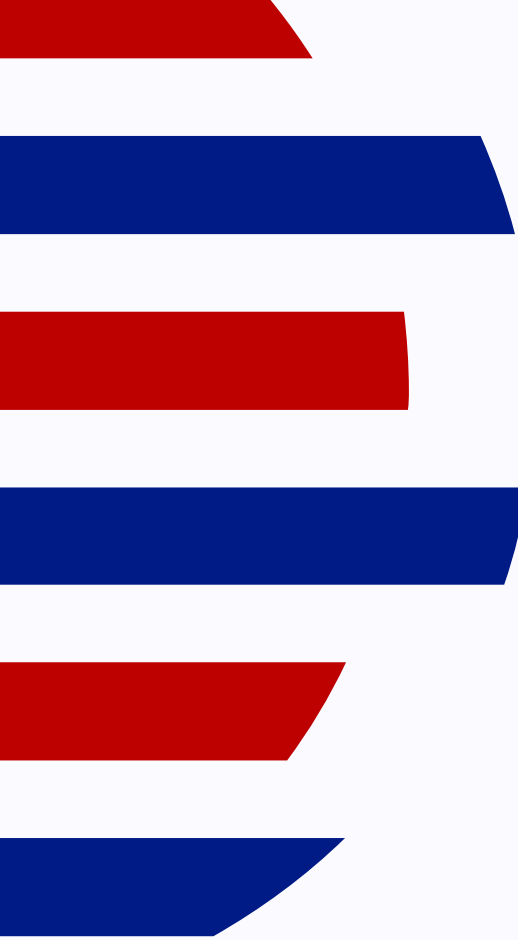




# Trickle down accounting

*Measuring real income growth in distributional  
national accounts*

Joseph Grilli

Beyond the traditional economy: well-being, inclusion and sustainability

Session 3

13th biennial IFC Conference, Basel

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# Data Gaps Initiative and Distributional National Accounts

A key focus of the Data Gaps Initiative (DGI) is to provide links between micro-level data and macroeconomic statistics to better inform policy decisions across a range of subjects. A key focus is to move beyond average measure to distribution measures that better represent heterogeneity.

One of the areas the DGI targeted was improved knowledge of household **income, consumption, and saving** (recommendation 8) and **wealth** (recommendation 9) to better measure the heterogeneity in the household sector.

This has led to the rise of **distributional national accounts (DNA)**, which use micro-level data to look at concentrations of income, consumption and wealth items within the household sector.



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# OECD Distributional National Accounts

The [OECD database](#) publishes quintile level breakdowns for income and consumption, with a view to creating regular annual collections in the future.

## OECD Data Explorer

[Back to the search results](#)

Refine your data selection:

Time period

1

Reference area

1

Accounting entry

1

Transaction

Expenditure

Unit of measure

1

Equivalised disposable income group

48 data points selected in this dataset with:

Reference area:

Canada

Accounting entry:

Balance (revenue minus expenditure)

Unit of measure:

National currency

Frequency of observation:

Annual

Time period:

Start: 2019

End: 2019

Clear all

Overview

Table

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### Household income and saving in the National Accounts: distributions by income quintile

Reference area: Canada • Accounting entry: Balance (revenue minus expenditure) • Time period: 2019

| Equivalised disposable income group                        |                                              |  | Total        | First quintile | Second quintile | Third quintile | Fourth quintile | Fifth quintile |
|------------------------------------------------------------|----------------------------------------------|--|--------------|----------------|-----------------|----------------|-----------------|----------------|
| Transaction                                                | Combined unit of measure                     |  |              |                |                 |                |                 |                |
| Balance of primary incomes, gross / National income, gross | National currency, Canadian dollar, Millions |  | 1 514 375.00 | 44 680.00      | 132 999.00      | 235 074.00     | 378 041.00      | 723 581.00     |
| - Operating surplus and mixed income, gross                | National currency, Canadian dollar, Millions |  | 207 999.00   | 14 407.00      | 29 404.00       | 36 805.00      | 47 740.00       | 79 643.00      |
| - - Operating surplus, gross                               | National currency, Canadian dollar, Millions |  | 120 271.00   | 7 955.00       | 16 935.00       | 22 599.00      | 27 704.00       | 45 078.00      |
| - - Mixed income, gross                                    | National currency, Canadian dollar, Millions |  | 87 728.00    | 6 452.00       | 12 469.00       | 14 206.00      | 20 036.00       | 34 565.00      |
| Disposable income, gross                                   | National currency, Canadian dollar, Millions |  | 1 280 362.00 | 80 065.00      | 162 418.00      | 222 558.00     | 298 307.00      | 517 014.00     |
| - Other current transfers                                  | National currency, Canadian dollar, Millions |  | -18 631.00   | -2 449.00      | -266.00         | -2 649.00      | -3 530.00       | -9 737.00      |
| Adjusted disposable income, gross                          | National currency, Canadian dollar, Millions |  | 1 630 217.00 | 144 375.00     | 238 462.00      | 296 084.00     | 369 222.00      | 582 074.00     |
| Saving, gross                                              | National currency, Canadian dollar, Millions |  | 27 022.00    | -97 387.00     | -44 115.00      | -19 595.00     | 34 739.00       | 153 380.00     |

# Quintile price indices

This paper builds upon the work in Grilli, Schreyer, & Zwijnenburg (2026), which combined the national accounts deflators with the DNA consumption by quintile to estimate quintile-level Fisher price indices.

Using chain-linked price indices, quintile-level disposable income can be deflated to estimate **real disposable income** and savings rates over the period. The paper uses these series to answer:

01

Is inflation heterogeneous across the income distribution?

02

How is growth in consumption financed by different households?

03

How do savings rates vary across households?

# Differential inflation, consumption, and savings

Using the chain-linked fisher price indices at quintile-level, difference within countries show that **poorer households face higher inflation** , contributing to the cost-of-living crisis.

The paper finds that, on average, annual inflation decreases **0.02 pp per quintile** .

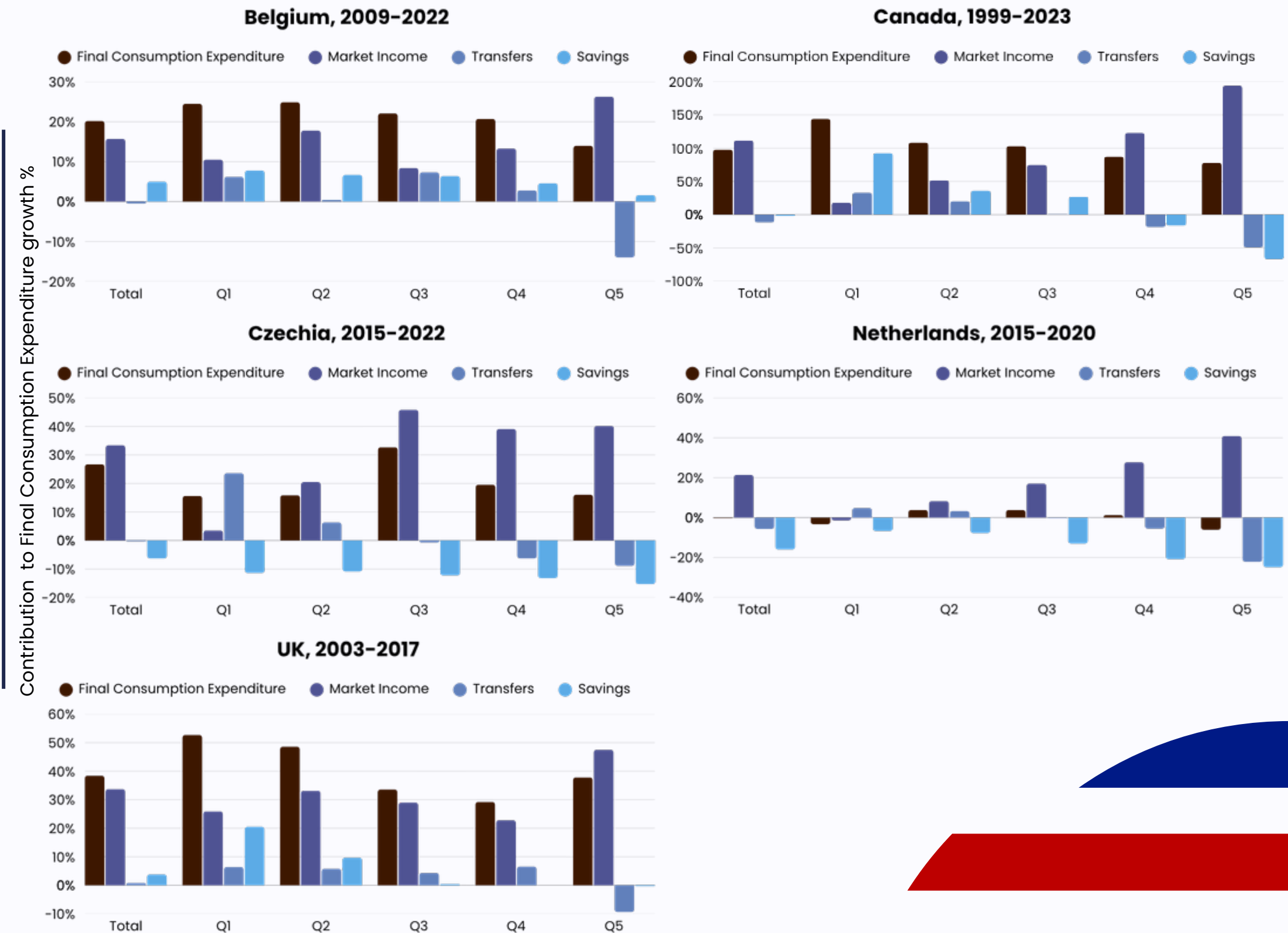
|                         | Total | Quintile 1 | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 |
|-------------------------|-------|------------|------------|------------|------------|------------|
| Belgium (2009–2022)     | 2.27% | 2.35%      | 2.31%      | 2.27%      | 2.24%      | 2.22%      |
| Canada (1999–2023)      | 1.80% | 1.82%      | 1.83%      | 1.81%      | 1.81%      | 1.79%      |
| Czechia (2015–2022)     | 4.11% | 4.24%      | 4.17%      | 4.12%      | 4.09%      | 4.06%      |
| Netherlands (2015–2020) | 1.64% | 1.67%      | 1.65%      | 1.64%      | 1.64%      | 1.64%      |
| UK (2003–2017)          | 1.82% | 1.91%      | 1.79%      | 1.74%      | 1.78%      | 1.87%      |

*The UK experiences deflation in only Paasche or Laspeyres in some periods, resulting in a non-real solution to the Fisher Price Index. We therefore instead report an average of these indices for the UK rather than the root product.*

# Differential inflation, consumption, and savings

Grilli, Schreyer, & Zwijnenburg (2026) established that poorer households face faster price growth but similar real consumption growth rates as richer households. This raises the question: **how do these poorer households fund the difference in cost of living?**

