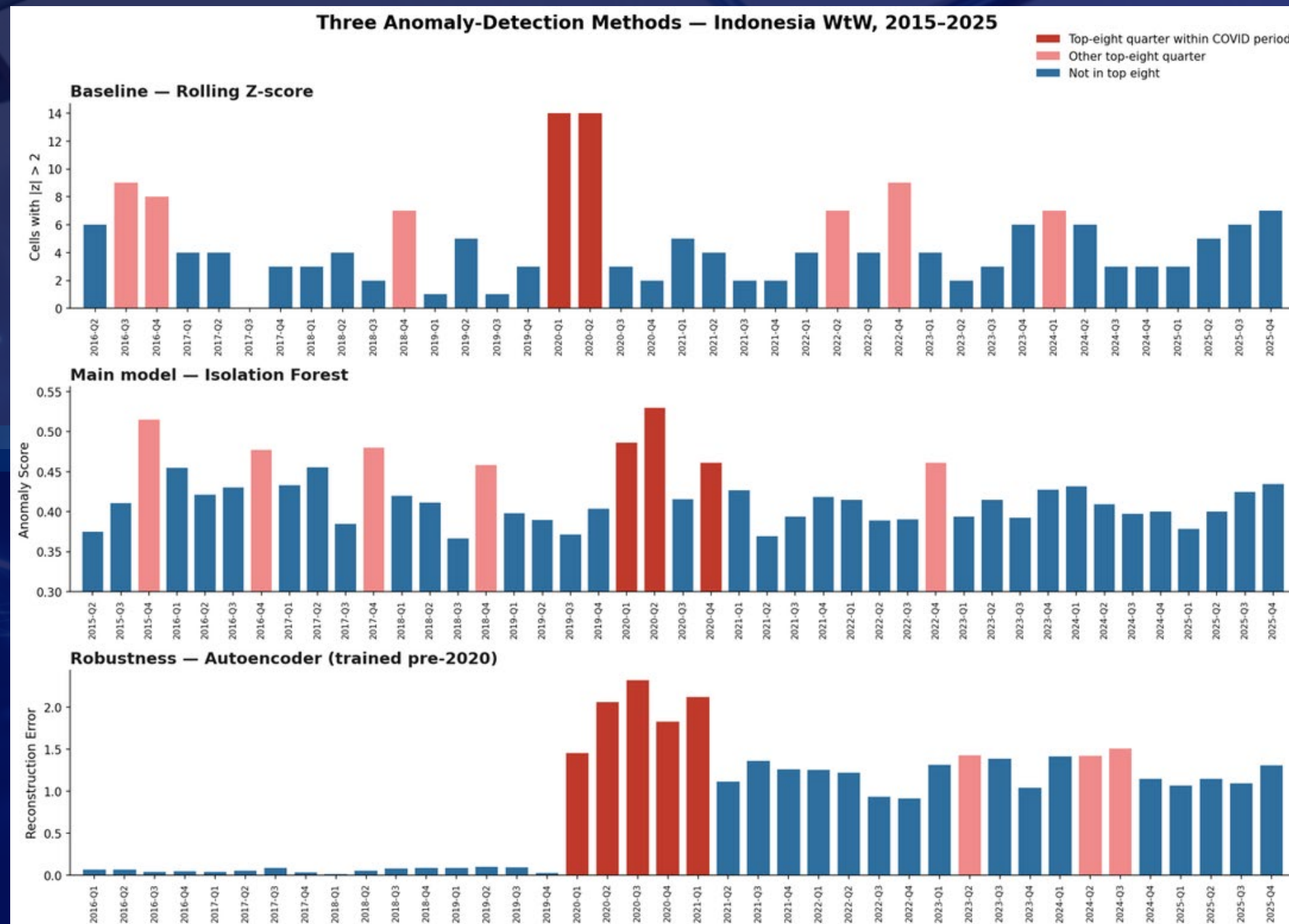
Learns the pre-2020 “normal” and measures reconstruction error—a regime-change detector.

Input:

- 44 quarterly WtW matrices, 2015–2025
- 8 sectors
- 56 active bilateral links
- quarter-on-quarter growth
- currency & maturity for debt securities and loans

Validation: flags are compared against periods of external pressure documented in Bank Indonesia’s Financial Stability Review (KSK) — 2015, 2018, 2020, 2022, 2025. These are periods of elevated pressure, not realised crises; the model detects pressure, it does not predict crises.

Result I - Three Methods, One Signal



Key insight

2020 Q1–Q2 (COVID)
flagged by all three methods, despite completely different logic.

Convergence matters

Cross-method agreement is far harder to dispute than any single result.

Result II - How Good Are The Flags?

