

# Improving the timeliness of the ESCB carbon indicators with nowcasting techniques

DeNederlandscheBank

EUROSYSTEM

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

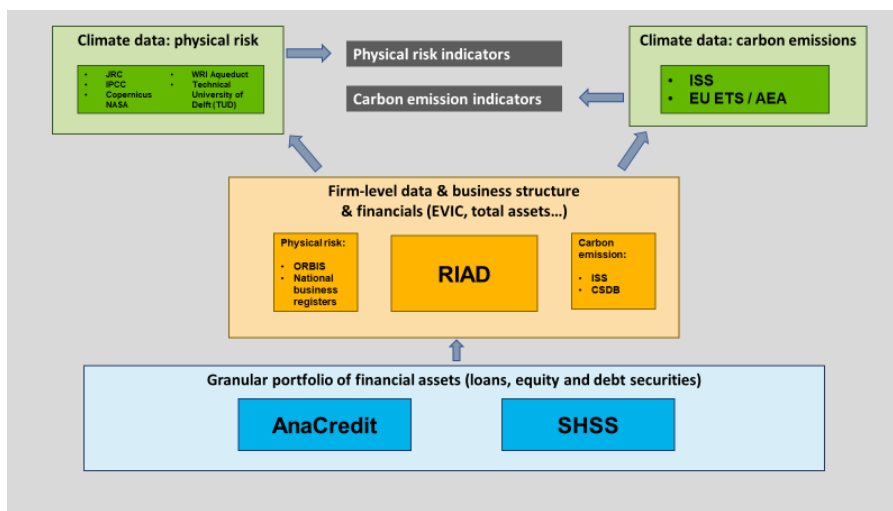


These four indicators show the amount (and share) of carbon emissions that can be attributed to financial institutions via their securities and loan portfolios.

→ 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

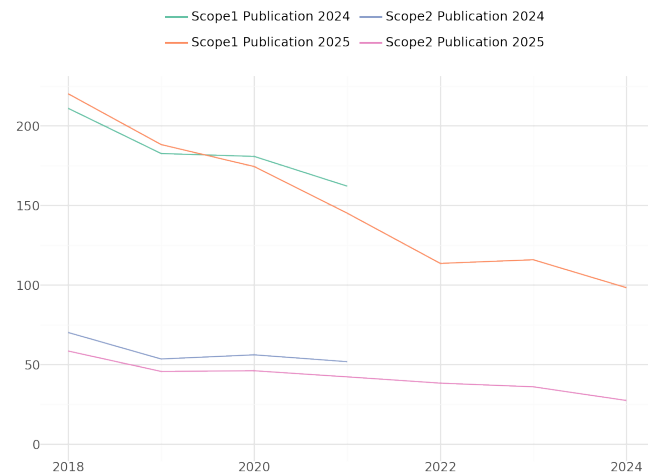
# Timeliness of 2024 publication was hampered by availability of counterparty data

## Weighted average carbon intensity

### 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



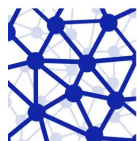
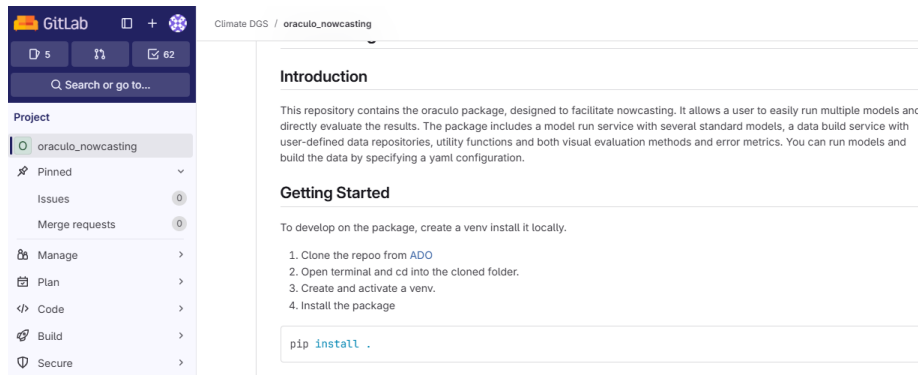
Source: ECB/EG CCS. The results of the 2025 publication are preliminary and only used to indicate the improvement in timeliness

