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How proxies and publicly available data can be used to construct indicators on transition risk, physical risks and green taxonomies[1]

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

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

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Abstract

In this paper, we 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). For transition risk, the publicly available OECD Trade in Value-Added (TiVA) and the accompanying Trade in Embodied CO_2 ($TECO_2$) database are employed to determine an optimal environmental (Pigouvian) tax on carbon emissions. This tax is used to determine an 'expected impact ratio', e.g. a carbon tax that is expected to absorb X% of the profits of a particular asset position. For physical risks, open-access historical macro-economic damage data on storms and floods are used to calibrate micro-economic damage functions. The micro-scale damage functions are subsequently used to estimate risks for real estate portfolios due to future storms and floods, e.g. to calculate the 99% Value-at-Risk of a real estate portfolio based on historically calibrated model predictions. Finally, we explore the distribution and demand of climate-aligned financial investments through green taxonomic criteria and remote sensing data. The results show that overall, there is substantial scope for financial institutions and central banks to better leverage publicly available data sources and models to develop climate risk proxies. In particular, there are promising results for transition risk and green taxonomy applications, while for physical risk the performance of the models could be improved if more granular data (e.g. historical damage data on ZIP-code level) were to be made publicly available.

Keywords: transition risk, physical risk, green taxonomies, open access data, proxies

JEL classification: G11, G17, H21, H23, Q54

[1] Views expressed in this paper are those of the authors, and do not necessarily reflect the official positions of de Nederlandsche Bank or the Eurosystem.

Contents

1. Introduction

There is substantial scope for financial institutions and central banks to better leverage publicly available data sources and models to develop climate risk proxies. 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. This paper is inspired by the call for research of the ECB STC Expert Group on Climate Change and Statistics (EG CCS) on three priority sets of indicators, namely indicator related to transition risk (and carbon footprint), physical risks and green taxonomies. The EG CCS recommends to develop pilot statistics for these three sets of priority indicators and pair them with transparent methodologies. Considering the combination of 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.[2]

At the same time, international organizations such as the G20 Sustainable Finance Working Group, the NGFS, and the FSB are studying the different ways to bridge the data gaps that are currently limiting practitioners in their ability to assess the current state of sustainable finance. At present, incompleteness and inconsistency in sustainability-related disclosures pose challenges to practitioners due to the proliferation of different disclosure frameworks. In addition, sustainability data is held and defined mostly by private sector data providers in an uncoordinated manner, which hinders its accessibility and transparency. Improving sustainability reporting standards and data governance and architecture will allow for a better identification of sustainability risks, impacts and opportunities.[3]

Until significant progress is made in this area, one of the often repeated recommendations is to make better use of proxies, modelled data, aggregates and estimates when (more) granular or reported data is currently unavailable. For example, industry averages can be used to estimate financed emissions when data is not (yet) available for a specific firm. The obvious downside being the lower accuracy of modelled (or aggregated) data when compared with reported data. As such, it is best to consider the use of modelled data as an intermediate step, which will help bridge some of the data gaps in the short term. In any case, postponing the identification of climate risks is not an option as market players acknowledge: data will never be perfect thus action should be taken with what is available currently.[4]

In this paper, new experimental indicators for transition risk, physical risk and green taxonomies based on the preliminary results of three MSc research projects performed at de Nederlandsche Bank (DNB). For transition risk, the publicly available OECD Trade in Value-Added (TiVA) and the accompanying Trade in Embodied CO_2 ($TECO_2$) database are employed to determine an optimal environmental (Pigouvian) tax on carbon emissions. This tax is used to determine an 'expected impact ratio', e.g. a carbon tax that is expected to absorb X% of the profits of a particular asset position. For physical risk, open-access historical macro-economic damage data on storms and floods are used to calibrate micro-economic damage functions. The micro-scale

2 ECB "Towards statistics on climate change relevant for Central Bank activities", Final Report by the STC Expert Group on Climate Change and Statistics (STC-SSM/2020/143), 15 October 2020.

3 G20, "Sustainable Finance Roadmap Draft", 24 August 2021.

4 Network for Greening the Financial System "Progress report on bridging data gaps", May 2021

damage functions are subsequently used to estimate risks for real estate portfolios due to future storms and floods, e.g. to calculate the 99% Value-at-Risk of a real estate portfolio based on historically calibrated model predictions. Finally, we explore the distribution and demand of climate-aligned financial investments through green taxonomic criteria and remote sensing data.

Our results show that overall, there is substantial scope for financial institutions and central banks to better leverage publicly available data sources and models to develop climate risk proxies. In particular, the results are promising for the transition risk and green taxonomy applications, while for physical risk the performance of the models could be improved if more granular data (e.g. historical damage data on ZIP-code level) were to be made publicly available.

The remainder of this paper organized as follows. The transition risk, physical risks and green taxonomies sections (in that order) each offer subsections that contain i) a short summary of the methodology, ii) the public datasets that are used, and iii) the results of the application on Dutch portfolio data that is provided by the Nederlandsche Bank. The three MSc research projects that allowed us to write this paper are available upon request.

2. Transition risk

In 2020, 84% of the world's total consumption of energy originated from fossil fuels (BP,2020). Stern (2007) argues that radical changes to the global economy and energy systems are needed to achieve the required reduction in GHG emissions. In his 2015 speech to the UK insurance sector, Mark Carney, then Governor of the Bank of England, warned that financial risks could arise due to this energy transition (Carney, 2015). He also introduced a distinction between physical and transition risks that has since then been adopted as the standard way of classifying financial risks related to climate change.

The literature shows that the impact of transition risk might be severe and that financial institutions need to adopt a forward-looking and comprehensive risk management approach to increase their resilience (NGFS, 2020). In this section, a new risk management tool is constructed that can assess the impact of the introduction of (new) carbon tax scenarios on any investment portfolio. Inspired by Smeets et al. (2021), an impact ratio is constructed that quantifies the risk a financial institution faces in terms of potential reductions in portfolio value and returns when a particular carbon tax is introduced.

2.1 Methodology

Taxes on environmental externalities are often referred to as Pigouvian taxes, acknowledging the pioneering work on pricing environmental externalities by Pigou (1929). In the literature, two carbon pricing instruments are often viewed as the main solutions for reducing GHG emissions, namely a carbon tax and an emission trading scheme (ETS) (Baranzini et al., 2017; Jenkins, 2014). A carbon tax fixes the price of GHGs emitted by taxing the quantity emitted by corporations but lets the quantity of GHGs emitted fluctuate. An ETS sets a cap on the total amount of GHGs emitted and emission allowances are allocated between corporations (Baranzini et al., 2017). In this case, the amount of emissions is fixed, while the price of GHGs fluctuates. Thus in a very simple world, a carbon price can be established either through a tax or an ETS. Here, we evaluate the impact of a carbon tax that is based on the Pigouvian, optimal environmental tax principle; the tax rate is set equal to (marginal) environmental damage caused by the negative externality. Based on the available literature on the social costs of carbon, three tax scenarios are considered: a global carbon tax rate of €38 (based on current politics; low scenario), €119 (policy-science estimate; medium scenario), and €175 per tonne CO_2 (based on the recent scientific literature; high scenario).