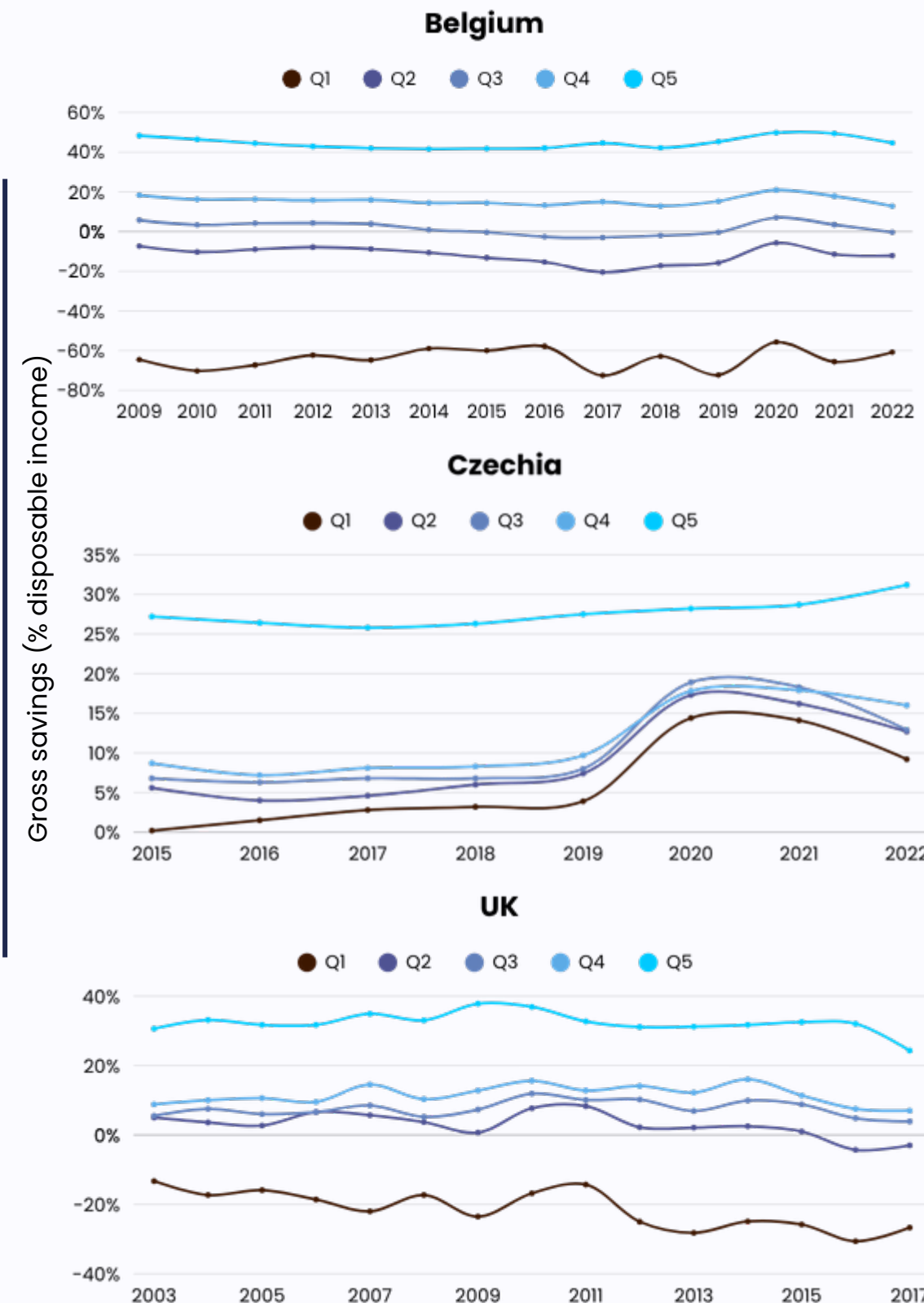
The paper shows that **poorer households** are reliant on **transfer payments** and **dissaving**, while richer households consume from market income earnings.



# Differential inflation, consumption, and savings

With poorer households financing real consumption using savings, this means that the saving rates increase across quintiles in each country.

Estimates in the paper show that savings rates increase with wealth, with the **lowest two quintiles** often reporting **negative saving rates**.



# Conclusions

The paper demonstrates how the distributional national accounts provide information on the heterogeneity of the household sector. The **key findings** of the paper are:

- Inflation rates **decrease** across the income distribution.
- Poorer households maintain increases in real consumption using dissaving, resulting in **negative** saving rates.
- Macroeconomic statistics in the national accounts may differ in **sign** to those for quintiles of the income distribution.

Behaviour such as negative saving rates and differentiated inflation will impact the **transmission mechanisms** of conventional policies. However, the use of distributional national accounts can improve the efficiency of policies by providing more information for **targeted interventions**.

# The Distributional Credit Channel of Monetary Policy: Microevidence from Consumer Loans in Peru

Sebastian Paz

Central Reserve Bank of Peru

13th Biennial IFC Conference, Basel

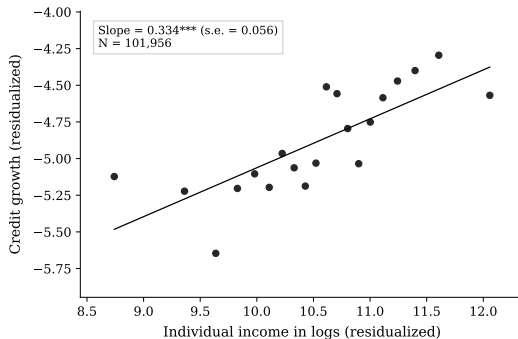
The views expressed are those of the author and do not necessarily reflect the position of the Central Reserve Bank of Peru.

## Question

- Monetary policy transmits through **credit conditions**. Growing focus on **heterogeneous** effects across households.
- Is the response of **consumer credit** to MP uniform across borrowers, or does it vary with **income**?
- Especially relevant in an **emerging, dollarized** economy with uneven financial inclusion.

## This paper

- Novel match: confidential **Credit Register (RCC, BCRP)** ↔ **Household Survey (ENAHU, INEI)**, via non-public keys.
- **Borrower-level** credit *quantities*; income  $\times$  shock interaction.



Credit growth vs. log income, residualized on region & entity FE. Slope 0.334\*\*\*,  $N = 101,956$ .

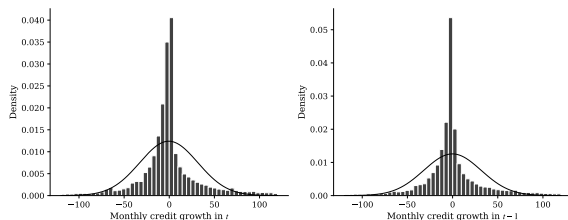
## Three findings

- ① A contractionary shock **reduces credit growth for higher-income borrowers**; lower-income borrowers show **no contraction — or mild expansion**.
- ② Heterogeneity is **specific**: it operates through **revolving credit** and **during contractionary episodes**.
- ③ **Non-revolving credit** shows no income heterogeneity (dynamics dominated by amortization).

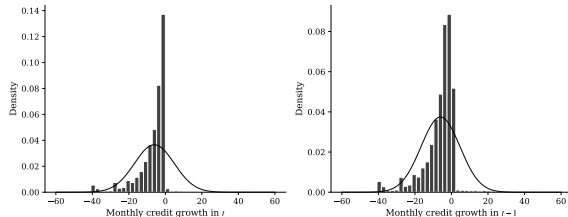
**Data.** Client–product–month, **2011M1–2019M12** (excludes COVID-19);  $\approx 80,000$  obs. (32,591 revolving; 45,329 non-revolving). Essentially **cross-sectional**.

- Dependent variable: **log difference** of outstanding balance; FX balances converted at the monthly rate.
- MP shock: **Pozo & Rojas (2025)**,  $\epsilon_t^{MP} > 0 = \text{contractionary}$ .

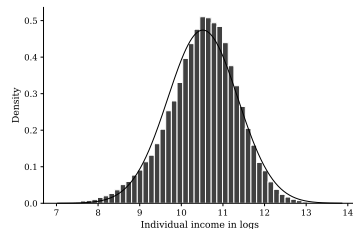
# The variables: distribution of credit growth by product and income



**Revolving credit growth ( $t, t - 1$ ):** approx. **normal**, both sides.



**Non-revolving credit growth:** **left-truncated** — balances only amortize.



**Log income:** symmetric, wide dispersion ( $\sim 7$  to 14).

- **Revolving** loans are more volatile (17.6% vs 8.9%) and *symmetric*  $\Rightarrow$  lets us later split **contractionary vs. expansionary** episodes.
- **Non-revolving** loans growth is markedly **left-truncated** due to amortization.
- Income variation **identifies** the heterogeneity.

To assess the heterogeneous impact of MP, we estimate:

$$\Delta y_{i,t} = \alpha + \beta_1 \Delta y_{i,t-1} + \beta_2 \epsilon_t^{MP} + \beta_3 \text{Income}_{i,t} + \underbrace{\beta_4 \text{Income}_{i,t} \times \epsilon_t^{MP}}_{\text{coefficient of interest}} + \nu_p + \gamma_e + \xi_c + \varepsilon_{i,t}$$

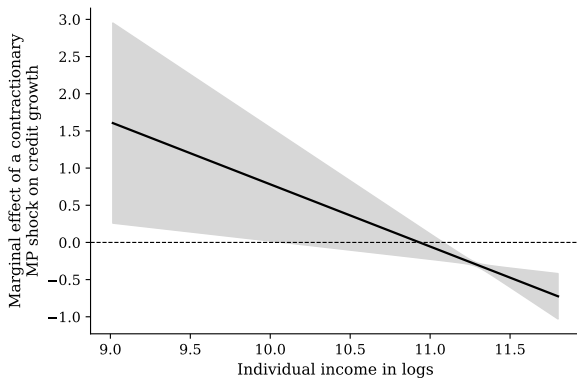
When **both credit types** (revolving and non-revolving) are considered together:

|                                        | (1)      | (2)                 | (3)                  |
|----------------------------------------|----------|---------------------|----------------------|
| $\Delta y_{i,t-1}$                     | 0.557*** | 0.557***            | 0.561***             |
| $\Delta y_{i,t-2}$                     |          |                     | 0.009**              |
| $\epsilon_t^{MP}$                      | 0.345    | 9.149**             | 8.955**              |
| $\text{Income}_{i,t}$                  | 0.134*** | 0.137***            | 0.155***             |
| $\text{Income} \times \epsilon_t^{MP}$ |          | -0.837**<br>(0.302) | -0.819***<br>(0.291) |
| $R^2$                                  | 0.269    | 0.269               | 0.278                |
| Obs.                                   | 88,253   | 88,253              | 83,293               |

All: region / entity / credit-type FE. Two-way clustered SE.  
Cols. (4)–(5) Tobit (in paper) confirm.

- Credit is highly **persistent**.
- Income enters **positively**.
- The shock **alone** is not significant, but the **interaction is negative and significant**.
- The higher the income, the **stronger the (negative) impact** of a tightening.

# Marginal effect and interpretation



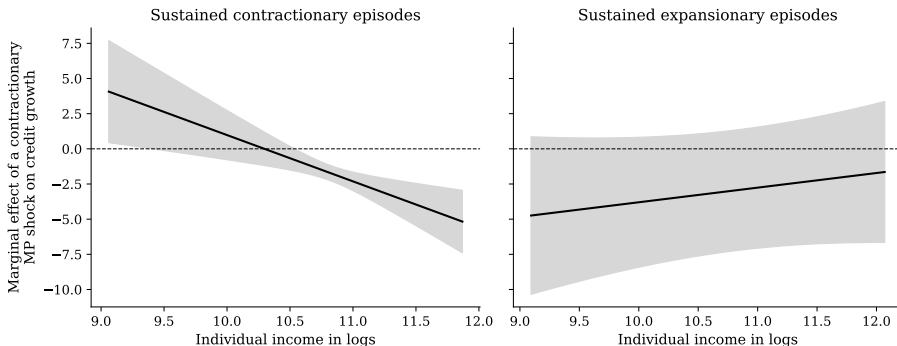
50 bp  $\Rightarrow$   $-0.52$  pp at  $+2\sigma$  income;  $+0.86$  pp at  $-2\sigma$ .

The marginal effect **declines monotonically** with income.

- **Higher-income:** more integrated into formal credit, fewer binding constraints  $\Rightarrow$  credit responds **elastically**; adjusts downward when MP tightens.
- **Lower-income:** closer to credit limits, credit for non-deferrable expenses  $\Rightarrow$  little room to contract — and sometimes **draw further** on available lines.

A channel of **differential sensitivity**, not uniform contraction.

## Where it operates: revolving credit, tightening only



**Contractionary episodes:** steep decline with income; band excludes zero at both ends. Tightening *raises* credit growth for low-income and *reduces* it for high-income borrowers.

**Expansionary episodes:** flat, statistically indistinguishable from zero throughout.

**Robustness.** The pattern is confirmed **non-parametrically across income deciles**, is **robust to alternative clustering** (region, entity, two-way, HC1), and is **absent for non-revolving credit**.

- MP transmission to consumer credit in Peru is **far from homogeneous**: a tightening compresses credit growth **most among higher-income borrowers**; lower-income borrowers show no significant contraction — or mild expansion.
- The heterogeneity is **specific, not pervasive**: **revolving credit, contractionary episodes**. Absent for non-revolving credit. Robust to clustering and to non-parametric estimation across deciles.