62.5%

ISOLATION FOREST

$\text{precision@8} \cdot 2.4 \times \text{base rate} \cdot p = 0.017$

50.0%

ROLLING Z-Score

$\text{precision@8} \cdot 2.2 \times \text{base rate} \cdot p = 0.065$

25.6%

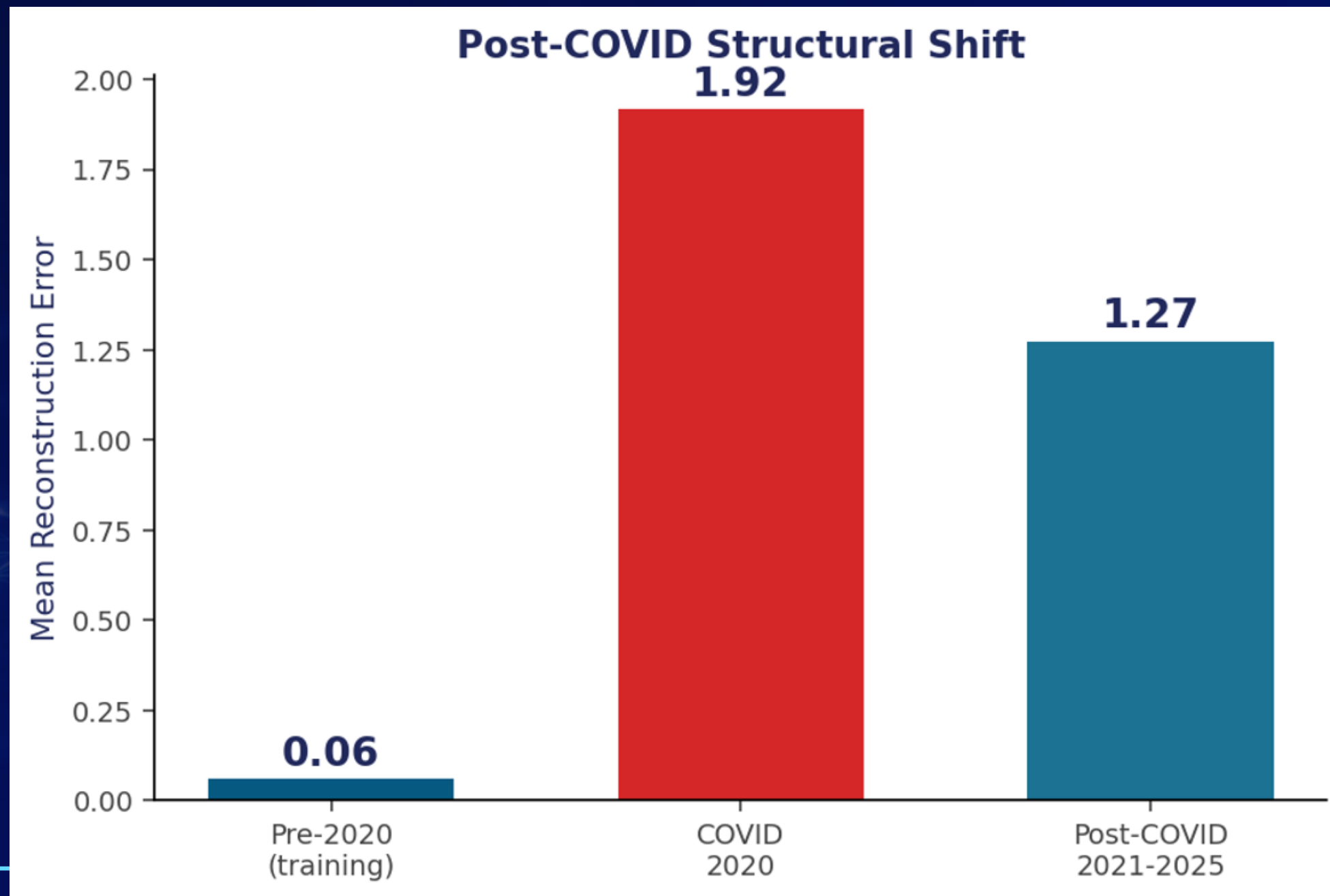
Base Rate

what random selection would give
Base Rate = $11 \text{ (KSK)} / 43 \text{ (Quarters)} = 25.6\%$

Read against the base rate, not against 100%. The model is unsupervised — no crisis labels enter training — and its job is to triage attention, not classify crises. Every one of the eight flagged quarters is economically explainable; three are structural changes (e.g. the 2016 tax amnesty), not false positives.

Sample is small (43 quarters) — results are indicative, not conclusive

A Permanent Post - COVID Structural Shift



Key finding

The autoencoder learns the pre -2020 “normal.”

COVID → error jumps sharply

the network moves far outside anything it had seen.
...and never returns

Post-COVID error stays elevated —sectoral interconnectedness shifted to a persistently different regime.

Extending the Model to Transaction Flows

What flows add

Positions show structure at a point in time. Flows show behaviour during a period — who is acquiring or disposing of claims.

Because a flow can be negative, a capital outflow shows up directly — invisible in the always-positive closing position.

The dual -alert design

Level alert = flow is extreme in absolute terms.

Deviation alert = flow departs from its own history (z-score).

Requiring both raises precision — the two-rule design filters most of the noise.

Dual confirmation improves precision ~6 × over the level rule alone

7% level only → 27% deviation only → 40% both rules together

What This Delivers

1

Detects known stress

Independently flags 2018, 2020 and 2022 —confirmed by three distinct methods

2

Surfaces structural change

Captures the 2016 tax amnesty, a 2017 data reclassification, and a permanent post -COVID shift.