Equation (1) offers a simplified version of how the environmental footprint, based on the ownership perspective or 'financed emissions', is determined for the investments in stocks and bonds. Consider a pension fund *p* that holds α_A EUR (€) in stocks and bonds of company A and α_B EUR (€) in stock and bonds of company B. Firm A operates in sector 1 and firm B produces its goods and services in sector 2, both active in country *x*. The environmental footprint (*ef*) of pension fund *p* can then be calculated as:

$$ef_p = \frac{\alpha_A}{Enterprise\ Value_A} * \mathrm{r}_A * ci_{1,x} + \frac{\alpha_B}{Enterprise\ Value_B} * \mathrm{r}_B * ci_{2,x} \qquad (1)$$

with ef_p the environmental footprint of pension fund *p* in tonnes of CO_2, *Enterprise* $Value_i$ the Enterprise Value (EV) of company *i*, r_i the revenue of company *i* and $ci_{k,x}$ the carbon intensity (in tonnes of CO_2/revenue) of sector *k* and country *x* that the firms operate in. Given that revenue drops out as it is the numerator and in the denominator, and the term α_i/Enterprise $Value_i$ is a simple weight factor in this equation, ef_p has tonnes of CO_2 (i.e. absolute emissions) as its unit. The formula is somewhat intricate due to the use of a combination of different data sources to calculate it. Revenue (r_i) and EV are typically available at third-party data providers whereas data carbon emissions is often not available or complete. That is why here carbon intensities at the country-sector level ($ci_{k,x}$) are employed and taken from an input-output model (see section 2.2 for more details). Equivalently, 'financed profits', the profits that can be assigned to a pension fund based on its ownership share, are given by:

$$\pi_p = \frac{\alpha_A}{Enterprise\ Value_A} * \pi_A + \frac{\alpha_B}{Enterprise\ Value_B} * \pi_B \qquad (2)$$

with π_p the financed profits of pension fund *p*, and as before, company level data for EV and profits, and α_A, α_B representing the EUR (€) amount in stock and bonds invested in companies A and B. Combining general version of equations (1) and (2), we end up with the following formula for the impact ratio of the portfolio of a pension fund (which can easily be applied to specific sectors separately by splitting up the portfolio dataset for each sector *k* of the input-output model):

$$\text{Impact factor}_p = \frac{ef_p}{\pi_p} * \tau_c \qquad (3a)$$

With ef_p and π_p representing financed absolute emission and financed profits, respectively, and τ_c the tax rate in scenario *c*. Given that ef_p is depicted in tonnes of CO_2, τ_c has € per tonne CO_2 as a unit, and π_p is in EUR (€) the resulting unit of the impact factor is simply a percentage (%).

2.2 Data

To determine the environmental footprint of the investment portfolios of the pension funds, we employ portfolio data provided by DNB for pension funds' direct and indirect investments in equity and corporate bonds. For 2020, these direct and indirect investments have a total value of EUR 851,6 billion based on the security holding statistics by sector (SHSS) dataset. Comparing this to the total balance sheet of the entire Dutch pension fund sector, the data in this study covers approximately 44% of the total assets of Dutch pension funds.

The portfolio data is provided by DNB for the end of the fourth quarter of 2020. Stocks and bonds are issued by (inter)national companies that operate in various sectors. In the portfolio data, these sectors are indicated by NACE codes. A stock can get issued by a head office, which results in the stock being assigned the NACE code M.70.1(0) corresponding to head office activities. Given that sector carbon intensities are used from the input-output model and assigned to the company level data based on the NACE codes it is important to "correct" sector codes for headquarters to the actual industry. As an example, if the stock of Heineken has NACE code M.70, it needs to be assigned to C.11.05, which is the NACE code for the manufacture of beer sector. As the correct NACE codes need to be determined manually based on expert judgement, the choice is made to correct only the largest equity and bond positions. This yields a list of stocks and bond for which the correct NACE sector is attributed of >80% for direct and indirect investment in equity and corporate bonds.

The Organisation for Economic Cooperation and Development (OECD) developed the Trade in Value-Added (TiVA) database to address the problem that the flows of goods and services are occasionally not reflected in measures of trade within global production chains. The TiVA database solves this by considering the value-added by each country-specific industry in the global production of goods and services. In this study, the 2015 data from the 2018 edition is taken. It comprises 69 countries (including 1 rest of the world (ROW)) and 36 industries, which use International Standard Industrial Classification Revision 4 (ISIC Rev. 4). From the 2015 TiVA data, the output vector is taken from the underlying Inter-Country Input-Output (ICIO) table to determine the carbon intensity of the country-specific industries. However, the data for Mexico and China is split into two categories: MX1 and MX2 for Mexico and CN1 and CN2 for China. These are placed at the end of the output vector, while within the vector there are zero values for Mexico and China (MEX and CHN respectively). Hence, MX1 and MX2 are aggregated and substituted for MEX and the same is done for China. Wiebe and Yamano (2016) combined the ICIO table with the CO_2 emissions from fuel combustion statistics from the International Energy Agency (IEA) and other industry statistics to create the Trade in embodied CO2 ($TECO_2$) database. This database embodies scope 1, 2 and 3 emissions, which are all direct emissions, all indirect emissions from energy purchase and use, and all other indirect emissions, respectively (Huang et al., 2009). The consumption-based emission data is then converted to production-based data, as a carbon tax is assumed to be levied on emissions emitted during the production process of companies.

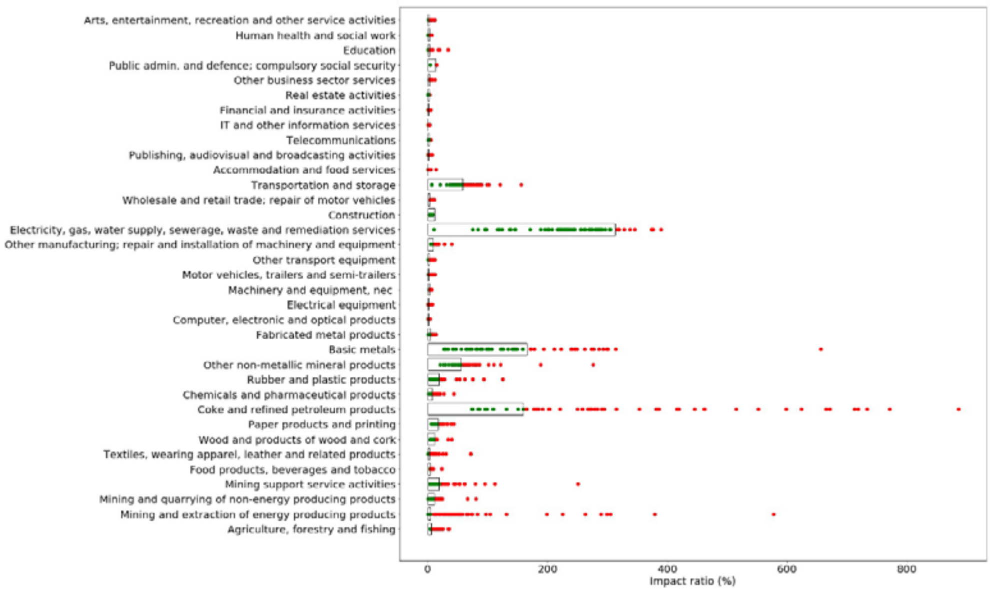
Finally, company level data are retrieved using Refinitiv Thompson Reuters EIKON (for profits, revenue and Enterprise Value) to determine financed emissions and financed profits based on the ownership approach. Details on how the social cost of carbon literature is used to determine optimal Pigouvian tax rates for the different scenarios is available upon request (i.e. the final thesis on which this section is based).

2.3 Results

For a global carbon tax rate of €38, €119, and €175 per tonne CO2, an impact ratio of 4,4%, 13,9% and 20,4% is estimated for the fourth quarter of 2020, respectively. Thus, the profits that the portfolios of the Dutch pension funds are exposed to through their investments would, ceteris paribus, be sufficient to bear the costs associated with a global carbon tax in all scenarios.

Comparing, at the sector level, the benchmark impact ratio to the impact ratios of investments by individual Dutch pension funds shows that there is room for improvement across nearly every sector (see Figure 1). Note that for the benchmark, it holds that investments are 'sector neutral'; a hypothetical portfolio with investment weights equal to EV_i divided by the sum of sector k's EV_i over all companies (*i*) is determined within the dataset. Figure 1 shows results for the (medium) €119 per tonne CO2 scenario. It shows that for nearly every sector, individual pension funds can improve on their impact ratio compared to the benchmark (in red). Also, there are large differences among pension funds. Many of them have sector positions where profits are insufficient to bear the env. damage cost (i.e. the impact ratio is >100%). The benchmark impact ratio also exceeds 100% for three sectors, namely refined petroleum products sector (159%), the basic metals sector (165%) and the electricity, gas, water supply, sewerage, waste, and remediation services sector (313%).

Figure 1: Benchmark impact ratio vs. the impact ratios of the portfolio positions of individual pension funds.



Note: The benchmark impact ratio of the sector is depicted by the bar. The green dots represent impact ratios of investments of pension funds that are below the benchmark, and the red dots represent impact ratios of pension funds above the benchmark.

