

# How proxies and publicly available data can be used to construct new indicators for transition risk, physical risks and green taxonomies

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EUROSYSTEM

# OBJECTIVE

Introduce **new experimental indicators** for transition risk, physical risks and green taxonomies based on the **preliminary results** of three MSc research projects performed at de Nederlandsche Bank (DNB)

Explain **methodologies, data and assumptions** used in the construction of experimental indicators

Share **conclusions** reached so far and discuss **next steps**

# BACKGROUND

Giving the urgency of climate change, the financial sector **does not have the luxury to wait** until 'perfect' or better data becomes available, and should consider **using the alternatives that are currently available.** – NGFS Bridging the Data Gaps

Given the **urgency** with which these indicators are needed, and the **practical barriers** that will need to be overcome, the EG CCS stresses that **feasibility** is a key variable in the prioritisation - STC  
EG Climate Change Statistics

Until significant progress is made in this area, [...] a recommendation is to **make better use of proxies, modelled data, aggregates and estimates** [...]. - NGFS Bridging the Data Gaps

# OVERVIEW

**1. Transition risk** - Financial risk of the transition to a less carbon-intensive economy (thesis finished July 2021)

Derek Dirks

**2. Physical risks** - Modelling physical risks due to storms and floods with an application to real estate (thesis finished Aug 2021)

Willemijn Ouwersloot

**3. Green Taxonomies** – Some preliminary results (thesis started Sep 2021, finished by Dec 2021)

Juan Pablo Trespalacios Miranda

These projects have been inspired by the priorities identified by the ECB STC Expert Group on Climate Change and Statistics (EG CCS), and aim to feed the discussion & eventual production of new financial sector climate statistics by the STC.

# 1. TRANSITION RISK – objective

## Objective:

- To show the use of IO-models' country-sector level data on environmental externalities as a proxy for company level emission data.
- IO-models can be employed to go beyond carbon/GHG emissions (air pollution, water pollution, etc.), cf. Exiobase application in Smeets et al. 2021 (DNB working paper).
- Emissions data of companies is often not available (particular for data beyond carbon emissions).



# 1. TRANSITION RISK – methodology and data

## Methodology:

Impact ratio per sector (unit:  $\frac{\$}{\$} = \%$ ):

$$\frac{\text{Emissions (CO}_2\text{)} * \text{CO}_2\text{ tax rate (\$/CO}_2\text{)}}{\text{Profits (\$)}}$$

*To determine the impact of different tax scenarios on the portfolio of financial institutions, i.e. the risk a financial institution faces in terms of potential reductions in portfolio value/returns per sector due to a particular carbon tax scenario.*

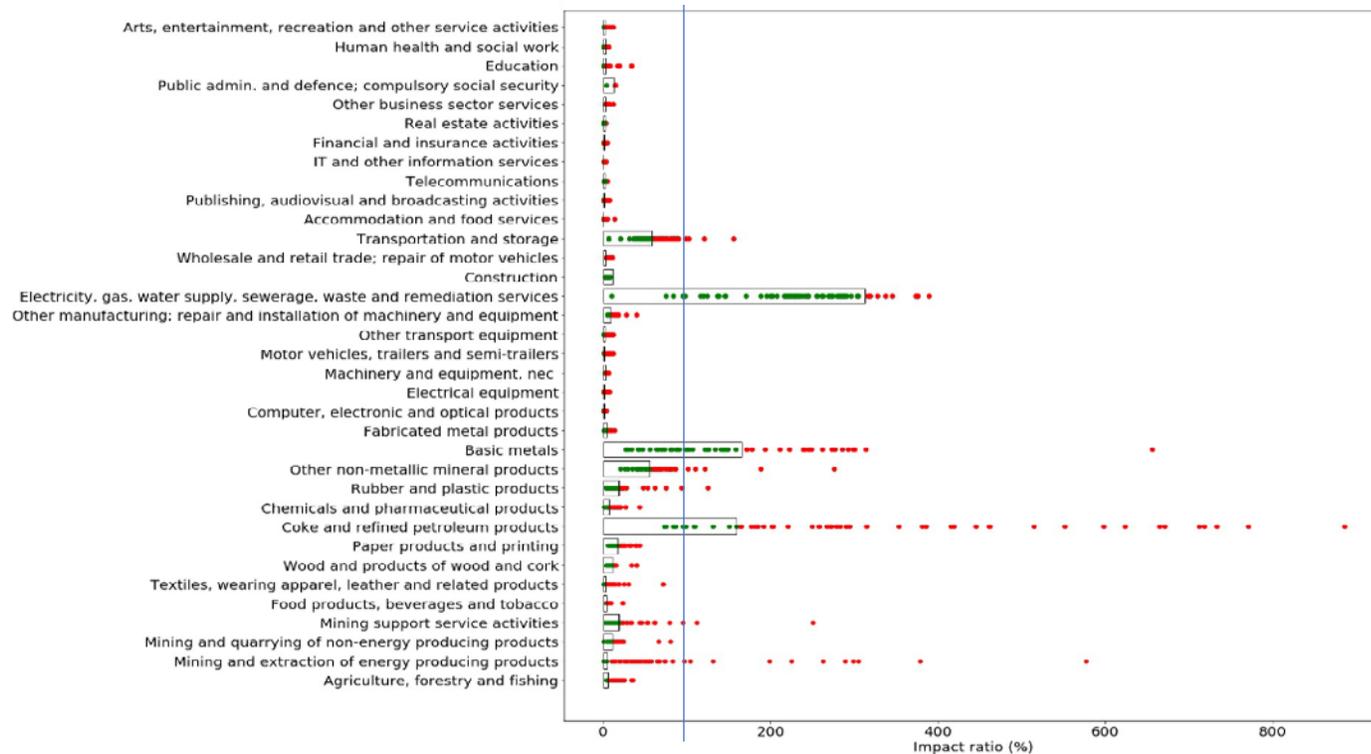
## Data:

- Direct and indirect investments of Dutch pension funds in corp. bonds and equity (Security Holding Statistics by Sector; ISIN level);
- Company level data from Refinitiv Thomson Reuters EIKON (profits, revenue and Enterprise Value; ISIN level) to determine emissions and profits (ownership approach);
- OECD trade in Value-Added (TiVA) database combined with the Trade in embodied CO<sub>2</sub> (TeCO<sub>2</sub>) database to determine carbon intensities (Scope 1,2,3) per sector and OECD country; 64 countries, 36 industries (ISIC Rev. 4);
- Social cost of carbon literature to determine optimal Pigouvian tax rates for different scenarios.

# 1. TRANSITION RISK – results

**Main result:** An impact ratio of 4,4 to 20,4% (low to high tax scenario) is estimated for the entire Dutch pension fund sector.

**Individual pension funds:** Impact ratio of individual Dutch pension funds by sector (dots) compared to a sector neutral benchmark (bars)\*



- Figure shows results for the (medium) €119 per tonne CO<sub>2</sub> scenario
- In nearly every sector, individual pension funds can improve on their impact ratio compared to the benchmark (in red)
- Large differences: Many pension funds have sector positions where profits are insufficient to bear the env. damage cost.

→ > 100% Profits are insufficient to bear env. damage costs

\* Investments are 'sector neutral' (hypothetical portfolio with investment weights equal to EV/sum of sector EV; within the dataset)

## 2. PHYSICAL RISKS – objective

### Objective:

- To assess the use of open access data, particularly (macro) historical damage data in calibrating physical risk models.
- The models in this research are fit solely based on open-access data. This led to (only) 35 and 36 historical damage records being available for storms and floods in Germany, respectively.
- More granular data is typically proprietary or only available upon subscription (e.g. through (re)insurers).