3

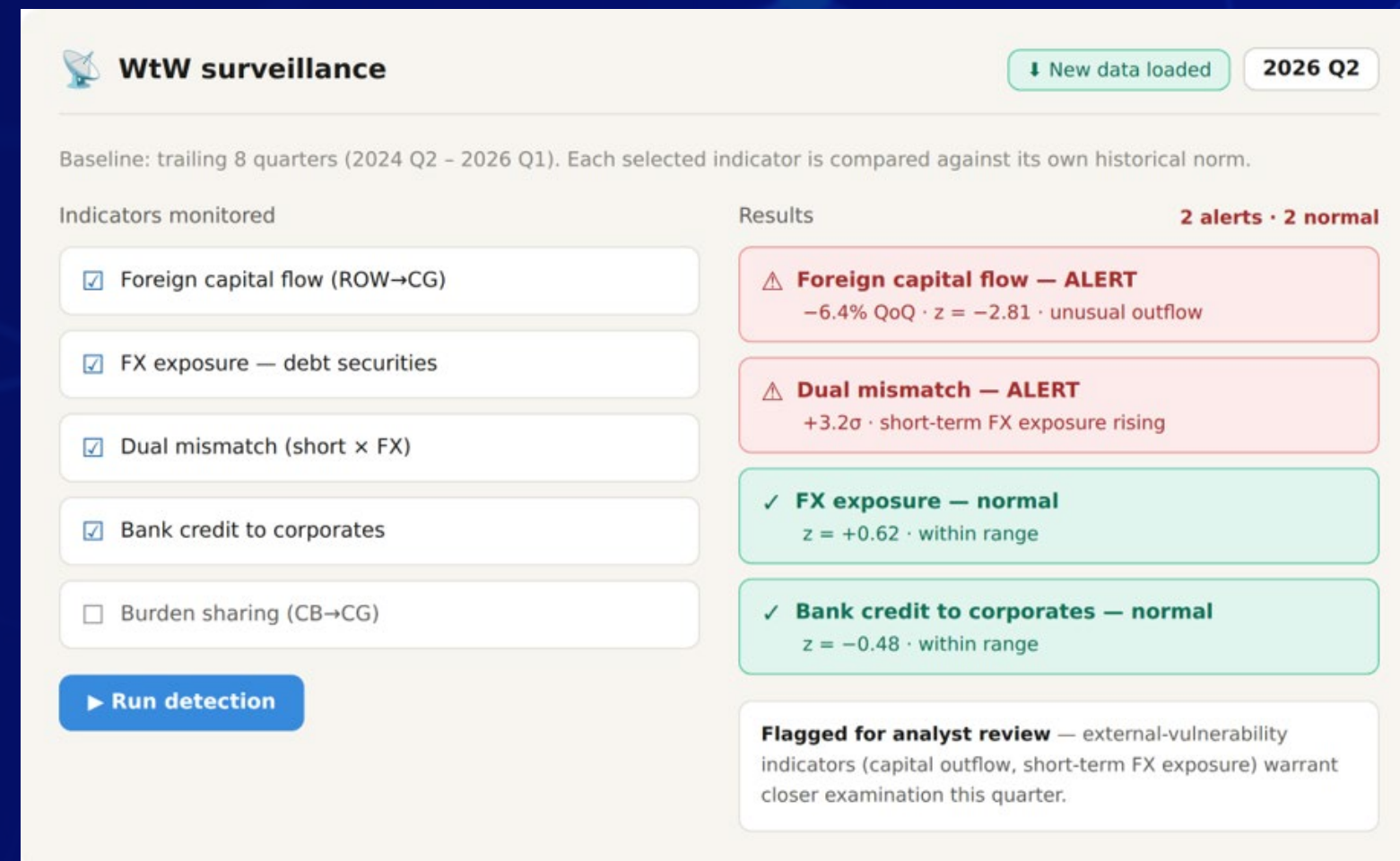
A by-product: data quality

Flagging anomalies also exposes reclassifications and data breaks —useful to compilers.

4

Runs on existing data

A practical, reproducible pipeline a central bank can operate on what it already compiles.



Next steps: richer instruments · flow -level currency & maturity · sensitivity analysis
· validation against internal stability indices



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BANK OF THAILAND

SupRisk AI: An Agentic AI Framework for Systemically Important Corporate Risk Surveillance

**Nontawit Cheewaruangroj*, Kawinwish Laobundit, Chinnawat Devahastin Na Ayudhya,
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*Data Management and Analytics Department
Bank of Thailand*

20-21 August 2026

Prepared for the 13th biennial IFC Conference “Filling information gaps in central banking: effectively leveraging data and innovative tools”, Basel



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BANK OF THAILAND

SiCorp Surveillance

What is a SiCorp?

A **SiCorp** is a corporate group whose size, concentration, and dense interconnections make it significant not just on its own but for the whole financial system — because distress can spread to other institutions and sectors.

Why supervise SiCorps?



Safeguard financial stability by identifying vulnerabilities in systemically important corporate groups before shocks propagate through the wider economy and financial system.



Reveal interconnected risks arising from ownership, financing, supply-chain, and counterparty relationships that cannot be captured through standalone firm analysis.



Enable timely action by consolidating fragmented information into a coherent and auditable view of group-level vulnerabilities and transmission channels.



Key Challenge: Information fragmentation

SiCorp risk signals are scattered across multiple data sources, systems, and documents. This fragmentation limits supervisors' ability to obtain a unified view of vulnerabilities, identify cross-entity linkages, and detect emerging systemic risks in a timely and auditable manner.



SupRisk AI Framework

In SupRisk AI Framework, structured and unstructured data are combined and constructed into a knowledge graph.

Data

1 loan dataset

period	institution	customer	outstanding	PD	stage
2025-12	Bank A	Company B	20 MTHB	0.1	SM

2 bond dataset

period	issuer	holder	face value	rate	maturity
2025-12	Company B	Company C	16 MTHB	3.00	2027-01-01

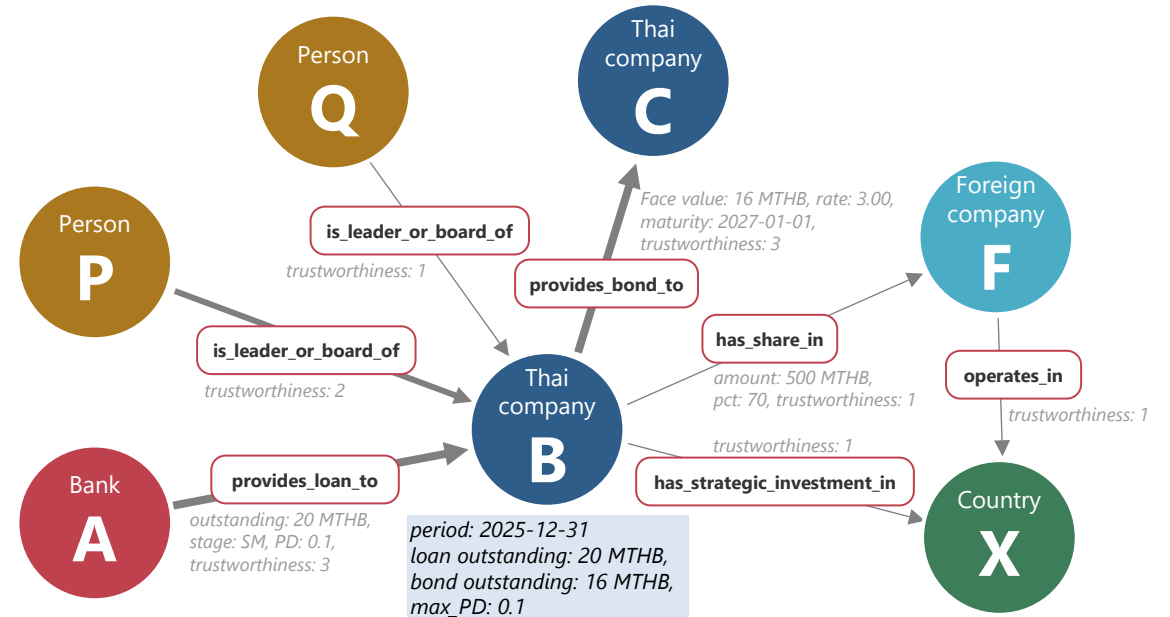
3 opportunity day video

"<Person P>, <Company B>'s investment general manager, ..."