3. Physical risks

Estimating physical risk for assets is important, especially in light of climate change. Physical risk is the risk that extreme weather events, or hazards, lead to large losses in assets. ECB/ESRB Project Team on climate risk monitoring estimates that between 1980 and 2017, about 453 billion Euros of economic losses in the European Economic Area and the United Kingdom were suffered due to climate-related events. Furthermore, they state that if no risk mitigation measures are taken, the economic losses due to these events will have grown to nearly 50 billion Euros per year by the end of this century because of climate change. Therefore, estimating the physical risk for assets is important. In this research, physical risk models are constructed based on historical damage data due to storms and floods in Germany.

3.1 Methodology

To model physical risk, damage due to hazards is often modelled as a function of hazard, exposure and vulnerability (Koks & Haer, 2020). A damage function maps hazard characteristics to expected damages to the exposure. Hazard characteristics concern variables that can be used as a proxy for the severity of the hazard. We focus on two specific hazards: storms and floods. For storms, the hazard characteristic is the maximum wind gust speed during the storm. For floods, the hazard characteristic is either the cumulative sum of precipitation in the three days prior to the flood or the weighted sum of precipitation in the seven days before the flood, which is the so-called antecedent precipitation index or API.

First, we ensure that all monetary values in the research are converted to the same reference year and currency. Moreover, we ensure that exposure data and hazard characteristics data are given on the same level of granularity. Then we model the damage to physical assets as follows. For each grid cell in the entire country grid, we model the expected damage ratio using some micro-scale damage function and the hazard characteristics for that cell. The damage ratio denotes the percentage of damage to the physical assets located on that grid cell. Physical assets are assets which are susceptible to damage due to extreme weather events. Multiplying the damage ratio with the physical asset exposure in that cell gives an estimate of damage to assets in that cell. Aggregating the damages of all cells results in an estimate for national damage due to a specific hazard. We subsequently explore which damage function best approximates the true damage on national level. We do this for both storms and floods.

We consider various storm damage functions: a benchmark function, the exponential function, logistic function, power law function, and several threshold functions, which are the ones based on Klawa & Ulbrich (2003), Emanuel (2011) and Heneka & Ruck (2008). For floods, the investigated damage functions are a benchmark function and the logistic damage function. For all functions except for the one based on Heneka & Ruck (2008) we estimate a univariate variant, including only the hazard characteristic as variable, and a bivariate variant, which also includes hazard duration.

As the samples for storms and floods are both small, we evaluate the accuracy of the estimated parameters by applying bootstrap. Moreover, we evaluate the models by investigating the mean absolute percentage error (MAPE) and the root mean squared error (RMSE). Furthermore, we test for significant differences in damage function accuracy in a pairwise manner by applying the Friedman test. We combine this sequential pairwise testing with the Holm step-down procedure to control the family-wise error rate (Derrac et al., 2011).

The models as investigated in this research are not yet able to approximate storm and flood damage enough to make reliable decisions on risk management. The mediocre performance of the models is due to a lack of sufficient(ly granular) data. The models in this research are estimated on 35 and 36 historical records for storms and floods, respectively. Moreover, for storms, the damage is reported on a national level, making it impossible to distinguish regions that may be less hard hit by the storm. For floods, it is known which regions are affected by the flood, but these regions still cover relatively large NUTS areas (See 3.2 Data).

The main difficulty in quantifying and modelling physical risk thus lies in a so-called data gap. In order to properly fit the models on historical data, that data should be available. The models in this research are fit solely based on open-access data. If, for instance, damage data on a more granular level, for example on ZIP-code level, were available publicly, this could improve the fit of the models. We therefore strongly suggest that such data, after being anonymised, should be made publicly available.

3.2 Data

We construct our models on exposure, hazard, and damage data for Germany. Note that, on average, a significant amount of the invested real estate of Dutch pension funds and insurers that is not situated in the Netherlands is located in Germany (7%). Data on the actual damage for real estate due to storms are either not available or only known at (re)insurance companies. This complicates modelling climate related risks, as endorsed by the Network for Greening the Financial System (2021). In order to model physical risk, we use several open-access data sources.

Exposure data

Exposure data are obtained from Eberenz et al. (2020). This data set contains, per country, the estimated total physical asset value per square kilometre. Physical assets are assets susceptible to physical risk. The estimated total physical asset exposure in 2014 U.S. Dollars (USD) is given for each grid cell with a spatial resolution of 30 arc-seconds. This corresponds to grid cells of a square kilometre, approximately. For Germany, there are in total 661,392 grid cells for which the value of the physical exposure is given. There are no missing values. Furthermore, for the simulation application, we about survey data of a German real-estate portfolio of 1 Dutch financial institution (incl. detailed location information of the real estate assets).

Total hazard damages

We use historical macro-economic damage data to calibrate micro-economic damage functions. Two data sets on historical damages are used to this end. First, macro-economic damage data due to storms are obtained from CRED / UCLouvain (2021). This data set contains data on damaging storms in the period 1979 through 2019. In this research, we include storms in Germany for which the total economic damage is known. This value is given in thousands USD in the value of the year of the storm occurrence. Moreover, for each storm it is known what the start and end date was of the storm. There are 35 storms in the data set.

Macro-economic damage data due to floods are obtained from Paprotny et al. (2018). We use data on 36 damaging floods in Germany in the period 1979 through 2016. For each flood, the total damage in millions of Euros, 2011 value, is known, as well as the start and end date of the flood. Moreover, it is known which regions were affected by the flood. The regions follow the Nomenclature of Territorial Units for Statistics (NUTS) classification from 2010, as given by Eurostat (2010).

Hazard characteristics

As described under 3.1 Methods, the storm and flood damage functions model damage as a function of wind gust speed and precipitation, respectively. These data can be obtained from Climate Data Store (2021). This reanalysis data set contains hourly estimates of wind gust speed and total precipitation at a 900 arcseconds spatial resolution. This corresponds to about 30 kilometres.

The wind gust speed is measured ten metres above the surface of the Earth. The maximum wind gust speed is taken as the maximum of the wind speed averaged over three second intervals (World Meteorological Organization, 2021) and is given in metres per second. The total precipitation is given in metres. In total, there are 1184 locations in Germany for which hourly wind gust speed and total precipitation are known. These values are known for the entire period 1979 through 2019 and there are no missing values.

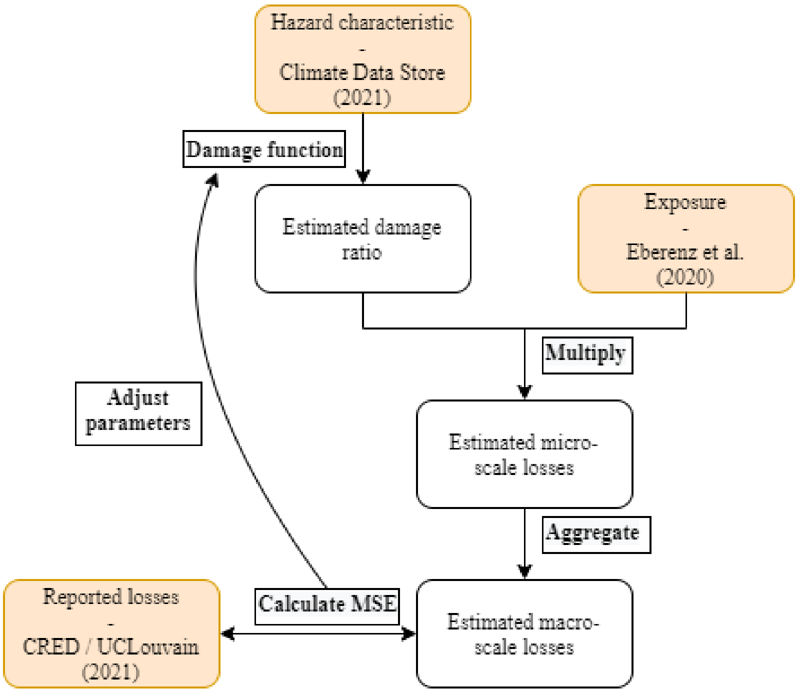
As mentioned under 3.1 Methods, we also incorporate a hazard duration variable in our damage functions. For floods, we simply take the reported start and end date of the flood and calculate the number of hours in that period. We define that to be the flood duration. For storms, we determine the 98th percentile wind gust speed for each location in the exposure data set. We take this value as a threshold above which we speak of gusts with potentially damaging speeds. For the reported duration of the storm, we determine for each location how many hours the maximum wind gust speed was above the threshold. This amount of hours is the value for the storm duration variable.