### Policy reading

Because higher-income borrowers are more integrated into formal credit markets, tightening compresses **their** credit more, while constrained lower-income borrowers adjust little along this margin. **The credit-side effects of monetary policy fall unevenly across the income distribution** — a dimension obscured in aggregate analyses.

**Thank you** · Sebastian Paz · Central Reserve Bank of Peru

## Navigating the value chain – from the top to the bottom and back again

A unified statistical framework for micro and macro level carbon accounting

**Ulf von Kalckreuth, Deutsche Bundesbank, DG Data and Statistics**

13th IFC Biennial Conference on 20-21 August 2026

The presenter is Principal Economist-Statistician at the DG Data and Statistics of the Deutsche Bundesbank and may be contacted as follows: Ulf von Kalckreuth, Deutsche Bundesbank, PO Box 100602, 60006 Frankfurt am Main, Germany. Email: [ulf.von-kalckreuth@bundesbank.de](mailto:ulf.von-kalckreuth@bundesbank.de). He is current or past member of the following groups: Scope 3 TWG of the Greenhouse Gas Protocol, the TWG supporting the development of the E-Liability protocol standard for carbon accounting, the G20 Data Gaps Initiative Task Team, the NGFS Expert Network Research and the ESCB Statistics Committee Expert Group on Climate Change Statistics. The paper represents the author's personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank or its staff, nor of any of the working groups and teams mentioned above.

# Indirect emissions are somebody else's emissions!

Direct emissions are under the reporting entity's control.

Indirect emissions are generated by other entities. They may occur:

**upstream:** suppliers, suppliers of suppliers, etc.

**downstream:** customers, customers of customers, users, disposal.

In most cases, counterparties have no reporting obligation to the firm.

Yet indirect emissions are crucial for:

sustainable finance,

transition risk,

product carbon accounting,

portfolio footprints.

**Question:** Can upstream and downstream emissions be estimated in one coherent statistical framework?

# Upstream, the well-known benchmark

For upstream emissions, the key relationship is a recursion:

*Product carbon content = direct emissions + carbon content of inputs*

For product or industry  $k$  :

$$\begin{array}{l} \text{carbon contents} \rightarrow c_k = d_k + \mathbf{c}' \mathbf{a}_k = d_k + \sum_i c_i a_{ki} \\ \text{direct emissions} \rightarrow \quad \quad \quad \text{indirect emissions} \end{array}$$

In matrix form:

$$\mathbf{c}' = \mathbf{d}' + \mathbf{c}' \mathbf{A}$$

Solving the system yields all product carbon contents simultaneously:

$$\mathbf{c}' = \mathbf{d}'(\mathbf{I} - \mathbf{A})^{-1}$$

**A** *input requirement matrix*

**c** *carbon content (direct + indirect intensities)*

**d** *direct emission intensities*

$(\mathbf{I} - \mathbf{A})^{-1}$  *Leontief inverse*

# Why downstream is different

**Upstream:**                    **suppliers → producers**

Inputs bring carbon content into the product. Emissions are accumulated

**Downstream:**                **producer → subsequent producers and users**

- Output is used in many subsequent production processes
- Subsequent emissions must be attributed back to earlier inputs
- This attribution is not unique!

**Example:** Steel, tyres, screws, chemicals or components may enter many different downstream activities

**Core difficulty:** there is no downstream analogue to carbon content unless we choose an allocation rule

# Setting up the downstream recursion

According to GHG Protocol, downstream emissions in processing are the *sum of direct and Scope 2 emissions* down the value chain. As above for upstream emissions, we set up a recursion:

Let  $N_i$  denote *induced emissions* by product  $i$ :

$$N_i = D_i + E_i + \sum_k r_{i,k} N_k$$

Induced emissions of  $i$

Direct ( $D_i$ ) and Scope 2 ( $E_i$ ) emissions of  $i$

Allocation factor  $r_{i,k}$

Induced emissions of downward production allocated to product  $i$

# The key step

As allocation factor  $r_{i,k}$ , consider the **value of input  $Z_{i,k}$  as a share of total value of output  $k$** :

$$r_{i,k} = p_i Z_{i,k} / p_k X_k$$

$Z_{i,k}$      *quantity of input  $i$  used in product  $k$*

$p_i Z_{i,k}$      *value of input  $i$*

$X_k$      *output product  $k$*

$p_k X_k$      *value of output  $k$*

Why this rule?

- intuitive and transparent
- compatible with cost accounting practices
- implementable with IO data
- yields a closed form solution!

**Important: this is an allocation rule, not a physical causation claim!**

# The downstream solution

## A Gosh-type inverse for downstream emissions

Let  $n_i$  be the *induced downstream emission intensity of product i*

After value allocation:

$$n_i = d_i + e_i + \sum_k s_{i,k} n_k = d_i + e_i + \mathbf{s}'_i \mathbf{n}$$

with

$$s_{i,k} = p_i Z_{i,k} / p_i X_i = Z_{i,k} / X_i \quad \text{the share of product i used as input for k.}$$

In matrix form:

$$\mathbf{n} = \mathbf{d} + \mathbf{e} + \mathbf{S}\mathbf{n}.$$

Solving for  $\mathbf{n}$ , one obtains:

$$\mathbf{n} = (\mathbf{I} - \mathbf{S})^{-1}(\mathbf{d} + \mathbf{e})$$

$\mathbf{S}$ : matrix of inter-industrial output shares.  $(\mathbf{I} - \mathbf{S})^{-1}$ : Ghosh inverse.

For GHG Protocol cat 10, subtract direct emissions  $\mathbf{d}$  and Scope 2 emissions  $\mathbf{e}$ .

# Downstream recursion – interpretation

Downstream induced emissions are obtained by walking down the value chain. This is **not a supply-shock interpretation** of the Ghosh model. It is an **ex post allocation** of emitted GHGs.

## Synopsis of upstream and downstream recursions

| Question             | Direction                                 | Matrix           | Coefficients           | Emission base       |
|----------------------|-------------------------------------------|------------------|------------------------|---------------------|
| Upstream emissions   | From inputs to output (cradle to gate)    | Leontief inverse | Input coefficients     | Direct emissions    |
| Downstream emissions | From output to later uses (gate to grave) | Ghosh inverse    | Value shares in output | Direct plus Scope 2 |

**Common:** direct emission intensities, production interlinkages, input-output-tables, emission accounts

**Difference:** upstream – accumulate emission forward, downstream: accumulate emission backwards

**Main contribution:** A parallel IO-based framework for upstream and downstream indirect emissions.

# Empirical illustration and conclusion

Table 1:

Emission intensities world-wide, according to broad activities:

Direct, scope 2, upstream indirect and downstream processing emission intensities in kg/€

| Broad activity          | Direct | Scope 2 | Upstream indirect | Downstream indirect Cat 10, processing |
|-------------------------|--------|---------|-------------------|----------------------------------------|
| Primary                 | 1.1224 | 0.0904  | 0.5575            | 1.1616                                 |
| Manufacturing & repair  | 0.2018 | 0.0818  | 0.8026            | 0.4841                                 |
| Energy, water, sewerage | 2.7204 | 0.4975  | 1.0927            | 1.5002                                 |
| Construction            | 0.0393 | 0.0239  | 0.6816            | 0.0620                                 |
| Trade                   | 0.0407 | 0.0383  | 0.2001            | 0.3906                                 |
| Transport               | 0.3131 | 0.0457  | 0.3511            | 0.6409                                 |
| Other services          | 0.0117 | 0.0374  | 0.1665            | 0.1965                                 |
| Total                   | 0.2437 | 0.0691  | 0.4500            | 0.4080                                 |

Note: Emission intensities based on FIGARO data, 2022 preliminary results, weighted averages

- Downstream processing emissions are material. Differ strongly across industries and countries.
- Official IO and emission data can provide consistent starting values for carbon accounting.
- The framework links carbon accounting, climate statistics and sustainable finance.

# Selected references

Ghosh, A. (1958), “Input-output approach in an allocation system,” *Economica*.

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WRI and WBCSD (2011, 2013), *GHG Protocol Scope 3 Standard and Technical Guidance*.

von Kalckreuth, U. (2025), “Product carbon contents – an encompassing and market based information system,” *Latin American Journal of Central Banking*.

von Kalckreuth, U. (2026), “Navigating the value chain – from the top to the bottom and back again,” *unpublished working paper*

Backup slides

# Four conclusions:

1. **Upstream emissions** are naturally handled by the Leontief framework.
2. **Downstream emissions** can be handled similarly using a Ghosh-type framework.
3. **Allocation by output value** is the key that makes the downstream solution tractable.
4. **The framework is immediately useful for:**
  - official statistics,
  - company carbon accounting,
  - product-level proxies,
  - sustainable-finance portfolio footprints.

Many thanks!

# From theory to statistics

## **Data requirements**

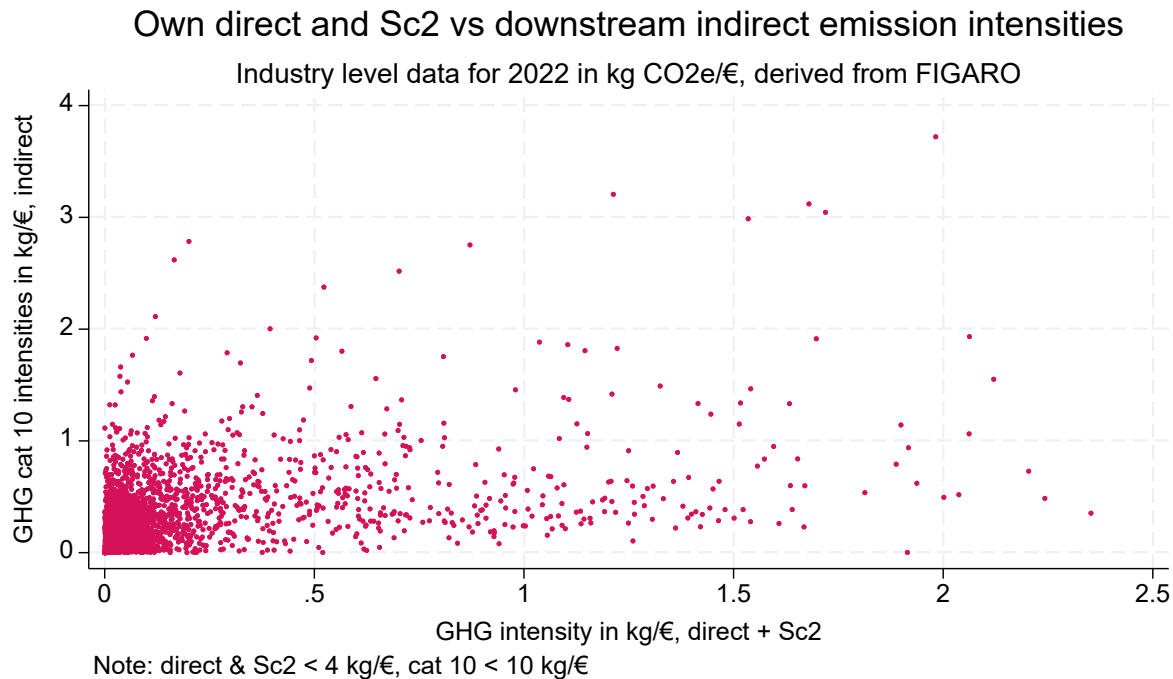
- Multiregional input-output data.
- Direct emission intensities by country and industry.
- Scope 2 estimates.
- Output-use shares.

## **Data source used**

- Eurostat FIGARO input-output data.
- Air emission accounts.
- 46 countries / regions.
- 64 industries.
- 2022 preliminary results.

Industry-level aggregates, not firm-level measures.

# From theory to statistics – dispersion of aggregate intensities



Each dot is one country-industry combination. We see:

- Strong dispersion
- Low direct emitters may have substantial downstream induced emissions.