4 news article

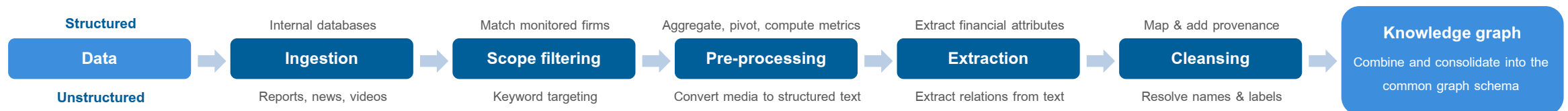
"<Company B>, controlled by <person Q>, agreed to buy a 70% stake in <Country X>-based trader <Company F> for 500 MTHB to expand its footprint ..."

Resulting Knowledge Graph



Process

Perform with rule-based calculation (structured data) & LLM (unstructured data)



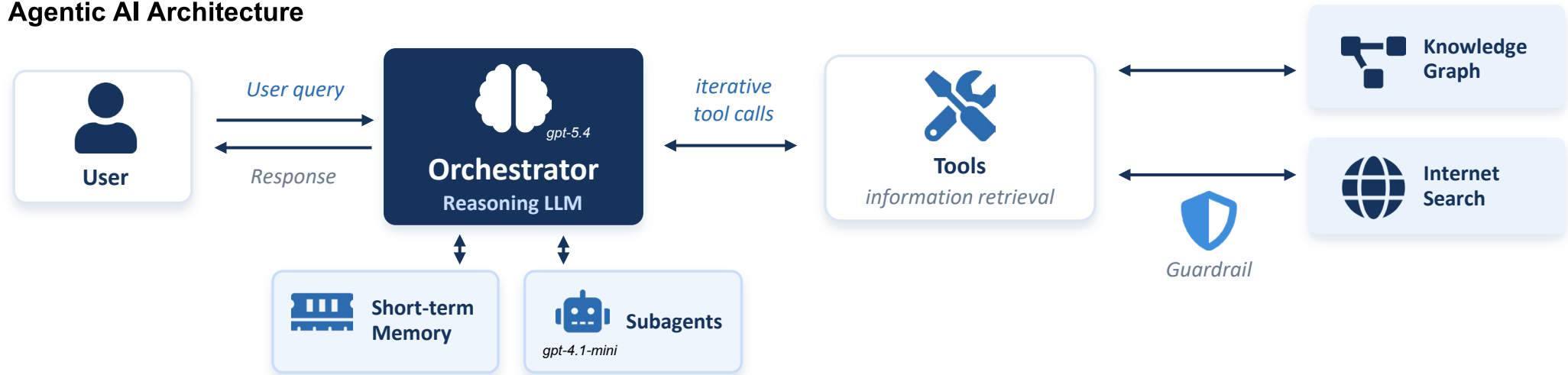


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SupRisk AI Framework

Agentic AI is then use to extract and analyse information from the knowledge graph.

Agentic AI Architecture



User interacts with the knowledge graph and AI system via our platform with 4 modules

SupRisk AI Platform



Vulnerability Analysis

Prioritise key internal vulnerabilities of target groups.



Emerging Risk

Track new and developing risks from related news.



Ask AI Agent

In-depth insights and AI recommendations on demand.



Corporate Structure

Explore group company structures clearly.



Home

Vulnerability Analysis

Emerging Risks

Ask AI Agent

Corporate Structure

Vulnerabilities

Several ownership chains include liquidity- and coverage-weak subsidiaries. This structure can create recurring upstream support needs that interact with already-evidenced funding pressure at key parents.

Organizational Structure

Investment

Strategy & Operations

Finance

Legal

A. Core Group-Level Vulnerabilities

Weak subsidiaries / JVs increase recurring parent support burdens

High

Several subsidiaries are liquidity- and coverage-weak, while their parent entities are also material borrowers. This raises the likelihood that periods are bridged by parent support: guarantees, intercompany loans, or covenant cures. When repeated and concentrated, this amplifies refinancing and liquidity risk at central parents.

Related Entities

Northwind Retail Co.

Summit Commerce Ltd.

Crestline Plaza Holdings

Harbor Logistics PCL

Meridian Development

Eastgate Ventures

- Central Commerce: current ratio 0.84, debt ratio 71% — H1 (2026-03-31).
- Summit Commerce: retained earnings negative; loans THB 0.31bn (2026-03).
- Eastgate Ventures: DSCR 0.78x, ICR 0.91x; refinancing window within 6 months.

Total Exposure

Total Internal Exposure

THB 1.92 bn

Total Bank Exposure

THB 4.10 bn

Severity: Strong evidence

Home

Vulnerability Analysis

Emerging Risks

Ask AI Agent

Corporate Structure

Risks Analysis from News

Select Target Corp

Search Analyzed Target

All

Event Start Date (YYYY-MM-DD)

Event End Date (YYYY-MM-DD)

Source Language

Topic

YYYY-MM-DD

YYYY-MM-DD

All

All

Meridian Group appoints new CEO; Crestline and Apex Materials announce business updates.

2026-06-02

Organizational Structure

Apex Group

Chinese

Crestline Holdings Ltd.

Content

Why Risk

Analysis & Details

Connection Reasoning:

Crestline Holdings Ltd. is contextually linked among high-growth, high-profile regional conglomerates pursuing global and innovation-focused strategies.

Vulnerability Analysis

- Identifies key vulnerabilities, risk concentrations, and potential transmission channels across corporate groups.
- Uses knowledge-graph traversal and AI-driven community analysis to uncover hidden interconnections and risk patterns

Emerging Risks

- Tracks external developments and emerging threats through continuous news monitoring.
- Uses AI to summarise events, identify related entities, classify risk types, and explain potential implications.

Mock-up; entity names and figures are fictitious



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[Home](#) [Vulnerability Analysis](#) [Emerging Risks](#) [Ask AI Agent](#) [Corporate Structure](#)

New Chat

Select Target Corp

MERIDIAN GROUP

Output Setting

Export Output

W DOCX

SupRisk Agent

What are the key exposures of the lead companies in the Meridian Group?

AI

Gathering Information

Quick Summary

From a supervisory view of linkages to the financial system, the main exposures of the lead companies in the Meridian Group currently fall into four areas:

1. Credit risk concentrated in non-bank and bank lenders,

2. High share of debt in Stage 2 across several lead companies,

3. Thin profitability / liquidity at some firms, limiting shock absorption, and

4. Some firms, especially retail / duty-free, rely heavily on cross-border trade.

1) Largest exposure: bank credit concentrated in 3 lead firms

Meridian Commerce International Ltd. approx. THB 29.4 bn

Meridian Retail Corporation Ltd. approx. THB 22.6 bn

Show risk heatmap by lender

Explain Stage 2 migration

Show DSCR / ICR by quarter

Ask a follow-up question.