## 2. PHYSICAL RISKS – methodology and data

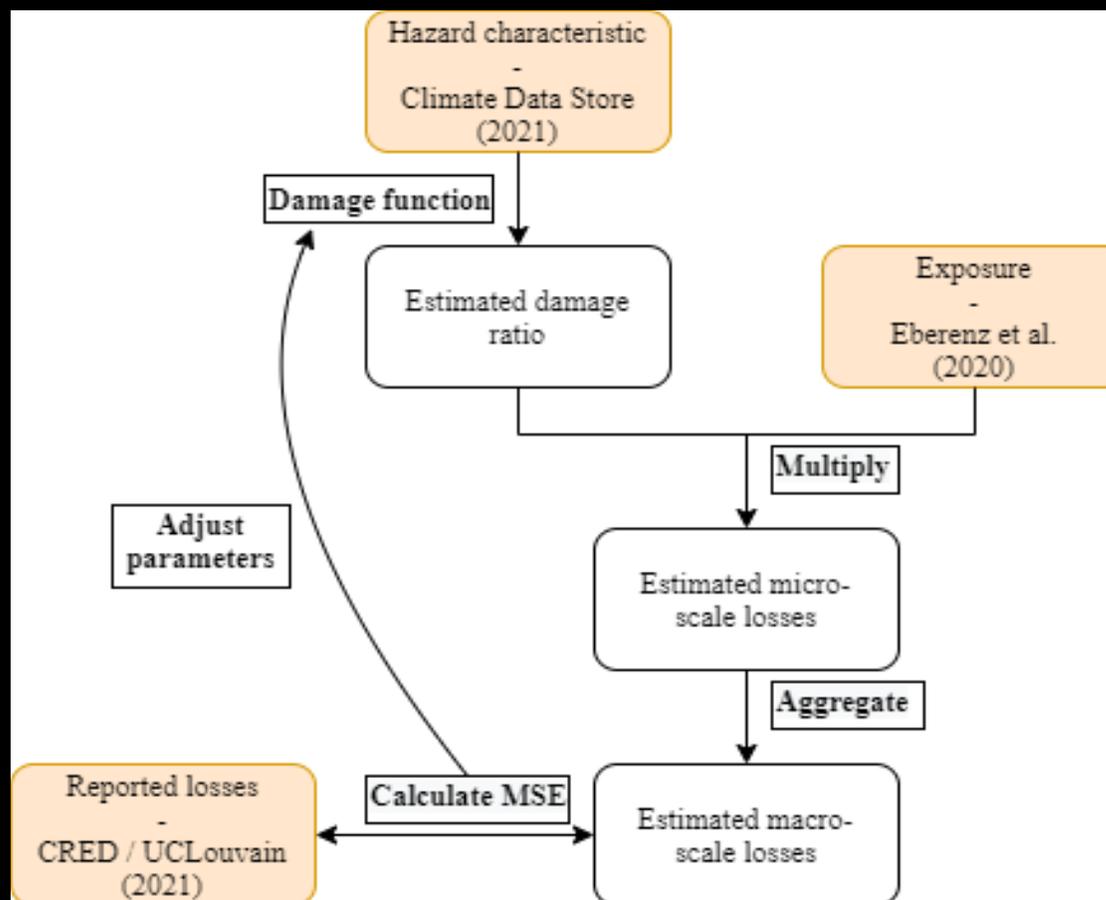
### Methodology:

- Calibrate several models using the available macro-scale data
- Simulation of storms: Expected Annual Loss
- Stress test for flood: ...

### Data:

- Assets: Survey data
- Assets: Eberenz et al. (2020) (intensity and geographical information)
- Damage: Center for International Disaster Reduction (CRED) / UCLouvain (monetary damage)
- Damage: Prapotnyk et al. (2020) (monetary damage)
- Hazard characteristic: precipitation (to model ...)

Graphical representation of method & data:



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## 2. PHYSICAL RISKS – results

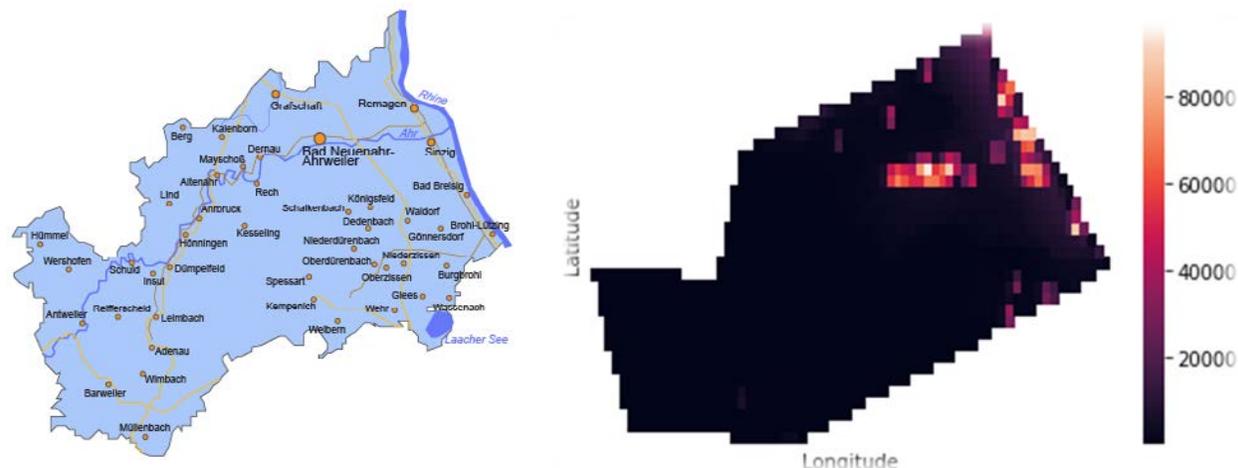
**Main result:** The models perform badly, most likely due to the lack of sufficiently granular data on historical damages to calibrate them. The applications that can be delivered, assuming better historical damage (are made public and) can be used in the future, are however very promising.