# From theory to statistics – intensities for large areas

Table 2:

Emission intensities world-wide, according to large areas:

Direct, scope 2, upstream indirect and downstream processing emission intensities in kg/€

|             | Direct | Scope 2 | Upstream indirect | Downstream indirect<br>Cat 10, processing |  |  |  |
|-------------|--------|---------|-------------------|-------------------------------------------|--|--|--|
| Large areas |        |         |                   |                                           |  |  |  |
| EA          | 0.0796 | 0.0141  | 0.2108            | 0.2094                                    |  |  |  |
| USA         | 0.1135 | 0.0273  | 0.1646            | 0.1603                                    |  |  |  |
| China       | 0.3361 | 0.1390  | 0.8768            | 0.6937                                    |  |  |  |
| Japan       | 0.1377 | 0.0437  | 0.3391            | 0.2744                                    |  |  |  |
| Total       | 0.1866 | 0.0651  | 0.4393            | 0.3683                                    |  |  |  |

Note: Emission intensities based on FIGARO data, 2022 preliminary results, weighted averages

- Emission intensities differ strongly between major regions.
- China has very high direct, Scope 2, upstream and downstream intensities.
- Euro area intensities are much lower.
- Differences reflect both output structure and technology and energy mix.

Note: Substituting one region's intensity by another can be highly misleading!

# From theory to statistics – broad activities in Germany

Table 3:

Emission intensities in Germany, according to large areas:

Direct, scope 2, upstream indirect and downstream processing emission intensities in kg/€

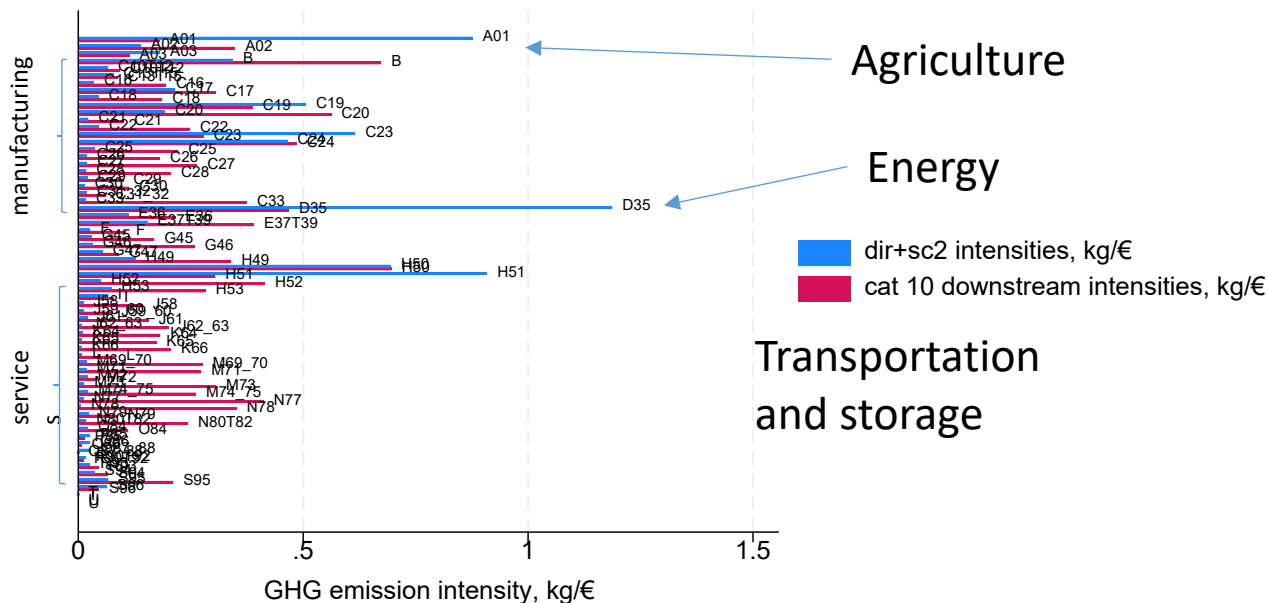
|                         | Direct | Scope 2 | Upstream indirect | Downstream indirect Cat 10, processing |  |  |  |
|-------------------------|--------|---------|-------------------|----------------------------------------|--|--|--|
| Broad activity          |        |         |                   |                                        |  |  |  |
| Primary                 | 0.7063 | 0.0232  | 0.2430            | 0.2823                                 |  |  |  |
| Manufacturing & repair  | 0.0801 | 0.0193  | 0.3329            | 0.2239                                 |  |  |  |
| Energy, water, sewerage | 0.7356 | 0.1388  | 0.3334            | 0.4385                                 |  |  |  |
| Construction            | 0.0180 | 0.0084  | 0.2248            | 0.1056                                 |  |  |  |
| Trade                   | 0.0216 | 0.0177  | 0.1134            | 0.1854                                 |  |  |  |
| Transport               | 0.1640 | 0.0146  | 0.2206            | 0.3874                                 |  |  |  |
| Other services          | 0.0089 | 0.0107  | 0.0783            | 0.1331                                 |  |  |  |
| Total                   | 0.0815 | 0.0196  | 0.1905            | 0.1945                                 |  |  |  |

Note: Emission intensities based on FIGARO data, 2022 preliminary results, weighted averages

- Germany has relatively low direct emission intensities.
- Indirect upstream and downstream intensities remain substantial.
- Sectoral structure matters – strong heterogeneity.

# From theory to statistics – industries in Germany

Germany: Downstream emissions by industry  
GHG intensities: direct/sc2 vs cat 10 downstream emissions



# Downstream recursion – reporting

Four categories of downstream indirect emissions in GHG Protocol relevant for the present analysis:

- Category 9                      *Downstream transportation and distribution;*
- Category 10                   *Processing of sold products;*
- Category 11                   *Use of sold products;*
- Category 12                   *Disposal of sold products.*

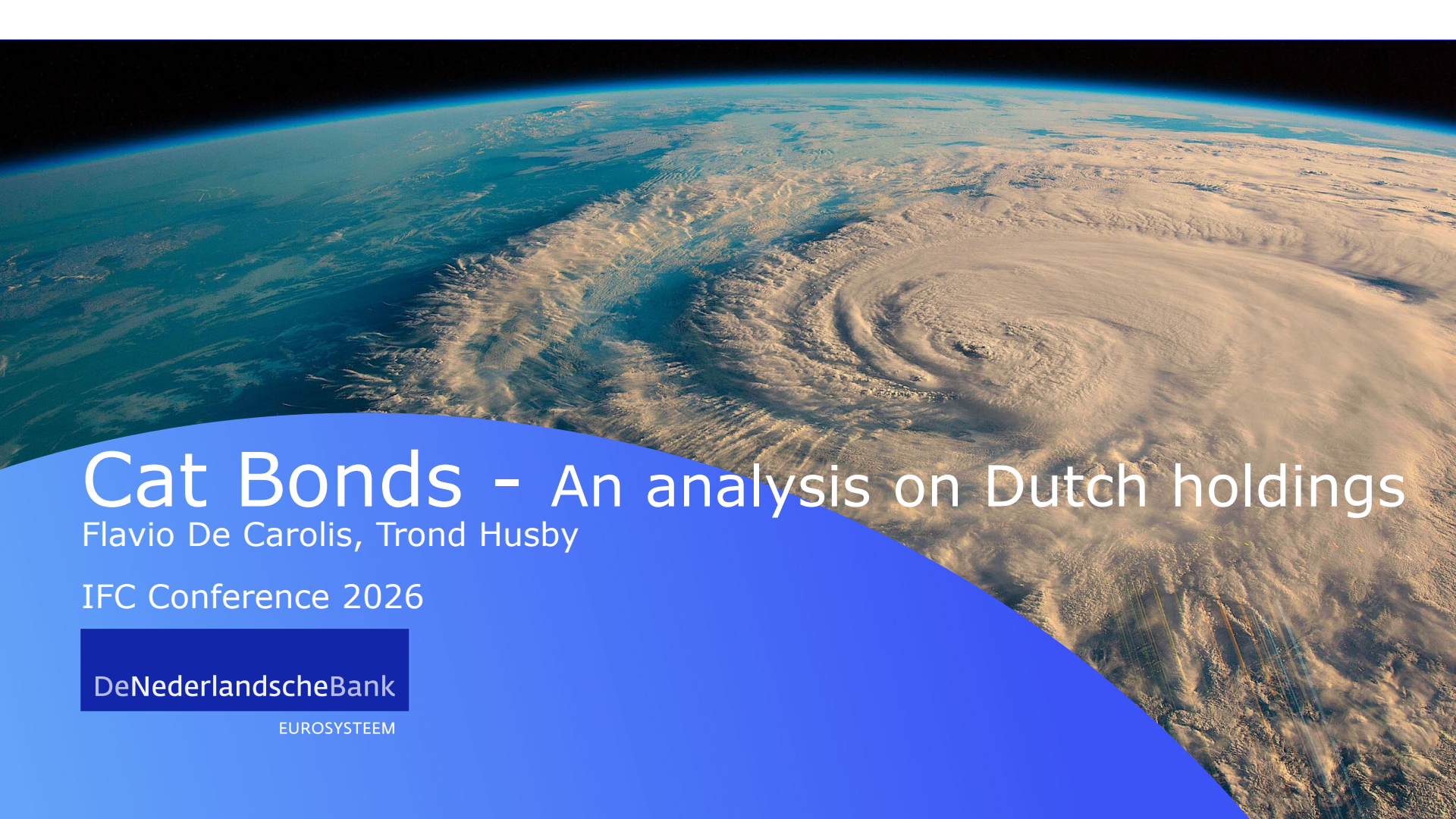
GHG emissions are to be reported category by category. Subtract direct emissions:

$$\mathbf{c}_{10} = [(\mathbf{I} - \mathbf{S})^{-1} - \mathbf{I}](\mathbf{d} + \mathbf{e}) = \mathbf{M}(\mathbf{d} + \mathbf{e}), \text{ with } \mathbf{M} = (\mathbf{I} - \mathbf{S})^{-1} - \mathbf{I}.$$

And likewise:

$$\mathbf{c}_9 = \mathbf{M} \cdot \mathbf{t}; \qquad \mathbf{c}_{11} = \mathbf{M} \cdot \mathbf{u}; \qquad \mathbf{c}_{12} = \mathbf{M} \cdot \mathbf{w}.$$

$\mathbf{t}$ ,  $\mathbf{u}$  and  $\mathbf{w}$  are intensity vectors corresponding to downstream transportation activities (cat 9), emissions due to final use (cat 11), and emissions for the removal of waste (cat 12).



# Cat Bonds – An analysis on Dutch holdings

Flavio De Carolis, Trond Husby

IFC Conference 2026

DeNederlandscheBank

EUROSYSTEM

# Intro

- **Motivation**

- i. Extreme weather events driven by a changing climate are increasing in number and magnitude.
- ii. Cat bonds are issued to insure from catastrophic event damages and are uncorrelated with financial markets downturns.

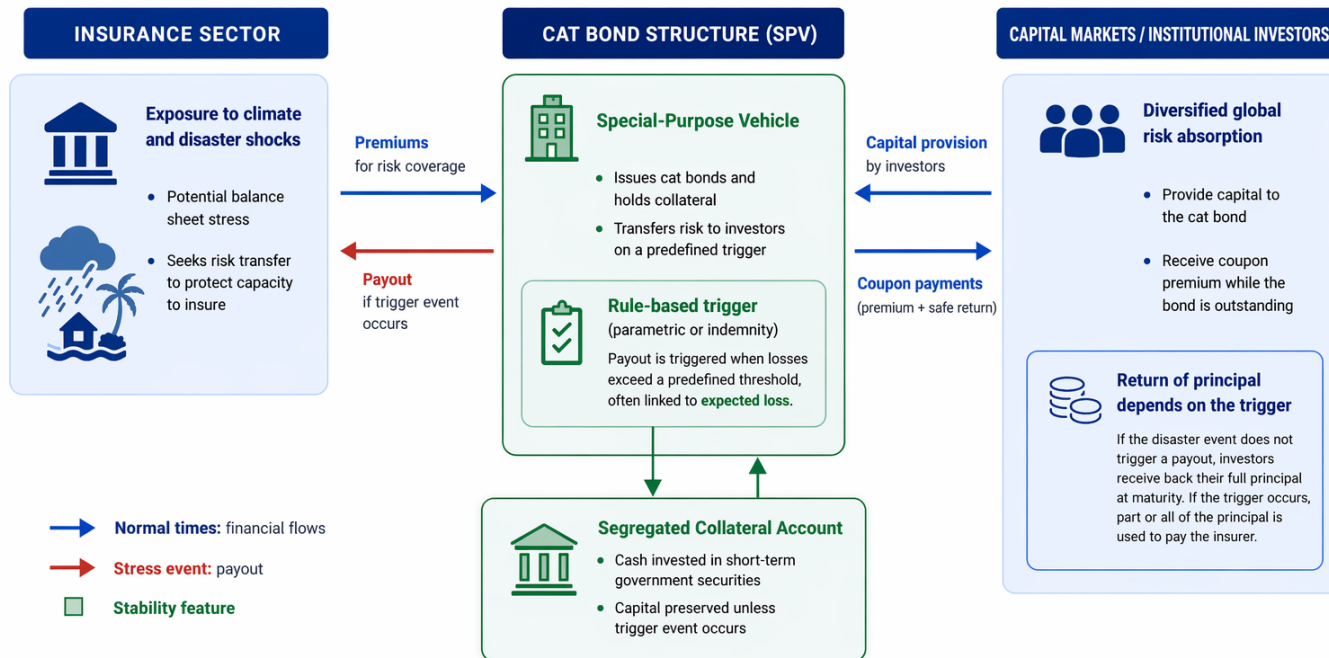
- **Research Question:**

- i. What are the trends for Cat bonds in Dutch financial institution holdings?
- ii. Is all relevant information available for the investor?