Ask AI Agent

- Enables users to ask natural-language questions and perform ad-hoc analysis.
- Combines knowledge graph retrieval, internet search, and agentic reasoning to generate contextualised responses.

SupRisk AI Platform

[Home](#) [Vulnerability Analysis](#) [Emerging Risks](#) [Ask AI Agent](#) [Corporate Structure](#)

Select Target Corp

Meridian Group

Reset to Target

Search company name...

Major Shareholders

A. Vance	B. Crest	C. Apex	D. Vance	E. Crest
3.83%	3.49%	3.47%	3.47%	2.68%
F. Apex	G. Vance	H. Crest	I. Apex	J. Vance
2.60%	2.50%	2.15%	2.15%	2.10%

Show 10 more

Meridian Department Store Co., Ltd.

Retail & Trade

Real Estate & Investment

Financial Services (excl. insurance)

Northwind Retail Co. Ownership 100.0% Click to expand

Eastgate Trading Co. Ownership 100.0%

Summit Property Co. Ownership 100.0%

Harbor Estates Co. Ownership 100.0%

Apex Capital Co. Ownership 100.0% Click to expand

Crestline Finance Co. Ownership 100.0%

Corporate Structure

- Provides an interactive view of ownership structures and group relationships.
- Extracts and visualises shareholding and ownership subgraphs to support cross-entity exploration.



Agentic AI Evaluation: Metrics-based assessment

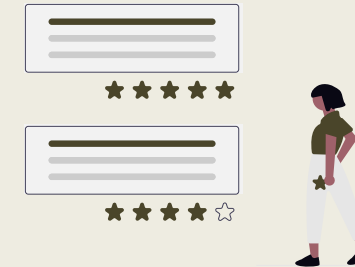
- Basic extraction
 - Conditional screening
 - Cross-dataset integration
 - Ranking
 - Statistical calculation
- Accuracy

Consistency

External Search

Reference
- Data consistency
 - Question sensitivity
 - Time consistency
 - Internet reference
 - Source hierarchy
 - Structured data ref.
 - Unstructured data ref.
- Analytical extraction
 - Event/timeline extraction
 - Non-numerical extraction
 - Numerical extraction
- The evaluation uses a **ground-truth / reference-based Q&A test** with 100 human-curated questions across four dimensions
 - Overall performance was strong, with **97%* overall score**, showing robust capability in data retrieval, reasoning, consistency, and external information use.

User Feedback: Observations from pilot group



Piloted by supervisory staff across financial-institution supervision, financial stability, and financial markets.

What worked

- **Faster to insight** — cuts fragmented review, speeding the move from information-gathering to risk interpretation.
- **Surfaced hidden risk** — prompted cross-functional discussion, revealing transmission channels and systemic vulnerabilities routine processes miss.

Limitations

- Occasional inaccurate responses
- Data gaps or delays in the knowledge graph
- Difficulty with calculations or reasoning beyond the designed scope
- Aligning the analysis with users' regular tasks can be challenging.



Conclusion

- SupRisk AI demonstrates that a knowledge-graph-driven agent can turn scattered supervisory information into timely risk insight.
- The value lies not in complex modeling but in unifying fragmented supervisory data into one AI-accessible framework.
- This unified view enables emerging-risk monitoring, cross-entity analysis, and scenario-based policy assessment.



Lessons Learned

- Knowledge graphs connect data across sources, but don't replace structured-data calculation.
- Broader coverage adds insight but also noise; metadata and provenance keep it reliable.
- Balance automation with judgment: agents may miss their own data gaps, so human oversight stays essential.



Further Work

- Improve complex calculations by drawing on structured data more effectively.
- Expand the pilot to more users, scale data coverage, and integrate live data sources.
- Refine analytical logic by leveraging existing risk-related documents to better support supervisory use cases.



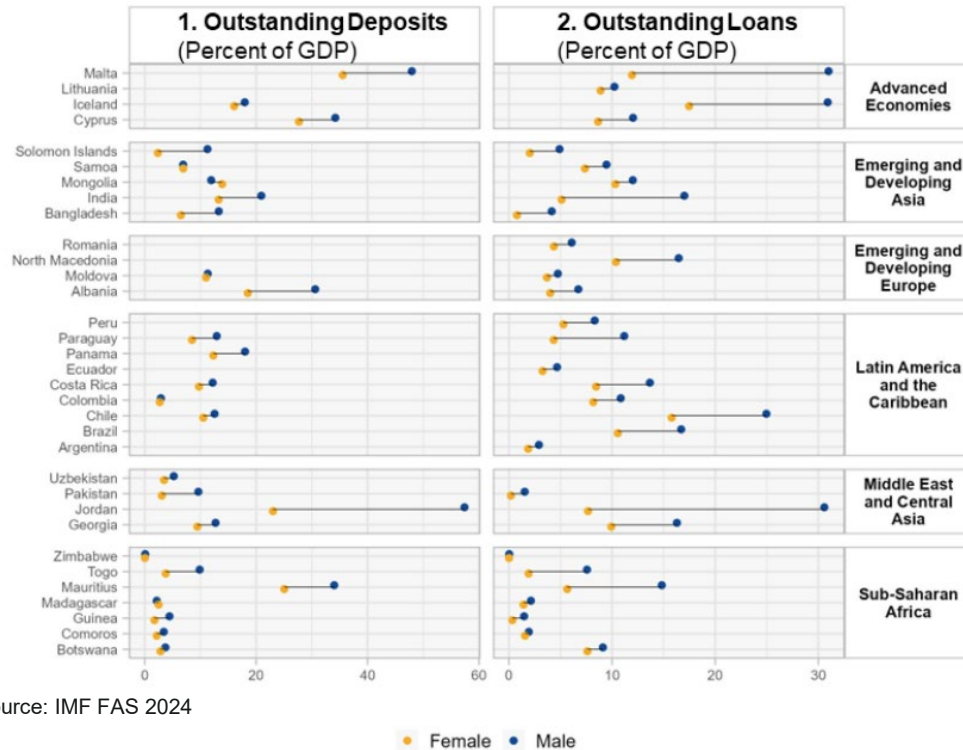
Disaggregated Regulatory Data for Effective Oversight: The Case for Sociodemographic Segmentation

13th IFC Biennial, Basel 20-21 August 2026

Tatiana Alonso

Why granular data and segmented analysis matter

Figure 10. Gender Gaps in Outstanding Loans and Deposits at Commercial Banks in 2023

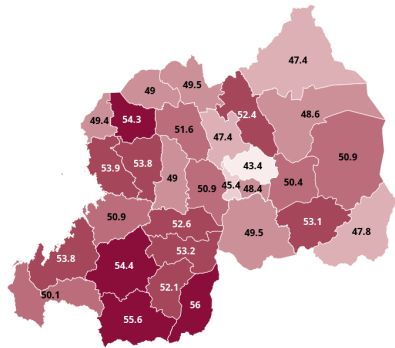


"WHAT DO YOU MEAN IT'S DEEP? IT'S NOT EVEN UP TO MY ANKLES."