# 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



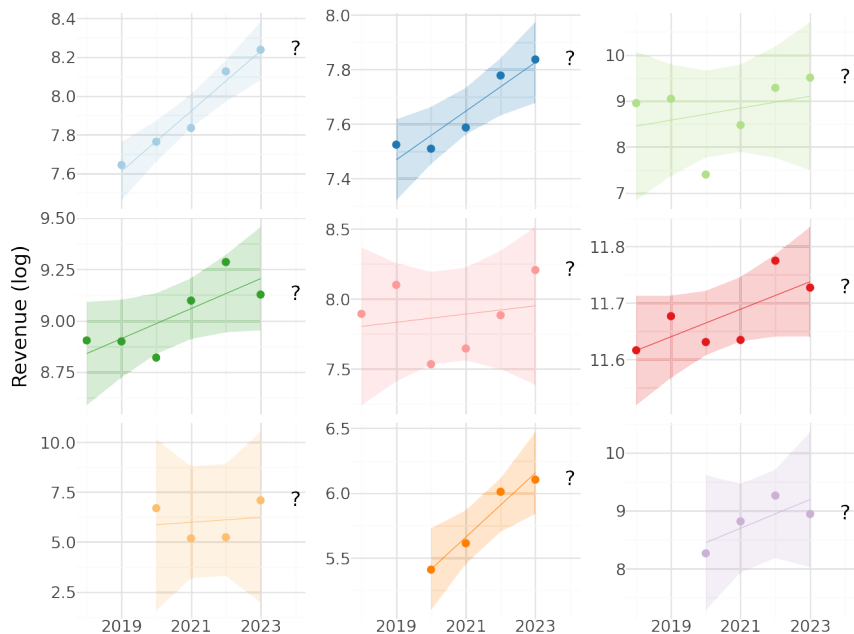
DataScience  
Hub

DeNederlandscheBank

EUROSYSTEM

BANCO DE ESPAÑA  
Eurosistema

# 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

# Nowcast of revenue

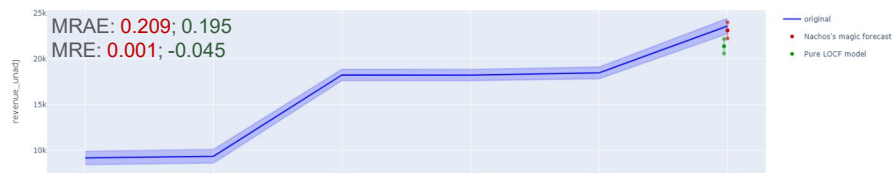
## Prediction model:

$$\widehat{\text{revenue}}_{i,t} = f(\text{revenue}_{i,t-1}, \Delta \text{credit rating}_{i,t})$$

- 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.

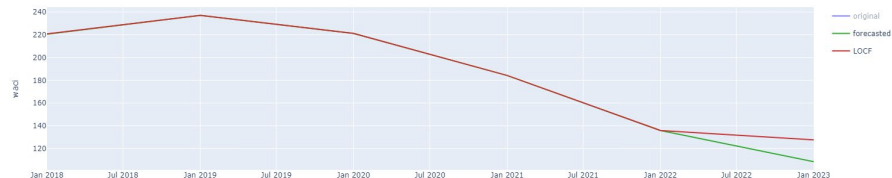
## Forecast year 2023



## Distribution of prediction errors



## Scope1 WACI EA S122



# Nowcast of scope1 and scope2 emissions

Prediction model:

$$\Delta \widehat{\text{emissions}}_{i,t}^{\text{scope}} = f(\text{emissions}_{i,t-1}^{\text{scope}}, \text{oil consumption}_{\text{country},t}, \text{EVIC}_{i,t})$$

- 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



# Questions?

Thank you for listening!

Feedback? Interested in using, or contributing to, the package? Please contact [t.g.husby@dnb.nl](mailto:t.g.husby@dnb.nl)

Oraculo team: Trond Husby, Milan Karsten, Michiel Nijhuis (DNB), Ignacio Felez de Torres (BdE)