- **Contribution:**

- Public disclosure of institutional investors Dutch holdings are scarce, exception made for one large Dutch pension fund.
- We fill this gap by investigating confidential security holdings.

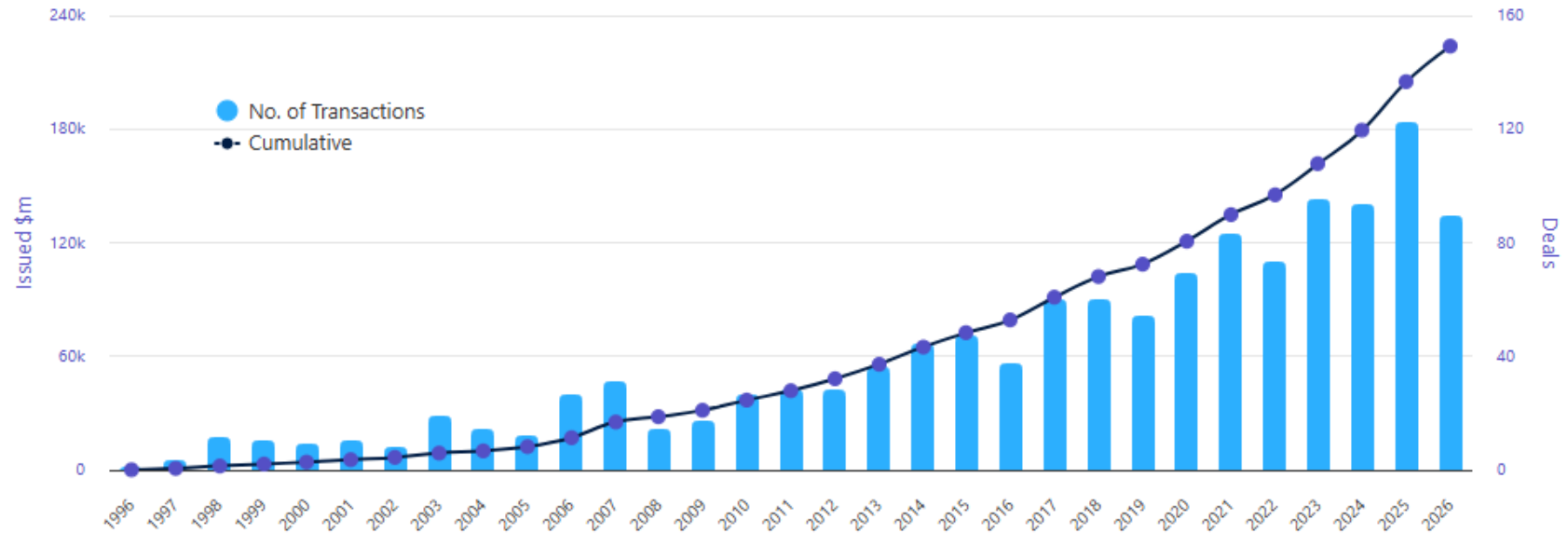
# Cat Bonds in a nutshell



# Issuance of Cat bonds increased over time

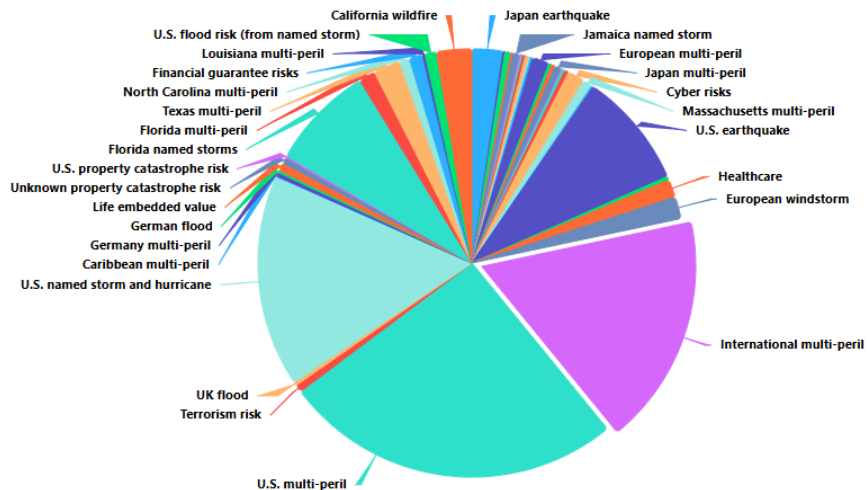
## Catastrophe bonds and insurance linked securities (ILS) cumulative issuance by year

Cumulative cat bond issuance and number of deals by year - From the Artemis Deal Directory

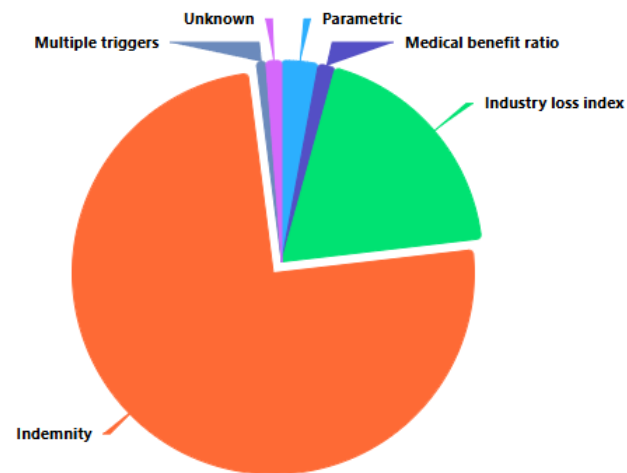


# Concentration: limited for hazards, high for trigger type

Catastrophe bonds & ILS risk capital outstanding by risk or peril

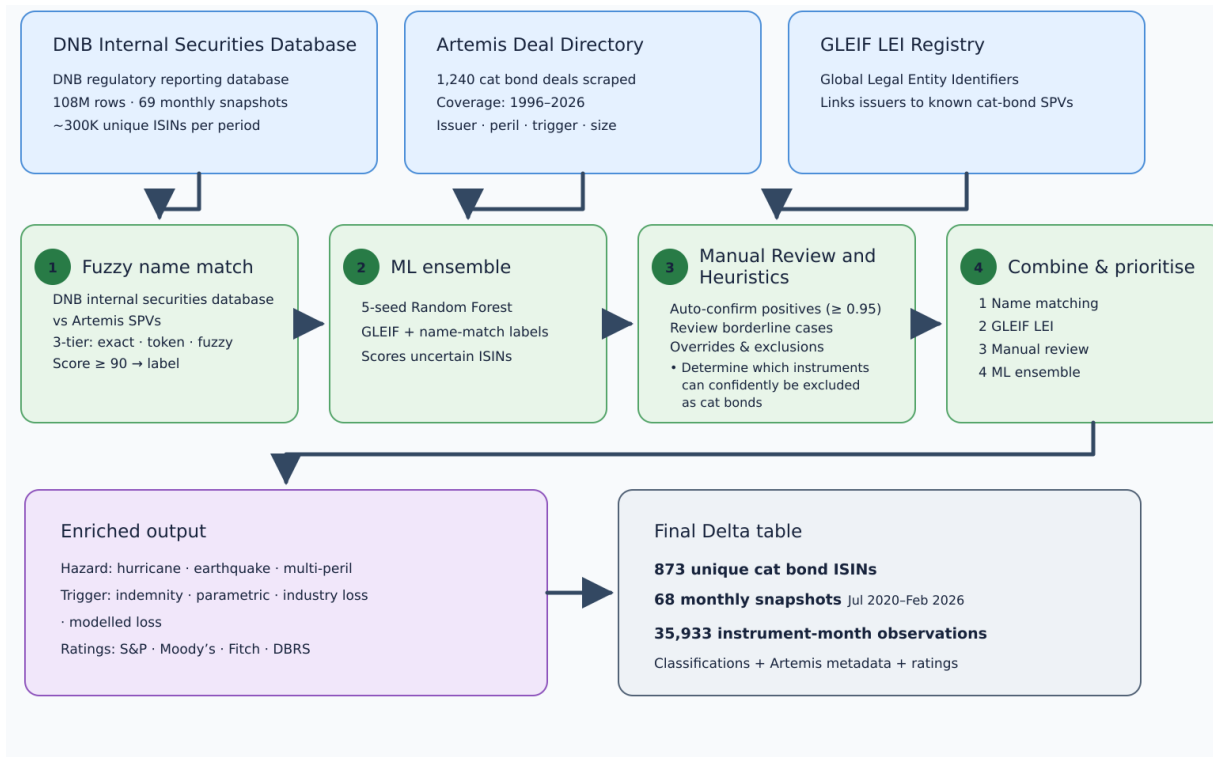


Catastrophe bond & ILS risk capital outstanding by trigger type

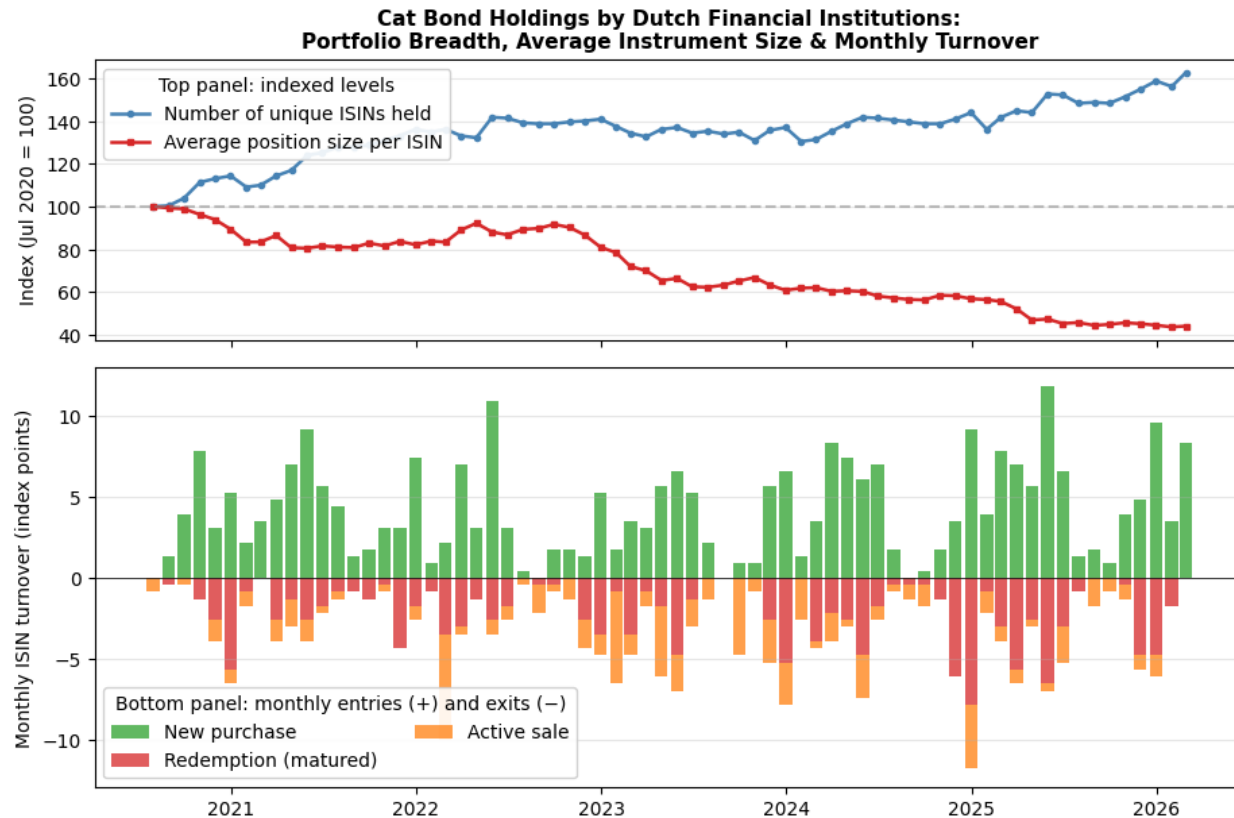


# Cat Bond Identification Pipeline

*Identifying ~630 Cat Bonds ISINs across ~300,000 Dutch Financial sector holdings*



# Dutch Institutions feature limited active trading in Cat bonds



# Cat bonds - a qualitative analysis of the holdings:

## Strengths:

- **Diversification benefits:** Cat bonds provide portfolio diversification.
- **Robust structural protections:** SPV legal isolation, high-quality collateral, and conservative rating methodologies offer important safeguards.