3.3 Results

Storm simulation

Figure 2 represents the model optimisation process, and shows how the input data sets are used in model calibration. We apply the best performing storm and flood damage functions to show, through two applications, how these functions could be used to estimate and quantify the physical risk for financial institutions.

Figure 2: Physical risk model optimization/calibration process and the use of the different data sources (orange).



In the first application we simulate storms. We then calculate the damage to the real estate portfolio for each storm on the portfolio of 1 Dutch financial institution. Using these values, we calculate the values for several risk metrics such as the expected annual loss, the Value-at-Risk (99%), and the expected shortfall at 98% level (Table 1).

Table 1: Risk metrics and their values in percentages of the total portfolio worth based on a simulation of damages due to 1000 years of storms.

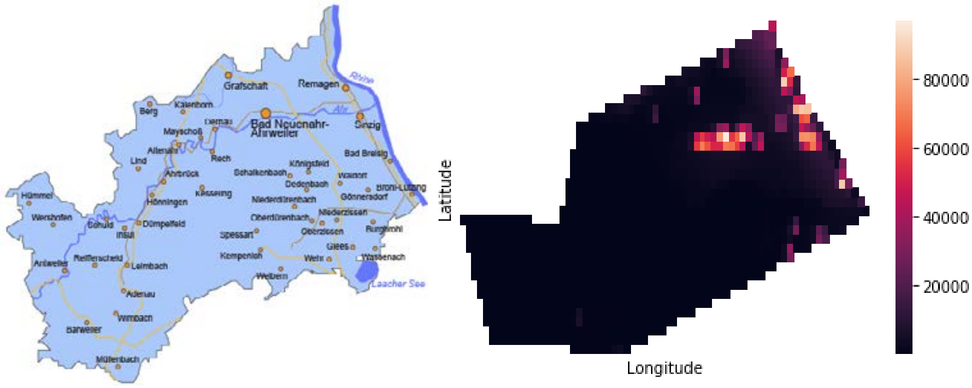
Risk metric	Value
$\widehat{\mathrm{EAL}}$	1.340%
$\widehat{\mathrm{VaR}}_{0.99}$	40.583%
$\widehat{\mathrm{ES}}_{0.98}$	41.445%

On average, about one percent of the total portfolio worth is estimated to be lost each year due to storm damage. The $\mathrm{VaR}_{0.99}$ and $\mathrm{ES}_{0.98}$ are about 40% of the portfolio's worth. As the real estate portfolio can represent a substantial amount of the total asset portfolio of an FI, such values for the risk metrics indicate that financial institutions would do well to take the physical risk due to storms into account on their balance sheet. However, given the lack of sufficient granular data on historical damages, the values that arise from this analysis are not reliable. The simulation does shows that very interpretable risk metrics can be calculated and risk mitigation matters could be taken based on these results. Furthermore, the distributional assumptions that are made in this simulation are not rejected. Therefore, with a suitable damage function, the estimates for the risk metrics for storms that result from this simulation would be quite interpretable and reliable. FIs could use this risk analysis to estimate their exposure to physical risk and take risk mitigating measures.

Flood stress test

One of the regions that incurred the most damage due to the July 2021 floods is Ahrweiler, Germany (Figure 3). For this region, we estimate the damage ratio as well as the losses for each exposure location in our exposure data set. We do this using the best performing flood damage function. The necessary precipitation data is obtained from Climate Data Store (2021). 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).

Figure 3: Map of Ahrweiler (left) and heat map of estimated damage in Ahrweiler due to the July 2021 floods (right).



If more granular data (e.g. historical damage data on ZIP-code level) would become available, we encourage that further research be done with these more granular damage data to determine whether other damage functions can better approximate storm and flood damage. Moreover, instead of constructing a model to approximate macro-economic damage, a model to approximate micro-economic damage could be estimated. This would lead to a more local model, but perhaps such a model would result in more accurate predictions of hazard damage. Another advantage of more granular damage data would be that other methods would become possible to implement, such as a fixed effect model. Such a model incorporates a location effect.

Furthermore, using more granular data, it could be researched whether other hazard characteristics, for instance flow velocity for floods, improve the damage models. A final suggestion for future research would be to examine whether a proxy for climate change should be included in the damage models. These directions of research could lead to physical risk models becoming more reliable and eventually becoming a tool to adequately predict and mitigate the risk for damage due to extreme weather events. The results show that, at least for the German case, the current open access data on historical damages are insufficient to produce reliable results for these such applications.

4. Green taxonomies

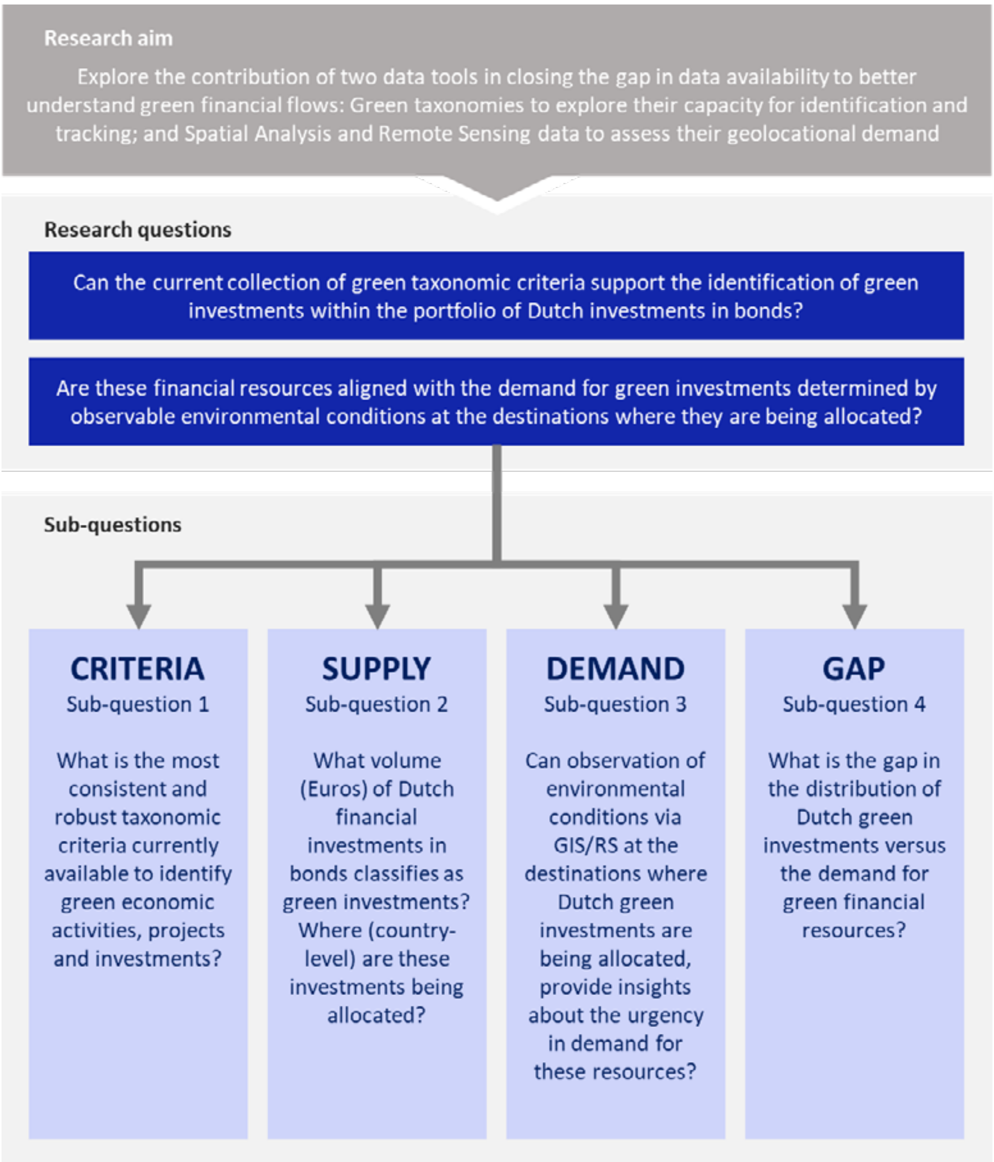
Over the past years, multiple green taxonomy approaches have been developed to assess the alignment of investments with various sustainability goals. Through the systematic classification and definition of 'green' assets, these approaches aim to drive capital more efficiently towards to high priority sustainable projects (World Bank, 2020). Several countries and jurisdictions that are scaling up sustainable financial investments, are in the process of establishing taxonomies for green finance (ICMA, 2021). However, important challenges must be addressed to guarantee their successful deployment. Some of the most significant challenges include: the lack of harmonization between taxonomies leading to higher transaction costs and market segmentation, low data availability based on consistent methodologies, capacity constraints to secure proper implementation and compliance to these mechanisms, and the absence of complementary mechanisms to secure optimal performance (e.g. brown taxonomies).