**Simulation (storms):** Risk metrics and their values in percentages of the total portfolio worth. The metrics are based on a simulation of damages due to 1000 years of storms.

Risk metric	Value
$\widehat{EAL}$	1.340%
$\widehat{VaR}_{0.99}$	40.583%
$\widehat{ES}_{0.98}$	41.445%

- The simulation shows that very interpretable risk metrics can be calculated and risk mitigation matters could be taken. Current results are however unreliable due to model performance.

**Stress test (flood):** Left: map of Ahrweiler. Right: heat map of estimated damages in Ahrweiler.



- Aggregating all expected losses for the region, we obtain a total expected loss of 5.8 million Euros for Ahrweiler (very low; unreliable?). The application shows the possibility to forecast total damages when an extreme weather event hits. With a better calibrated damage function, those forecasts will be more reliable (and likely much higher).

# 3. GREEN TAXONOMIES – illustrative example (project just started)

A preliminary exercise has been conducted to exemplify the type of analyses and indicators to be produced by this research

## Objective

Fix a lack of further sub-sectoral classification of green activities within NACE-codes, i.e. renewable vs. non-renewable electricity production, based on current EU Taxonomy.

e.g. D.35.1.1 issue : Production of electricity that does not have further subcategories for coal, wind, etc.

## Methodology

- Provide granular data from alternative source to complement ‘sub-subcategory’ or ‘NACE activities’ unavailable at central banks
- Combine with portfolio data to flag assets that are potentially “green”



## Data



AnaCredit: Loans (EUR million) provided by Dutch banks to sector D35.1.1 in electricity production (aggr. per country) for 2019K4.



Breakdown of electricity generation per fuel/source at country level

**GREEN** (hydro, solar, wind, other renewables)

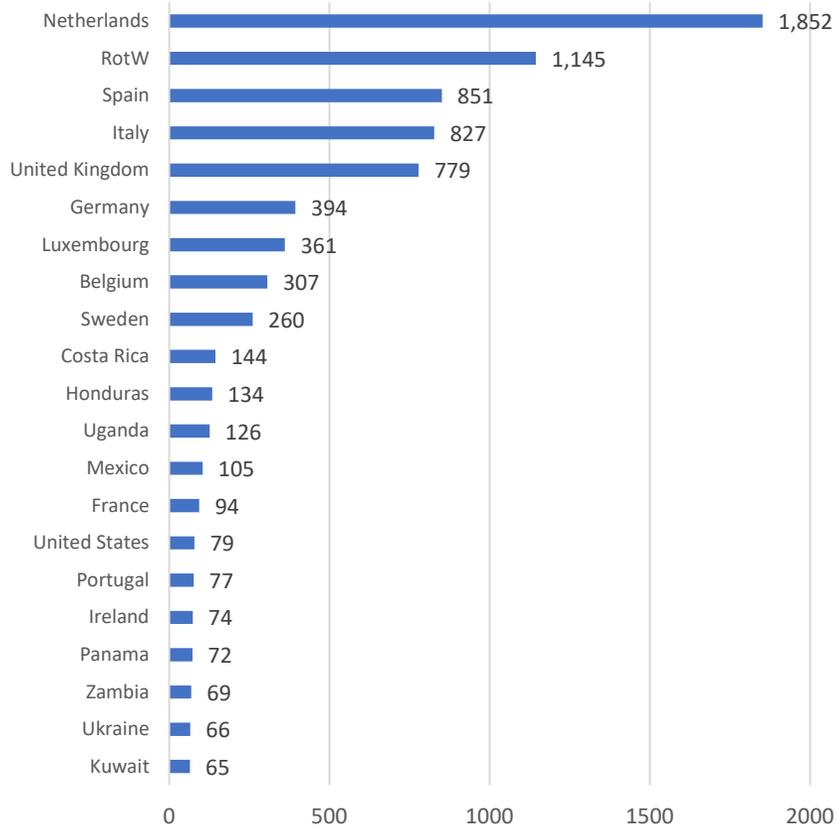
**BROWN** (nuclear, coal, gas, oil)