## Weaknesses:

- **Limited transparency:** Although catastrophe models are disclosed, key inputs, such as expected loss, climate assumptions, and model uncertainty, remain only partially disclosed.
- **Concentration and liquidity risks:** Exposure is often concentrated across perils and geographies, while secondary market liquidity deteriorates around catastrophes.
- **Non-negligible financial and reputational risk:** Financial risk remains high due to model dependence and event clustering.
- **Credit rating:** Cat bonds ratings are often either missing or tied to the issuer.

# Conclusions

- **A Credit rating is often lacking, or disclosure limited.**
- **Dutch Institutional investors holdings in Cat bonds:**
  1. Increased trend on issuance side is reflected in holdings.
  2. Diversification across perils but concentrations in trigger types.
  3. Dynamics are primarily driven by purchases and redemptions, and to a less extent by active sales.
- **Extensions:** The Dutch sample is too small for further research. However, the analysis can be extended to the holdings of European Financial institutions using SHSS.
  - Pension Funds invest more or less than Insurance companies in Cat Bonds?
  - Have any similar studies been published in central banking?
- **Action points:** European wide analysis through replication and knowledge sharing.

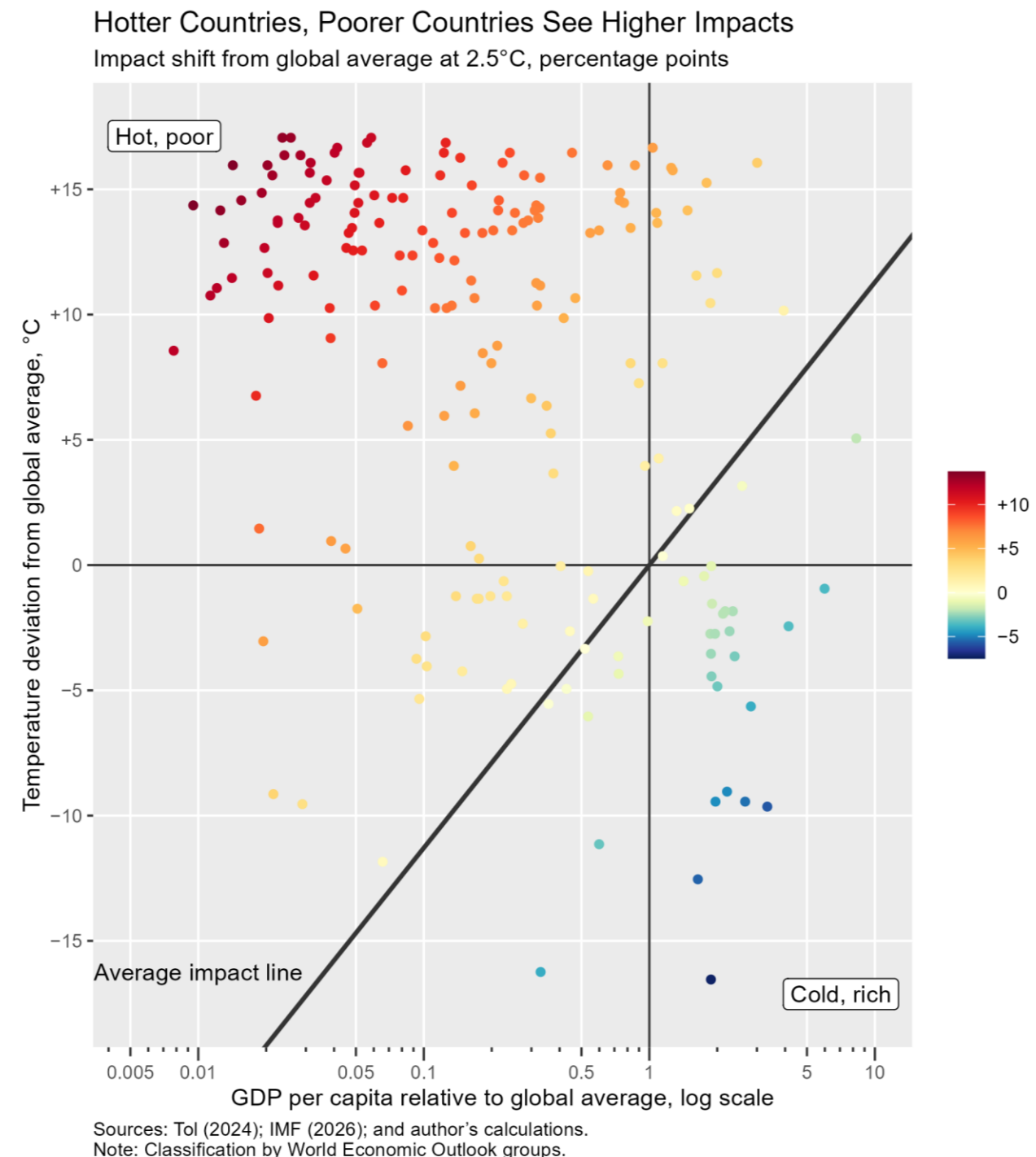
# Climate Change Statistics: What We Measure Vs What We Need *Hot, Poor, and Under-Measured*

Jens Mehrhoff, August 20–21, 2026



# Climate Statistics Have An Impact Problem

- My argument today is simple: as a community, we have made real progress on climate statistics — but much of that progress serves reporting, disclosure, and transition-risk analysis in **advanced economies**. That is not the same as producing the data countries need to reduce losses, design adaptation policy, and invest in resilience.
- Aggregate climate damage estimates hide strong distributional differences. Countries that are already **hotter and poorer** tend to experience higher marginal damages, reinforcing the need for granular, country-level physical risk modeling.

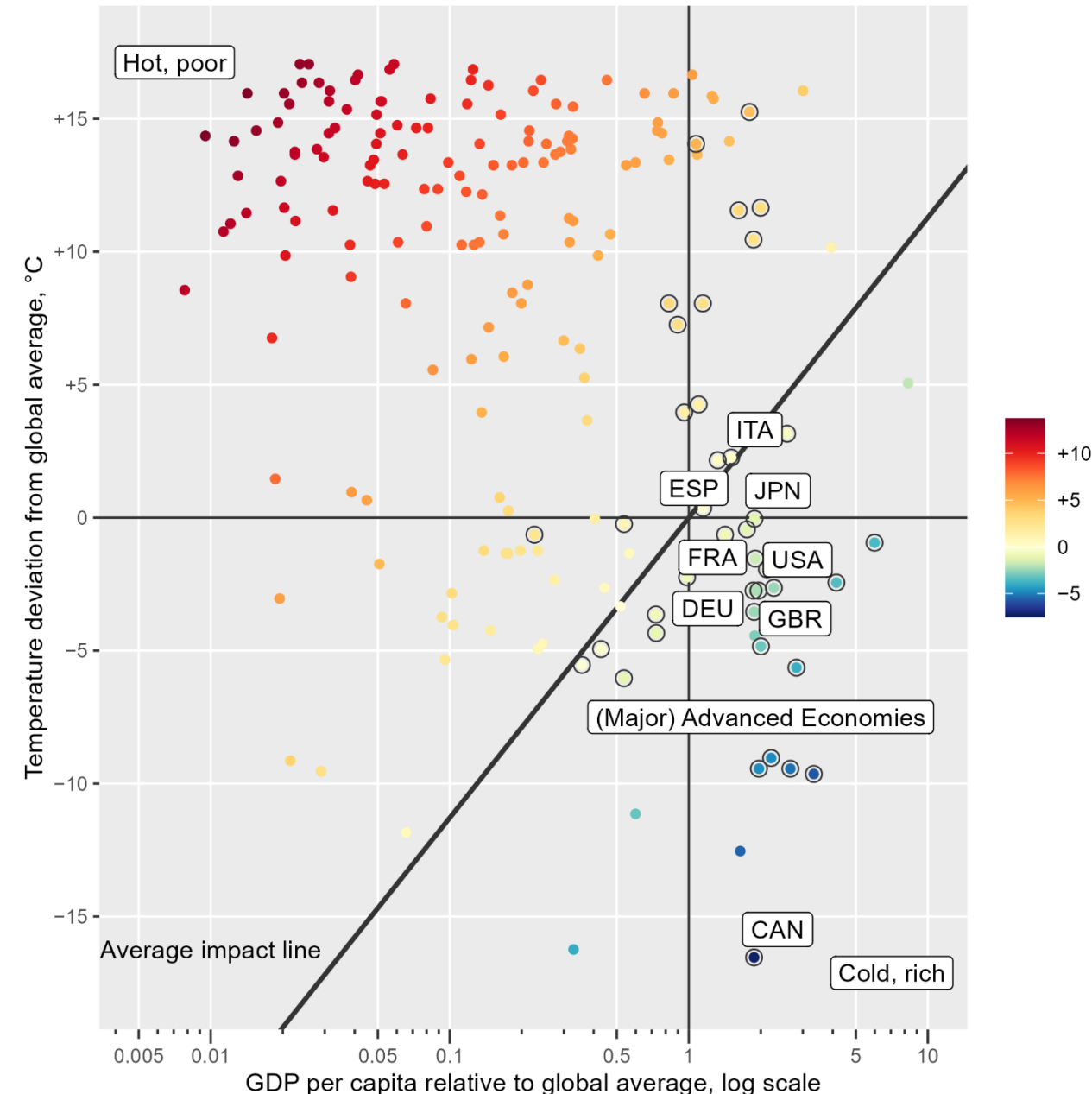


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Hotter Countries, Poorer Countries See Higher Impacts

Impact shift from global average at 2.5°C, percentage points



Sources: Tol (2024); IMF (2026); and author's calculations.