This research aims to contribute to closing the gap in data availability by exploring the contribution of two building blocks: a harmonized green taxonomies analysis to explore the identification and tracking of green investments, and spatial analysis based on remote sensing data to assess geolocational demands for green investments. According to the International Capital Market Association (ICMA), "*a green taxonomy is a classification system identifying activities, assets, and/or project categories that deliver on key climate, green, social or sustainable objectives with reference to identified thresholds and/or targets*" (Plaff et al., 2021). By providing a systematic and science-based classification and definition of economic activities that deliver positive environmental objectives, capital can be located and tracked more efficiently across these priority projects and infrastructure (World Bank, 2020). Spatial Analysis and Remote Sensing corresponds to the "*detecting, monitoring and processing of an area's physical data by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft)*" (United States Geological Survey, 2021). This type of data has the potential to support the green financial sector. Evaluation and interpretation of aerial photography and satellite imagery can be used to assess and manage climate change risks, as well as to enable evidence-based allocation of financial resources in accordance to spatial observation of environmental conditions. The following sections describe the first steps of an analysis to contribute to these challenges. We study the corporate bond portfolios of Dutch investment funds focusing on corporate bonds issued by the Top 500 companies (in terms of revenue) operating across 38 OECD countries.

4.1 Methodology

Figure 4 describes the aim of this research and its targeted questions: two overarching questions and a set of four sub-questions represent the main objective of this paper.

Figure 4: Green taxonomies methodology

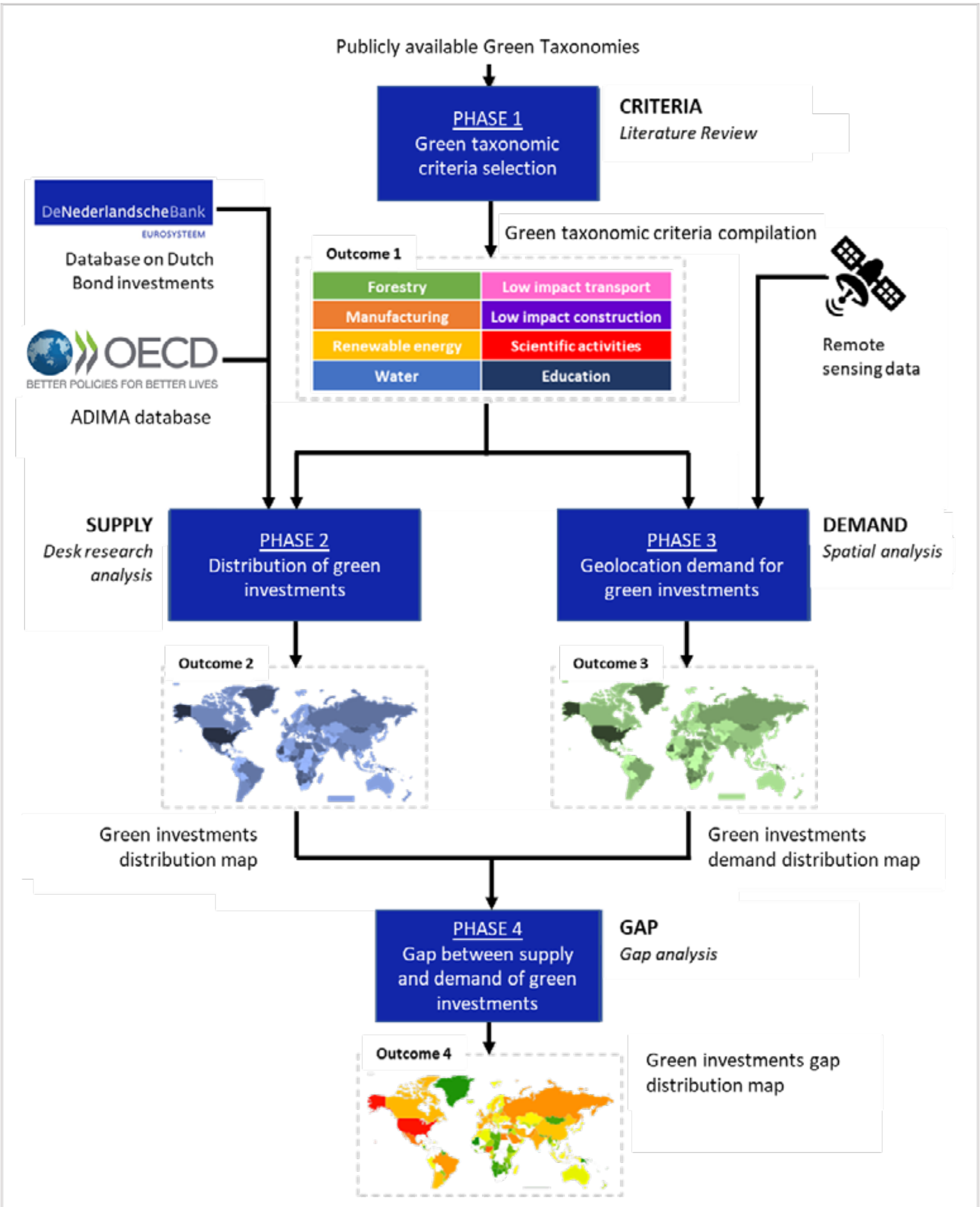


We explore the level of harmonization between publicly available green taxonomies by conducting a literature review. The evaluation of the green taxonomies is conducted to prioritize and select the most suitable and robust taxonomic criteria available. Suitability is determined by assessing all identified green taxonomies (GTs) against 3 criteria: (i) the GT has an official and publicly available file published (in English) by the national government or organization responsible for its design; (ii) the GT has concrete taxonomic criteria describing economic activities and assets that positively contribute to environmental objectives, as well as their performance thresholds; (iii) the GT is independently designed and does not constitute an adaptation of a previous one. GTs meeting these criteria are then prioritized and scanned to assess the robustness in their taxonomic criteria. This assessment is conducted by applying the Framework of Classification Principles for Green Taxonomies designed by Ehlers et al. (2021). GTs developed with a clear structure and in accordance with scientific criteria were considered as robust and selected for further analysis. Finally, the selected GTs were fully scanned to review the complete structure of the taxonomy, the list of economic activities and assets suggested to deliver on the environmental objectives, and in-depth specifications, screening criteria or performance thresholds that are required to classify as 'green'. All identified criteria were then grouped together and signalled according to the level of compliance between the assessed GTs.

4.2 Data

Figure 5 presents a flow diagram describing how the 4 phases of analysis of the methodology are performed. The diagram describes the data inputs used for each phase, as well as results and outcomes delivered and their interactions across phases. Phase 1 is described in the methodology section above. The phases correspond to the sub questions in Figure 4. For phases 2, 3 and 4 below, we focus on the data and results of a case study on investments and demand for solar energy facilities.

Figure 5. Data sources flow diagram. Phase 1 maps and comprises most robust set of publicly available green taxonomic criteria; Phase 2 contrasts taxonomic criteria to identify and geographically locate investments classified as green; Phase 3 uses spatial observation data at destinations of green investments to determine demand for resources to finance green activities; Phase 4 compares the distribution of green investments with the demand for green investments.



For phase 2, we test the applicability of the selected green taxonomic criteria by applying it to Dutch investment funds' investments in corporate bonds for December 2020 and determine the share of climate-aligned assets. Information from the publicly available database Analytical Database on Individual Multinationals and Affiliates (ADIMA) was linked to the corporate bond data to provide information on the geographical location of affiliates of corporate bond issuers. The ADIMA database corresponds to a new data framework offering information on both the physical and digital presence of top 500 multinational enterprises operating within the OECD region at country-level (OECD, 2022). Corporate bonds are matched to the ADIMA database by using the LEI (Legal Entity Identifier) code. This selection provided a sample of corporate bonds issued by (an affiliate of) a top 500 company with locational information from any of the OECD countries. Corporate bonds are classified as 'green' if the economic activity of the issuer was compliant to the list of green taxonomy criteria from Phase 1. The analysis was conducted through a manual inspection of the issuer's economic activity reported by Bloomberg. Finally, the supply of green investment is then classified for every country. For the solar facilities case study, total country-level investments are classified according to their level of investment in Table 2.