- **Problem:** Aggregate data conceals differences in activity, risks and outcomes across customer segments, undermining inclusion, efficiency, safety and stability
- **Solution:** Customer-segmented analysis, complementing provider-level (FSP) prudential and conduct analysis, to improve diagnose and decision making

Illustration for Rwanda

TOTAL CUSTOMERS WITH AN ACTIVE CREDIT ACCOUNT

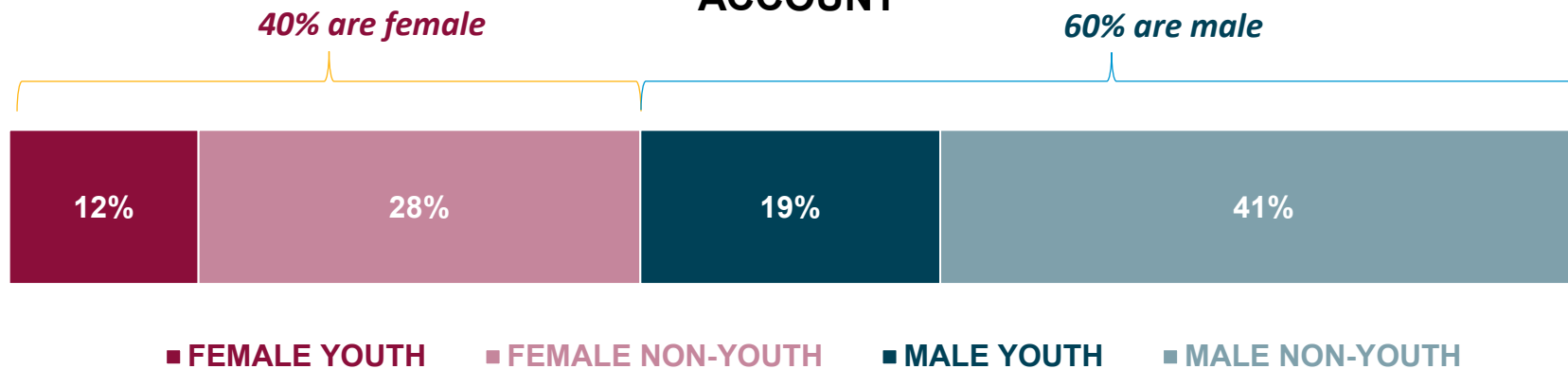


1.05 MILLION CUSTOMERS

HOLD 2.00 Mn ACTIVE CREDIT ACCOUNTS

(~ 12% of Rwandan adults aged 16+)*

GENDER AND AGE SEGMENT OF CUSTOMERS WITH AN ACTIVE CREDIT ACCOUNT

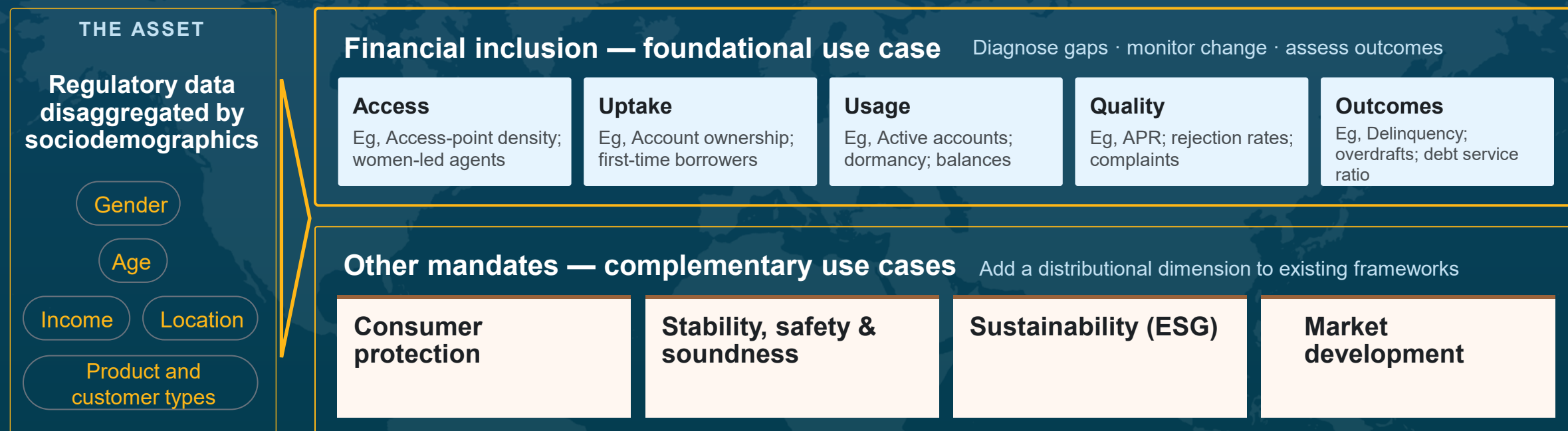


Source: NBR Financial Inclusion Dashboard as at **03/09/2025**

Note: *Population estimates based on medium projected adult population size for 2025 from the 2022 Census

Use cases for sociodemographic disaggregation of regulatory data

Granular data assets **collected once** and **used widely** across FSA mandates, under robust governance and **privacy** protections



IN PRACTICE

Pakistan — Banking on Equality required more women agents; women's account ownership rose 39% → 52% (2021–25).

Rwanda — NBR's granular data anchored the National Financial Inclusion Roadmap 2026–30 and its M&E framework.