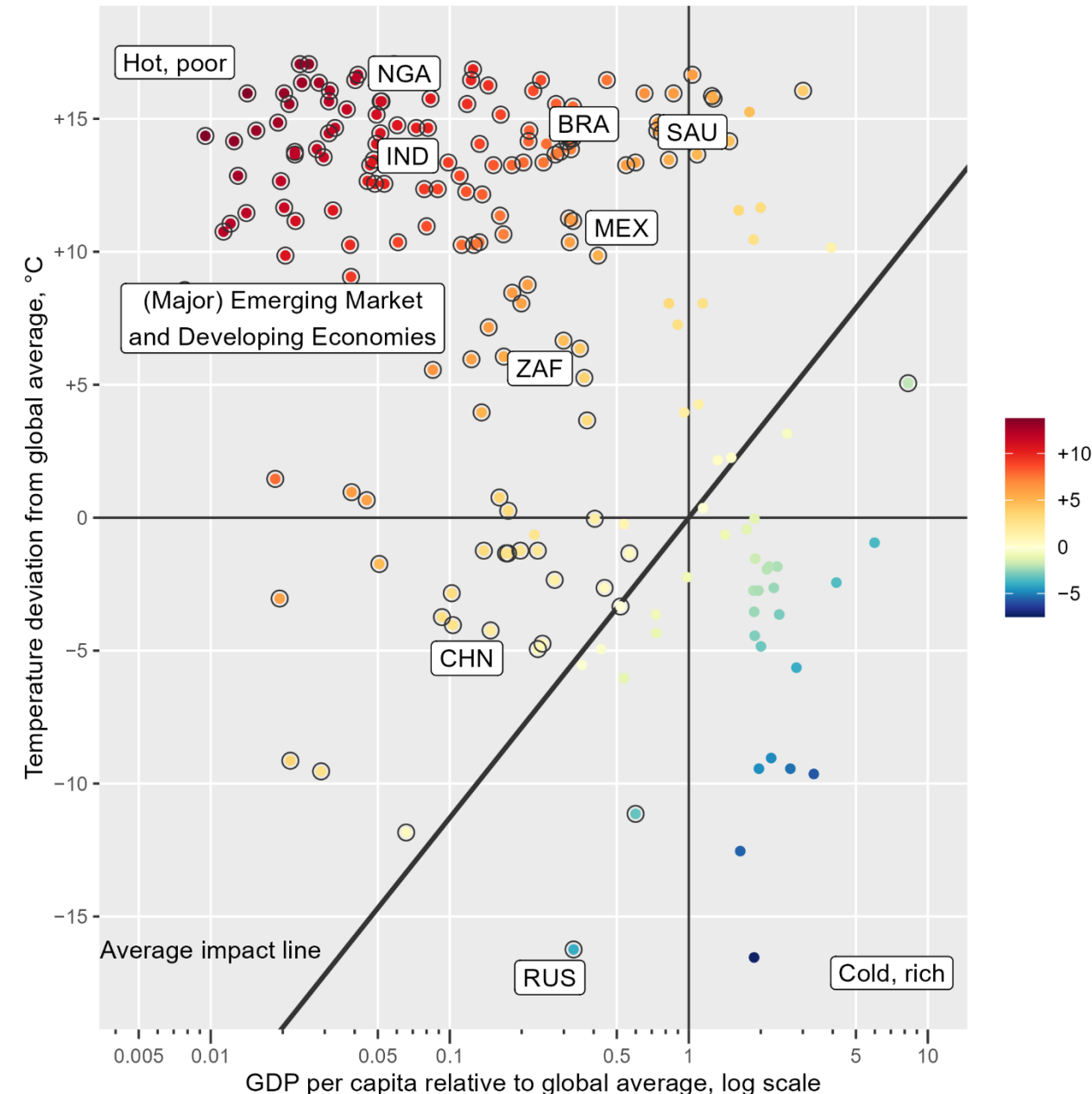
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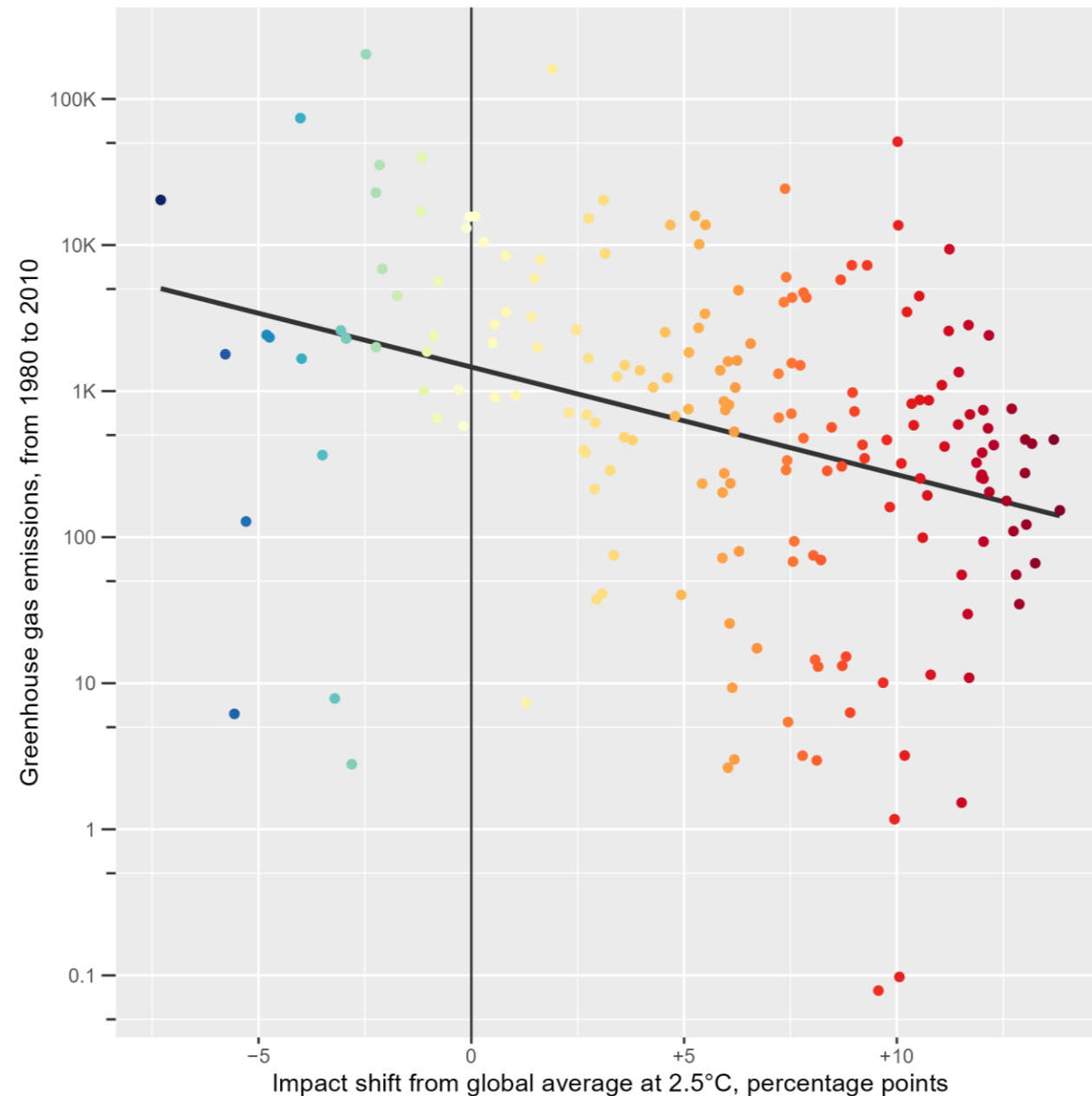
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# Those Who Emitted Least Face Higher Damages

- The chart makes the responsibility–risk mismatch visible. Countries projected to experience above-average damages at 2.5°C are typically not the countries that contributed most to historical emissions; many **low-income developing economies** sit on the high-damage, low-emissions side of the distribution.
- For climate-risk statistics, this means emissions data alone is not enough. **Physical-risk indicators** must connect hazards to exposed assets, vulnerable sectors, and country-specific damage channels.

High Climate Impacts, Low Historical Emissions  
Million tonnes of CO<sub>2</sub>-equivalents, log scale



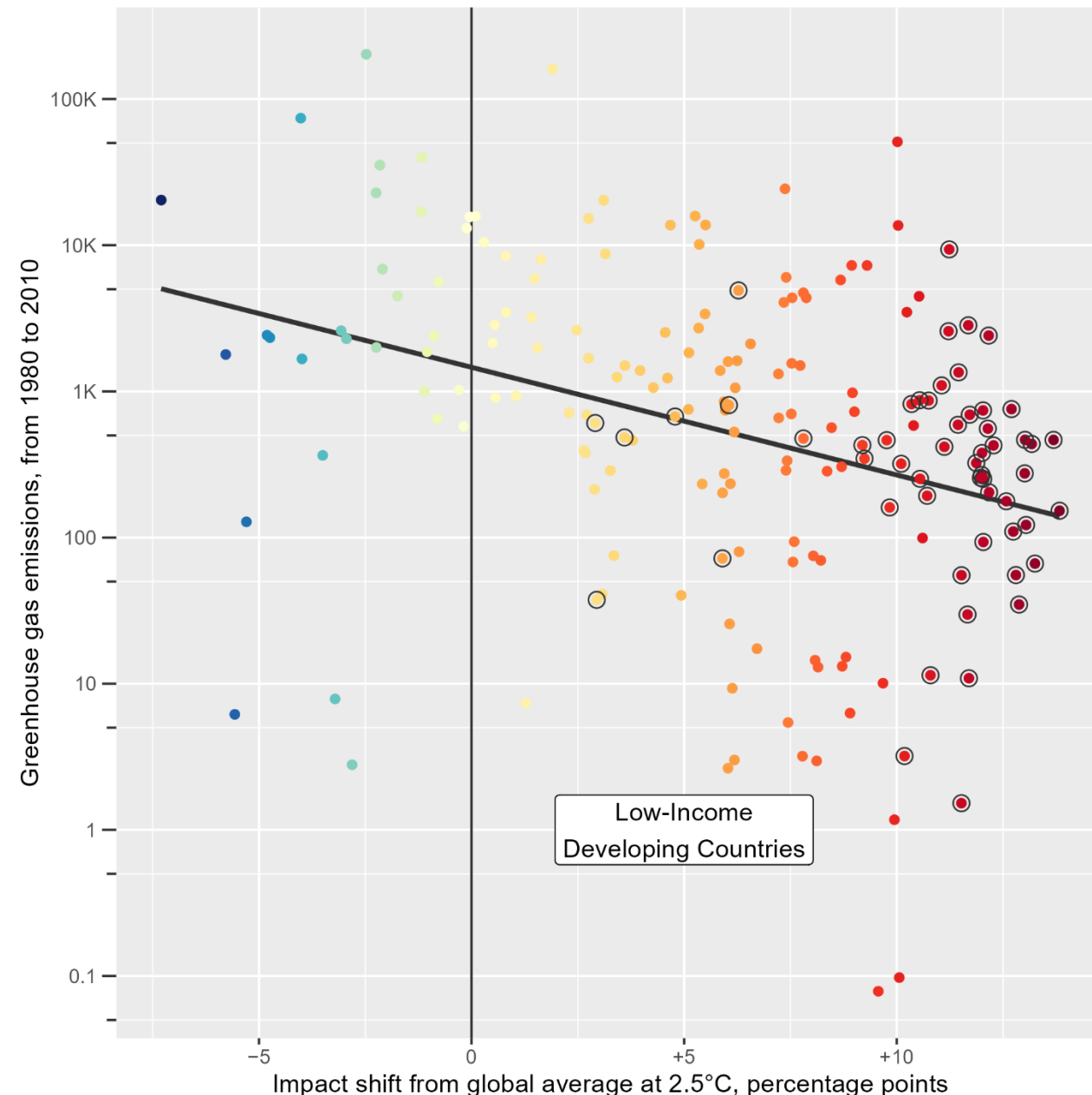
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# The Impact Problem: Physical Risk Is Local

- Climate statistics often stop at the hazard: hotter days, heavier rainfall, stronger storms. But for policy and investment, the relevant question is different: “Where will climate hazards hit exposed people, assets, infrastructure, firms, and ecosystems — and how vulnerable are they?” This requires linking three layers:
  - **Hazard**
  - **Exposure**
  - **Vulnerability**
- Only when these are combined do climate statistics become usable for estimating damages, prioritizing adaptation, and directing resilience investment.

## IPCC Risk Propeller



Source: IPCC (2022).

Note: The role of responses in modulating the determinants of risk is a new emphasis (AR6).

# From Hazard Data to Risk Accounting

- Climate data become decision-useful when they are linked to exposure, vulnerability, damages, losses, and financial transmission. The statistical agenda is therefore not only to measure hazards better, but to build **open, granular, reproducible risk-accounting systems** that countries can adapt to their own physical risks.