Table 2. Classifications for country-level investments on solar energy facilities.

Classification	Investment	Project financing
Very low investment	€0,00 Mi - €3,75 Mi/year	0,25 10MW solar plant
Low investment	€3,75 Mi - €7,50 Mi/year	0,5 10MW solar plant
Medium investment	€7,50 Mi - €15,00 Mi/year	1 10MW solar plant
High investment	€15,00 Mi - €30,00 Mi/year	2 10MW solar plant
Very high investment	€30,00 Mi - €85,00 Mi/year	≥ 2 10MW solar plant

The breaks in between these classifications are determined according to the average cost of a medium-sized photovoltaic (PV) power plant of 10 MW. The average size of small to big was determined against the network of solar power plants installed in the USA (EIA, 2019) and an average cost of EUR $1,00 per watt capacity (average value between USD $0,75 to USD $1,25) was used as reported by Solar Energy Industries Association (SEIA, 2020). Finally, these classification are linked to the number of PV powerplants that could be financed with the totality of investments in solar energy allocated per country.

For phase 3, the demand for green investments on electricity generation from solar energy is determined according to the potential for photovoltaic (PV) power output from countries pertaining to the OECD. Potential PV power output in every country of the world has been calculated by Solar Irradiance data in collaboration with the Energy Sector Management Assistance Program (ESMAP) of the World Bank, and released in the form of consistent high-resolution data sets via an online tool: Global Solar Atlas. In the Global Photovoltaic Power Potential by Country (2020) report, the PV power potential is described as "*the conversion of the available solar resource to electric power considering the impact of air temperature, terrain horizon, and albedo, as well as module tilt, configuration, shading, soiling, and other factors affecting the system performance*", and measured in kilowatt hours per installed kilowatt peak (kWh/kWp). This indicator is produced through standard GIS operations produced from statistical evaluation of satellite-based imagery (compilation from sensors GOES-East and GOES-West by NOAA, Meteosat PRIME and IODC by EUMESAT, MTSAT and Himawari-8 by JMA, MACC-II/CAMS atmospheric data by ECMWF, MERRA-2 atmospheric data by NASA, GFS data by NOAA) containing data layers of: Global Horizontal Irradiance (GHI), air temperature at 2 meters, index of seasonal variability, wind and snow, atmospheric pollution, and dust.

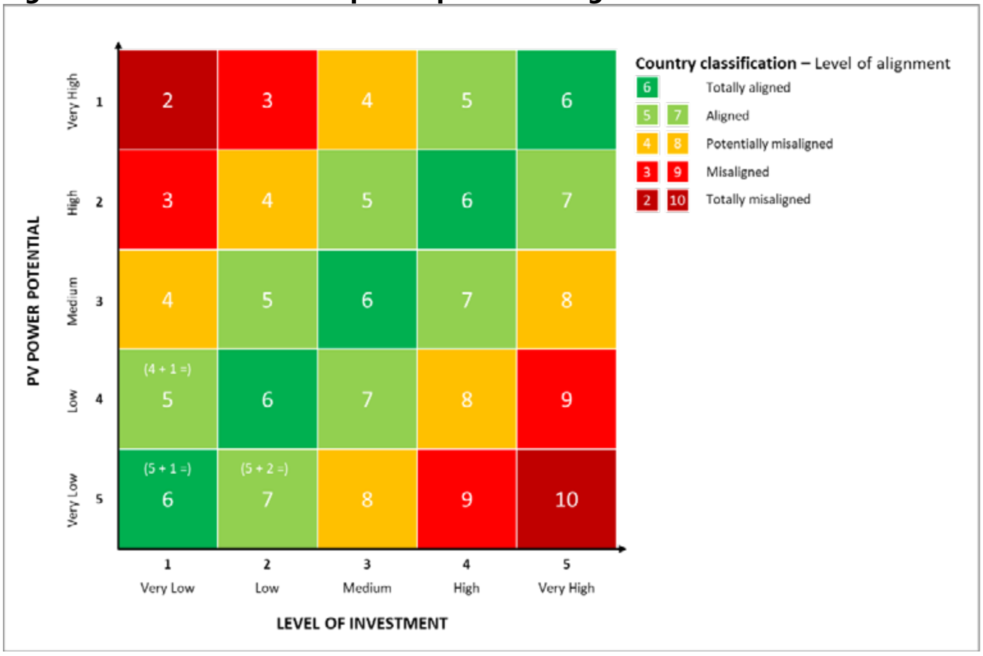
Based on this data, the demand for investment in electricity generation through solar energy was then classified at a country-level according to its average PV Power potential. This classification is given in Table 3. The breaks in between these classifications are identical to the thresholds described in the Global Photovoltaic Power Potential by Country Report (2020).

Table 3: Classification of average PV power potential per country.

Classification	Investment
Very low potential	0,00 – 2,80 kWh/m^2
Low potential	2,80 – 3,40 kWh/m^2
Medium potential	3,40 – 4,20 kWh/m^2
High potential	4,20 – 4,80 kWh/m^2
Very high potential	4,80 – 8,00 kWh/m^2

Finally, for Phase 4, we conduct a qualitative gap analysis on green investments allocated to OECD countries. Each variable is reclassified into a new numeric value. The 5 clusters of solar investment ranging from Very Low Investment to Very High Investment are assigned a number from 1 to 5 (ascending order). The 5 clusters of PV power potential ranging from Very Low PV Power Potential to Very High PV Power Potential are assigned a number from 5 to 1 (descending order). Numeric values assigned to each variable are added together following a matrix structure described in Figure 6. The resulting number is then assigned a classification describing the level of alignment between the size of the investment and the potential for electricity generation from solar energy for every country, according to 5 clusters: (i) Totally misaligned; (ii) Misaligned; (iii) Potentially misaligned; (iv) Aligned; (v) Totally aligned. Final results are then plotted into a map describing the level of alignment between investments on solar energy and PV power potential across OECD countries. All data is merged and contained within a Geodatabase in ArcGIS.

Figure 6: Investment vs. PV power potential alignment matrix



4.3 Results

The pool of green taxonomies that is part of the analysis consists of documents produced by diverse jurisdictions establishing comprehensive classifications of sustainable finance and assets. This analysis takes into account both the official – i.e. produced and legislated by governments and central banks (relevant examples including the EU Green taxonomy, the Green Bond Catalogue of the People's Bank of China, Green Taxonomy of Malaysia) – and market-based taxonomies produced by private enterprises (e.g. the Climate Bonds Initiative taxonomy and the ISO Green Debt Instruments). Figure 7 presents the final outcome of the study of a total of 21 taxonomies and sustainable finance definitions that are identified globally and the 3 taxonomies that provide the best reference of green taxonomic criteria based on the methodology described in section 4.1. The 3 taxonomies that are prioritized and selected as the most consistent and robust collection of green taxonomy criteria are: the European Green Taxonomy (EUGT), China's Green Bond Catalogues (CGBC) and the Climate Bonds Initiative Taxonomy (CBIT). The limitations identified in the remaining 18 GTs that were studied are: 6 GTs remain still under construction in their corresponding jurisdictions and no official version has yet been made public; 7 GTs do not contain concrete taxonomic criteria but rather define guidelines or decision frameworks for the identification of GIs; and 5 GTs have been developed based on previous taxonomies and constitute an adaptation of criteria according to local context and needs. Figure 7 provides details on how the remaining 3 GTs differ in terms of their criteria for activities/assets where full consensus is not reached. In this case, either green activities/assets are categorized as reaching partial consensus (at least one GT mentions it and others do not include it) or categorized as controversial (contradictions in environmental objectives exist).