The prudential frontier

Most prudential returns sit at Visibility
Tier 0 — segmented analysis is still
largely absent from financial oversight

Stability, safety and soundness

Credit risk Are there disparities in delinquency and NPLs across customer groups, by loan type?
Do firms with diverse board or senior management hold healthier portfolios?

NPLs · delinquency · restructured loans · gender diversity

Operational & conduct risk Is agent gender correlated with fraud events? Do firms with greater diversity
in board and staff present different performance?

Frauds faced · fraud losses · complaints · gender diversity

System-level stability Are deposits held by women or low-income depositors more stable? Is a
more diverse financial sector more stable?

Deposit flow & volatility · gender diversity

FRONTIER DECISION-MAKING

Refine regulatory requirements on evidence;
publish findings; treat sociodemographics as risk
factors / mitigants in RBS models.

EXAMPLE

Mexico — CNBV applied special loan-loss
provisioning on certain loans to women, based on
evidence of lower default rates.

Findings are **signals prompting further inquiry**, not automatic triggers for supervisory
or regulatory action.

SAME DATA ASSET, THREE MORE MANDATES

Consumer protection

Which segments are overcharged or treated unfairly, by which
providers and products — sharpening “customer vulnerability” as a
prioritization driver.

Complaints · rejection rates · processing fees · insurance claims

Sustainability (ESG)

Do green and sustainable products reach low-income women,
female farmers and women-led MSMEs? Does provider diversity
track better governance?

Gender diversity of staff · green loans · green insurance

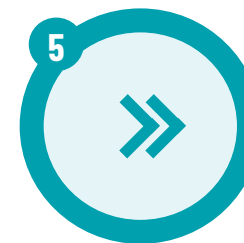
Market development

Who has choice in practice: switching barriers by segment,
concentration of portability rejections, equitable access to capital
markets and crowdfunding, and use of open finance.

Portability · data-sharing consents · Crowdfunding transactions

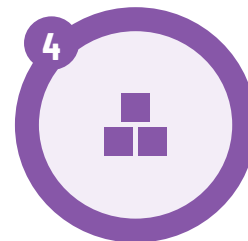
CGAP's (upcoming) Package

TOWARDS GREATER CUSTOMER VISIBILITY



SECTION 5 Design your **IMPLEMENTATION PATHWAY**

- Identify your visibility tier
- Ensure legal & governance foundations
- Design the data strategy
- Ensure proportionality of a phased approach
- Adopt a collaborative approach
- Monitor & evaluate progress



SECTION 4 Understand the **BUILDING BLOCKS**

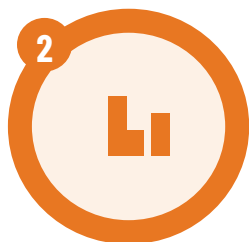
- Data strategy
- Data governance
- Data quality
- Analytical capacity
- Inter-agency data sharing
- Public dissemination
- Technology



SECTION 3 Explore the **USE CASES**

ACROSS FSA MANDATES

- Financial inclusion
- Consumer protection
- Stability, safety & soundness
- Sustainability (ESG)
- Market development

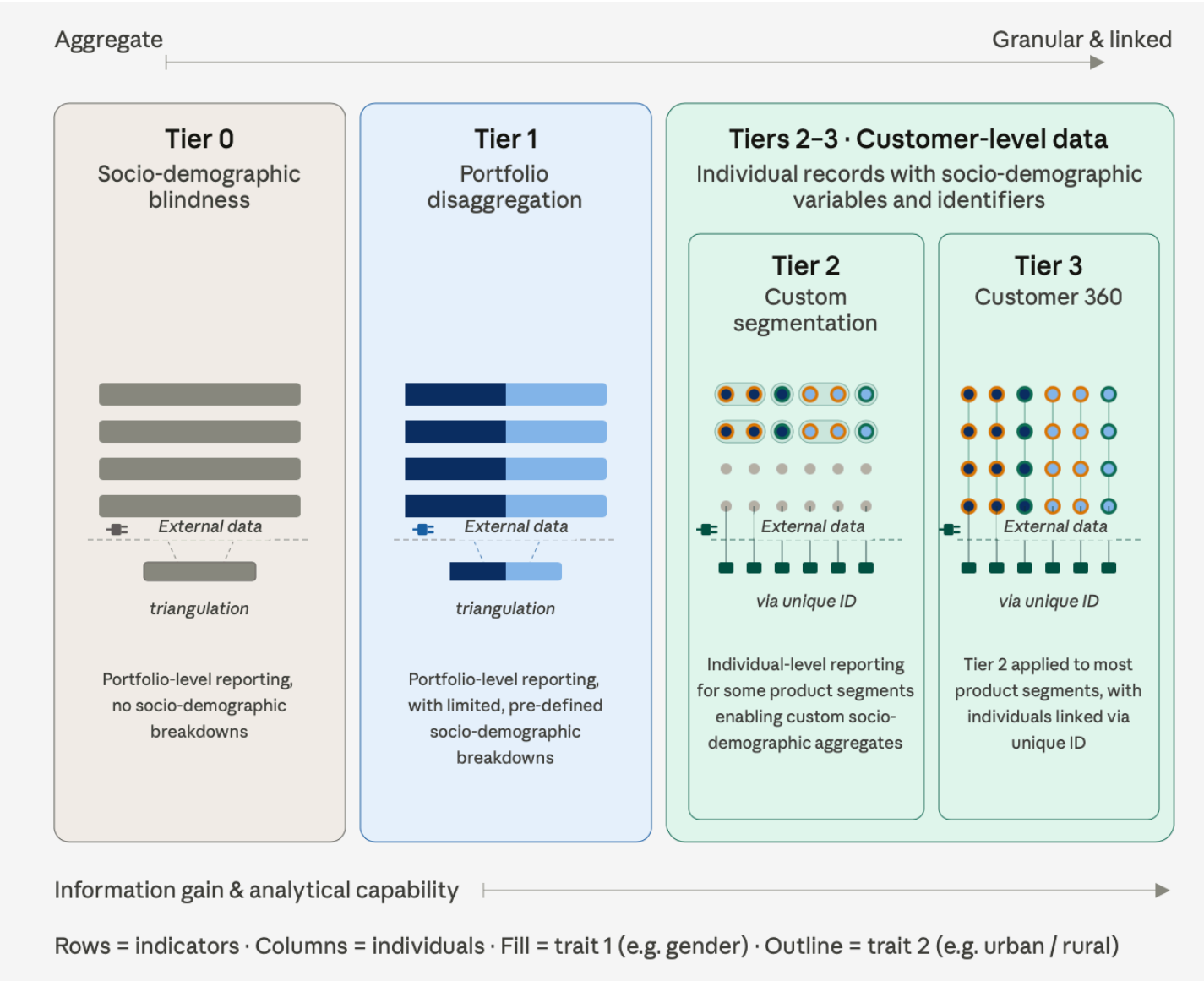


SECTION 2 Identify the necessary **FOUNDATIONS**

FOR SEGMENTED ANALYSIS

- Customer Visibility Tiers (Tier 0 → Tier 3)
- Indicators **CGAP LENS**

CGAPs customer visibility tier framework



CGAP LENS

Non performing loans (NPLs)