## Chain With Increasing Difficulty

*Hazard*



*Exposure*



*Vulnerability*



*Damages/Losses*



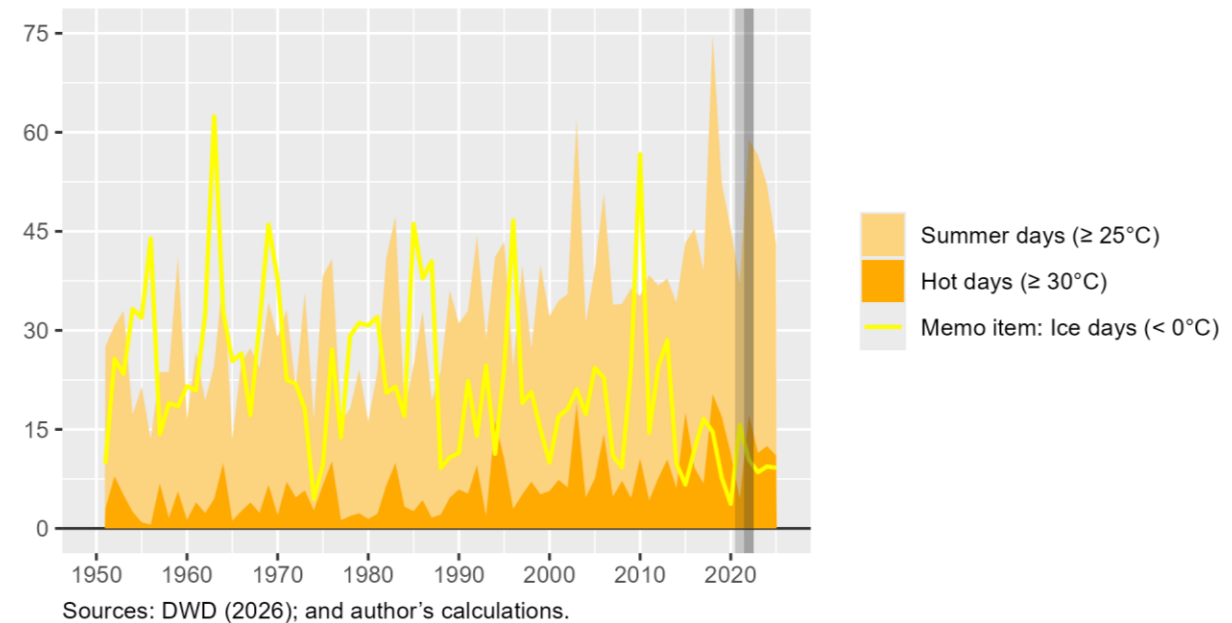
*Financial Stress*

**Enablers:** Open data • Reproducible workflows • Local validation • Documentation • Technical assistance • GenAI support

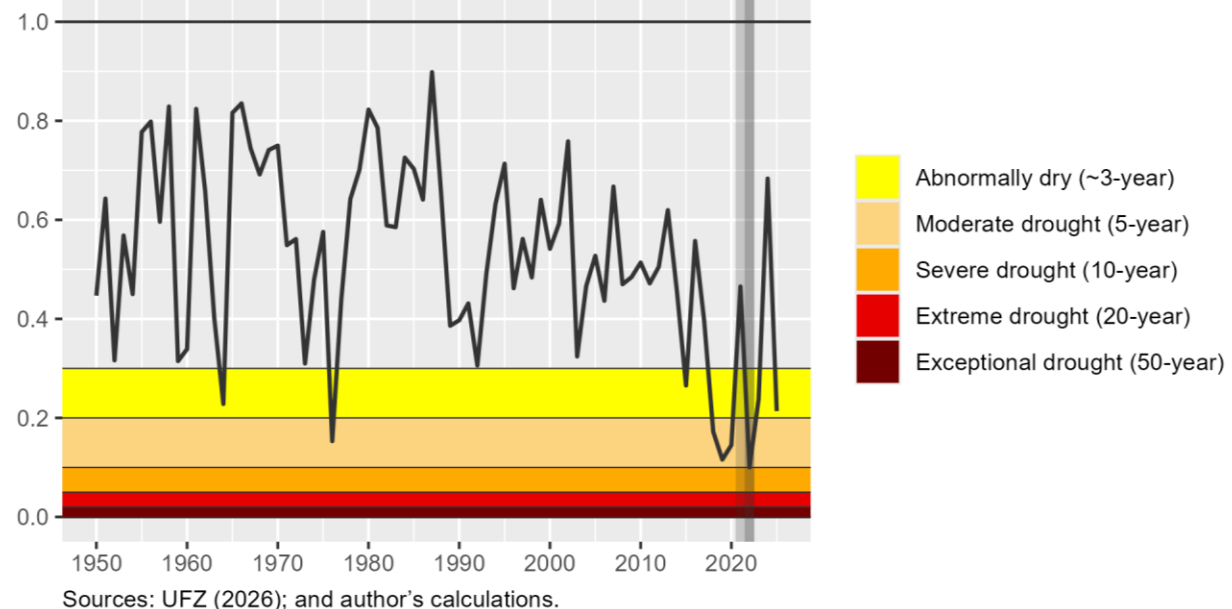
# National Averages Hide Local Hazards: Germany

- This is the **familiar statistical view**: a national time series. Heat conditions have shifted and soil moisture has become an increasingly relevant drought indicator.
- But the national series cannot tell us where conditions were most severe. The national series gives us context, but it does not tell us which regions were hottest or driest. The **spatial view**: the drought year 2022 is clearly hotter and drier overall. But the important statistical point is the regional variation. The national average hides where the hazard is concentrated.
- National indicators show the trend; granular data show the hotspots. And this is still **only the hazard layer**.

Annual Number Of Summer And Hot Days in Germany



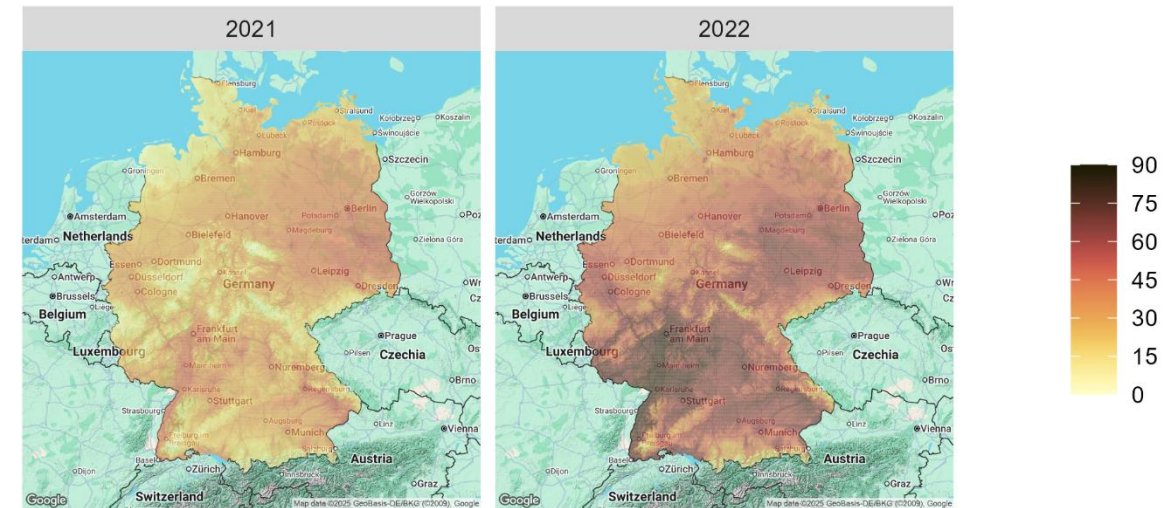
Soil Moisture Index During Meteorological Summer in Germany



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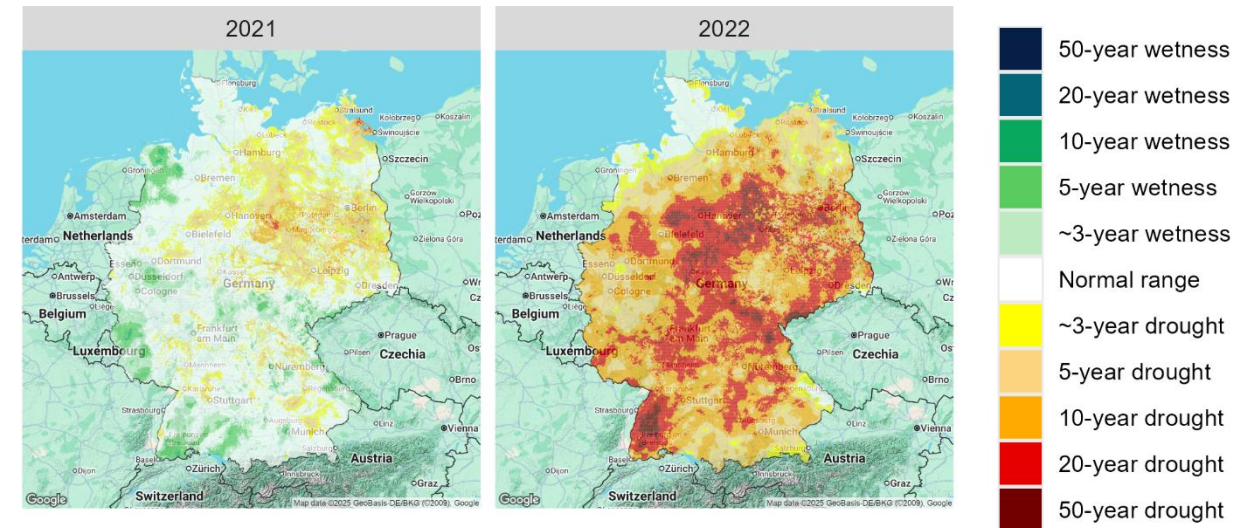
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## Number Of Summer Days During Meteorological Summer



Sources: UFZ (2026); and author's calculations.

## Soil Moisture Index During Meteorological Summer



Sources: UFZ (2026); and author's calculations.

# GenAI Can Help Scale Physical-Risk Workflows

- Germany was only a hazard-layer example — but even that required granular data, geospatial processing, coding, documentation, and interpretation. The bottleneck is not only data access. It is turning climate and geospatial data into **reproducible, locally validated workflows**. GenAI can help non-climate specialists move from policy question to reproducible workflow:
  - Learn climate-risk concepts;
  - Navigate data sources, manuals, papers, and metadata;
  - Code, debug, document, and adapt workflows;
  - Support training through reusable explanations and examples.
- Meta-example: I used GenAI as a **drafting and sparring tool** for this talk — but not as a substitute for judgment, validation, or ownership.
- Guardrail: GenAI should support **open, inspectable workflows** — not become another black-box risk model.
- Takeaway: AI **accelerates the workflow**; it does not validate the risk.

# From Shared Methods to Country-Owned Capacity

- GenAI **lowers the entry barrier** — but durable capability requires shared skills, reproducible workflows, country application, and expert networks.

## 1. Shared foundation

- Climate-risk concepts
- Geospatial workflows
- Hazard/exposure/vulnerability
- Documentation
- Responsible GenAI use
- ***Bundesbank example:*** focus seminar on scenarios, extremes, spatiotemporal data, hazard/exposure, and damage functions.

## 2. Country application

- Local hazards
- Local data
- Local institutions
- Local policy questions
- Financial-stability channels
- ***Central-bank use:*** credit risk • collateral • insurance • fiscal exposure • external resilience • financial stability

- Takeaway: Standardize the scaffolding. **Tailor the risk analysis.**

# Institutional Greenwashing — or Impact Assistance?

- We have come a long way: from glossy climate-risk slides to real data and analysis — even if still presented in PowerPoint. But the climate-statistics agenda still leans toward what is **easier to measure and most demanded** by advanced economies: emissions • mitigation pathways • transition risk • disclosure • global indicators. For many emerging market and developing economies — and increasingly for advanced economies — the **binding challenge is physical impact**: localized hazards • exposed assets • vulnerabilities • damages • financial transmission.
- If the goal is country-owned physical-risk capacity, three priorities follow:
  1. **Open granular data and accessible tools**: Public-good workflows; less vendor lock-in.
  2. **Hazard/exposure-specific damage functions**: From climate hazards to economic and financial losses.
  3. **Nature-related risks, including biodiversity loss**: From climate-only risk to the climate–nature nexus.
- Provocative opinion: – The test is not whether institutions can report climate risk.  
– **The test is whether countries can use the data to reduce it.**