Figure 7: Three consistent and robust green taxonomies and the further classification of activities/assets

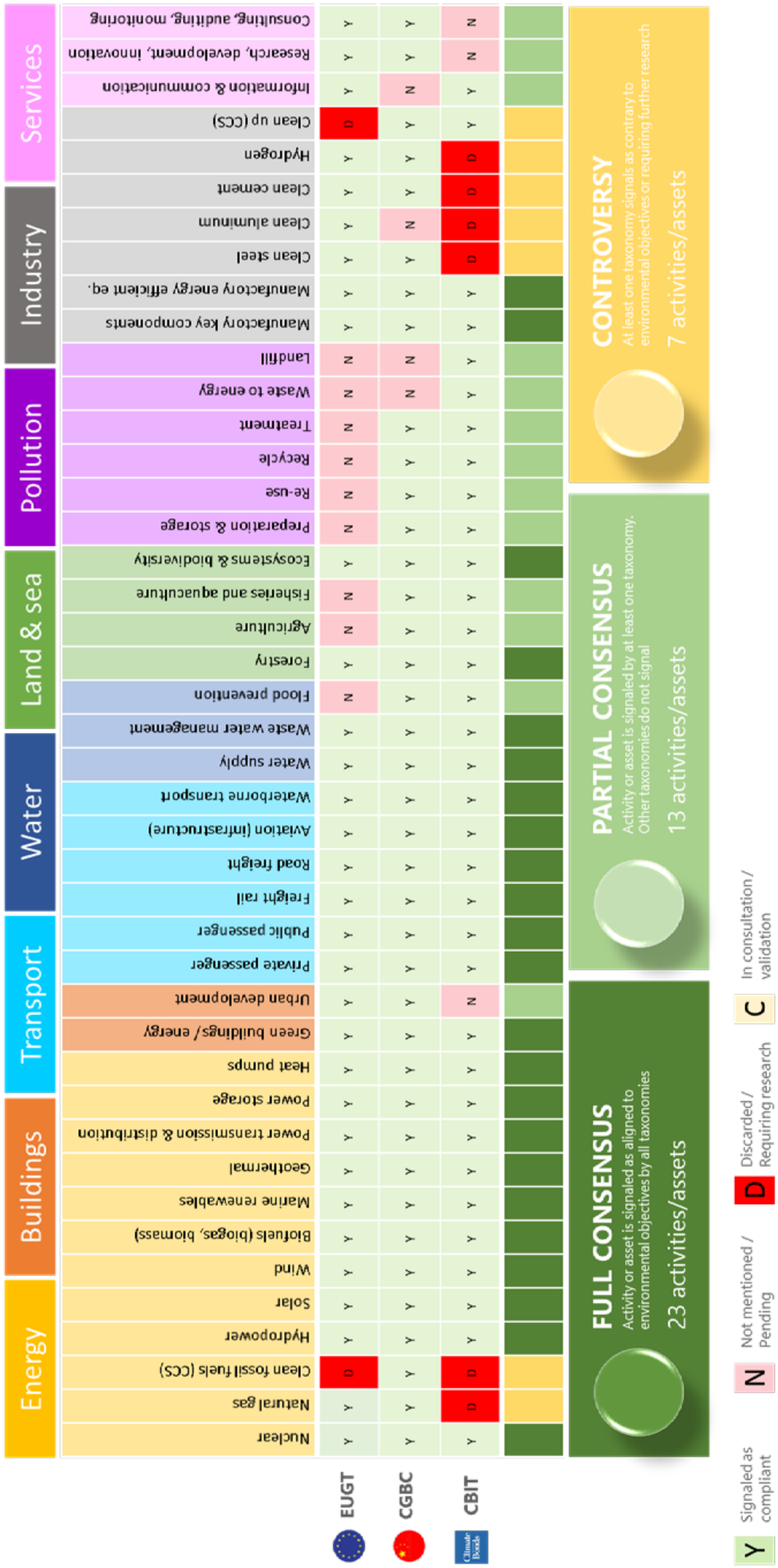


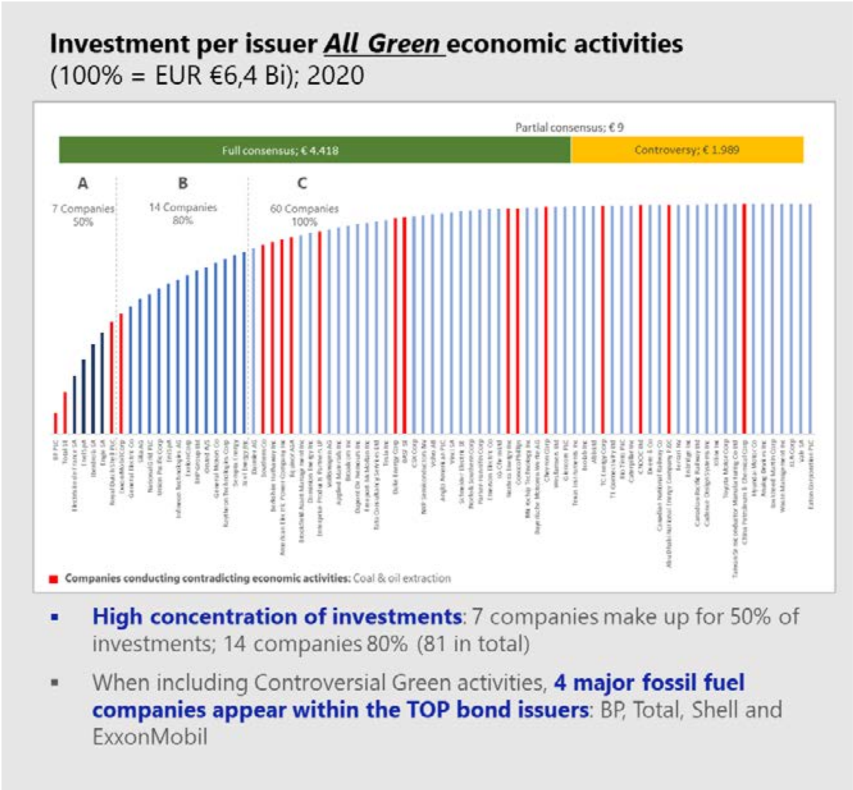
Figure 8 shows the results for *potentially* green corporate bonds (incl. partial consensus and controversy categories). Narrowing down the sample to issuers pertaining to the Top 500 companies (in terms of revenue) operating within the OECD region that could be linked to a LEI code, results in a list of 618 private entities. The individual assessment of economic activities performed by these companies resulted in the identification of 35 bond issuers exclusively conducting economic activities that fully comply with green taxonomic criteria. A group of 131 issuers where identified to have a partial alignment to green taxonomic criteria. A partial alignment was established when bond issuers conducting a diverse array of economic activities, performed at least one activity that was considered as green. This added to a total amount of 166 bond issuers (pertaining to 81 MNEs) with a potential compliance. At the closing of December 2020, these issuers had consolidated a total value of EUR €6,40 Bi provided by Dutch investment funds. EUR €1,9 Bi of the total value of investments are identified to be directed towards 'controversial' economic activities such as: natural gas, nuclear energy, CCS, hydrogen, clean aluminium, steel and cement. When investments for these activities were removed 17 MNEs issuing potentially green corporate bonds no longer complied with the taxonomic criteria.

Figure 8: Consolidation of investments on potentially green corporate bonds. Portfolio of investments made by Dutch investments funds by December 2020.