Credit risk

Credit

Non performing loans rate in the retail loan portfolio



LENS Beta



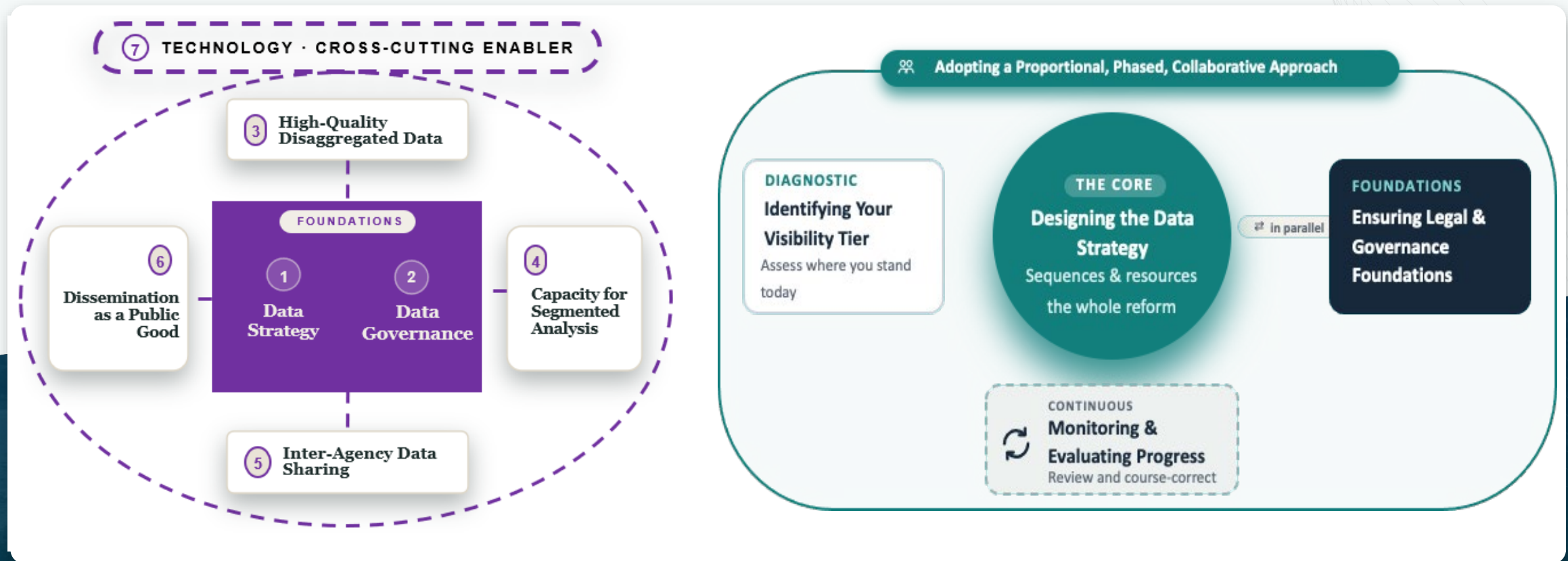
+ Add

Description	Non performing loans rate in the retail loan portfolio
Detailed description	- The NPL indicator for the retail loan portfolio quantifies the share (or absolute value) of consumer and MSME loans that are unlikely to be fully repaid. Because retail credit typically involves high volumes of granular, often unsecured exposures, a build-up of NPLs signals mounting credit risk costs, pressure on provisioning, and potential stress. Supervisors track this metric to assess lenders' underwriting standards, resilience to economic shocks, and the effectiveness of arrears management. Definitions and concepts: An NPL is defined as a loan that is past-due for a minimum amount of days (e.g., 90 days). The definition can vary across countries but the Basel Committee has set common standards. The retail portfolio encompasses exposures to individuals and qualifying MSMEs treated under the retail asset class. The most common ratio is Gross NPLs ÷ Gross retail loans. Aggressive charge-offs or "evergreening" can temporarily lower the NPL ratio without improving underlying asset quality. Seasonality and relief measures: Payment holidays or pandemic moratoria may defer delinquencies, masking latent credit risk.
Exploratory questions that can help guide analysis by socio-demographic segments	Are there gender disparities in NPL rates? Variations in this indicator may be explored across customer gender, customer type, FSP type, product type, loan size, and loan term. Do FSPs with greater gender diversity in their workforce, management, or board, show different performance in this indicator? Do FSPs with different levels of gender balance in their customer base, show different performance in this indicator? This indicator can be analyzed alongside delinquency rates in the retail loan portfolio to explore whether socio-demographic patterns in early-stage delinquency are a reliable leading indicator of NPL outcomes by customer group.
Unit of analysis	For analyses with a primary focus on financial inclusion, for this indicator it is recommended that only retail customers and/or financial products held by retail customers are considered. Where data permits, this indicator can be examined separately for MSMEs.
Suggested breakdowns for segmentation analysis	- Customer type ⓘ - Customer gender ⓘ - Customer age ⓘ - Customer location ⓘ - Customer income category ⓘ - Financial service provider (FSP) type ⓘ - Financial service provider (FSP) main activity ⓘ - Loan type ⓘ - Loan size ⓘ - Loan term ⓘ - Interest rate category ⓘ
Main mandate (main objective)	Stability, safety and soundness (Credit risk)
Secondary mandate (secondary objectives)	Financial inclusion (Quality), Consumer protection (Suitability)
Main financial service	Credit

Links:

- [LENS](#)
- [User Guide](#)
- [Tutorial](#)

Building Blocks and Implementation Considerations





Thank you

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