# 3. GREEN TAXONOMIES – illustrative example (project just started)

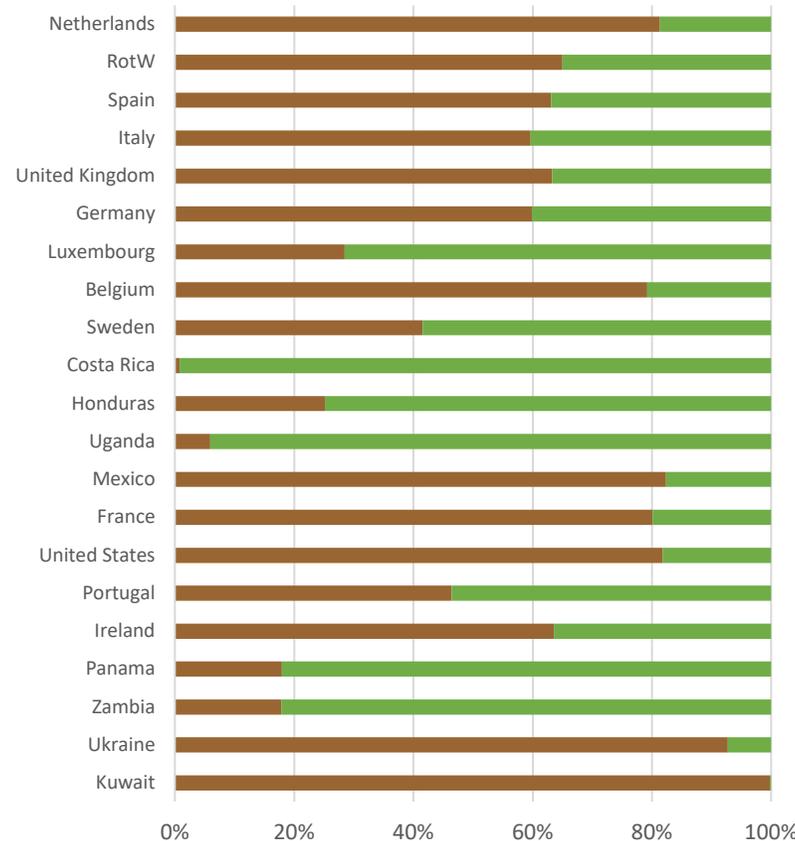
A preliminary exercise has been conducted to exemplify the type of analyses and indicators to be produced by this research

## Results

Loans provided by Dutch banks to sector D35.11 electricity production (EUR million per country)



Electricity mix per type of source – Green vs Brown (Percentage per country)



- A total of 11,600 TWh of electricity were generated in 2019; 24% generated from green sources.
- 7.9 billion EUR in loans to D35.11, about 37.5% or 2.96 billion EUR can be labelled as green.
- Likely new loans to D35.11 are more often green than the current energy mix of a country. A parameter value needs to be estimated to adjust for this. How? Literature available? Other options?

# CONCLUSION / NEXT STEPS

- 1. Transition risk:** Promising results, obvious next step is to apply the Exiobase MRIO model and go beyond GHG emissions. Exiobase is however rather outdated (2011). Call for an update of the OECD & Exiobase model (or similar alternatives).
- 2. Physical risks:** Call to make publicly available, e.g. on ZIP-code level & after being anonymized, historical damage data on storms and floods to improve model calibration and our confidence in the results of the applications. Apply model to other countries, add climate change sensitivity to the model.
- 3. Green Taxonomies:** Very preliminary results, project has just started. Other ideas/avenues for research are highly appreciated at this stage!

Feed the discussion & eventual production of new financial sector climate statistics (STC EG CCS)

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