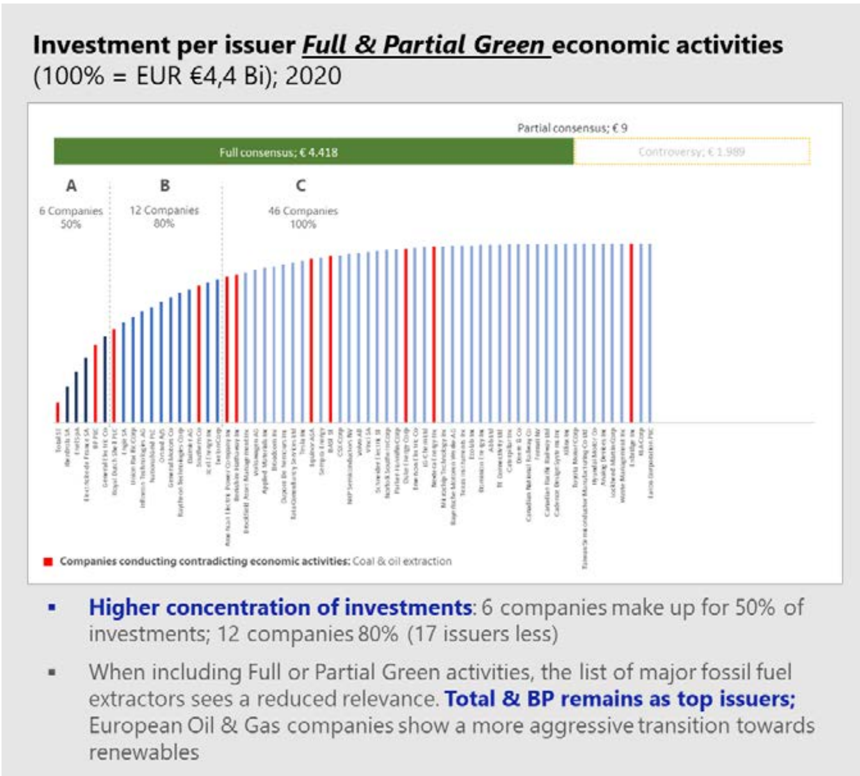
When investments for controversial activities were removed 17 MNEs issuing potentially green corporate bonds no longer complied with the taxonomic criteria. Investments across green issuers where identified to be highly concentrated with only 6 to 7 companies (depending on the inclusion of controversial green activities) consolidating up to 50% of all corporate bond investments provided by Dutch investment funds at the end of 2020. A closer observation of the list of potentially green issuers resulted in the identification of 18 companies conducting economic activities that were contradicting to the delivery of positive environmental impacts, while at the same time they conduct activities compliant to green taxonomic criteria. These are companies identified to conduct activities in the field of oil and coal extraction, processing and commercialization, as well as companies dedicated to mineral extraction and mining. Top MNEs with a contradicting profile included BP PLC, Total SE, Royal Dutch Shell PLC, Exxon Mobile Corp (see Figure 9a/b).

Figure 9a/b: Accumulated distribution of investments on potentially green corporate bonds per issuer (2020)

9a:



9b:

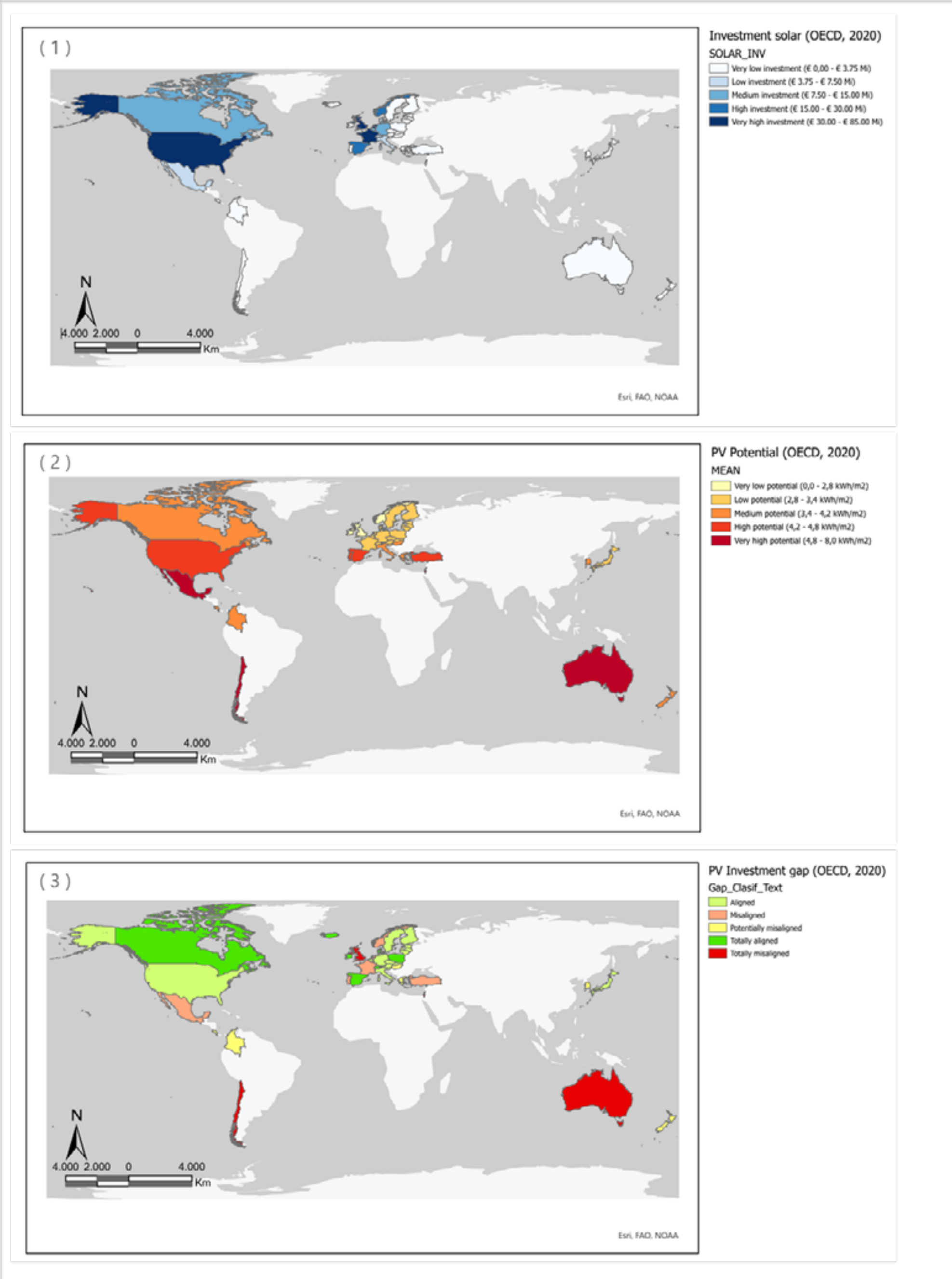


Solar energy case study

Looking at the results at a more granular level, we find that solar energy is identified amongst the top 5 subsectors consolidating the highest amounts of potentially green investments, within the clean energy generation and distribution sector. Figure 10 offers the Phase 2, 3 and 4 results of a closer analysis of the regional distribution of these solar investments made by Dutch investment funds.

The results identify 5 countries as top destinations for these financial resources, concentrating over 80% of the potentially green investments: France, the Netherlands, Great Britain, USA and Spain. The remaining countries receiving potential investments on solar energy did not exceed the EUR15 Million/year for 2020 (per country). Very low (below EUR 1,75 Million/year) to no investments on solar where identified in eastern European countries, middle eastern countries (Israel), South America (Chile, Colombia) and Pacific region (Australia, Japan and South Korea). Contrasting against the potential for PV power generation across the OECD countries, the countries most suited for the generation of energy from this renewable source where countries located in latitudes closer to the equator with desertic ecosystems: Chile, Mexico, Israel and Australia. This distribution between investment and PV power potential resulted in the identification of only two countries with high potential receiving high levels of investment: USA and Spain. The Netherlands, France and Great Britain instead were identified as countries with high concentrations of investments, misaligned however with the local potential for power generation from this renewable source. On the other side, all countries identified to have very high potential did not show significant concentrations of green investments, and here classified as totally misaligned, which was the case for Mexico, Chile, Israel and Australia. Remaining countries were classified as aligned in their investments mostly given to low potentials for PV power generation and limited amounts of investments allocated into these countries.

Figure 10. (1) Supply of solar energy investments across OECD territory; (2) Average PV power potential across OECD territory; (3) Alignment between investment and potential for solar power in OECD territory (2020)



To understand the exact reasons behind misalignment can only come from a further in-depth evaluation of local conditions of the renewable energy market. In its yearly Renewable Energy Report, the International Energy Agency (IEA) makes a revision of the outlook for PV power generation per country (IEA, 2021). In line with results obtained from this research, the Netherlands and France are identified as countries with high concentrations in investments derived from a strong push in the transition towards renewables by local government. Public policy within these two markets promotes investments in the solar energy system through a portfolio of mechanisms that contemplate from taxing incentives to regulation enforcing the installation of PV panels on new warehouses or other similar infrastructure. Also for countries with high PV power potential and low investment, as is the case for Mexico and Australia, the report describes a significant reduction in the concentration of investment also determined mostly by local regulatory frameworks and decisions, including the delays in permissions granted from the government to install PV power plants to increasing their operational requirements.

5. Conclusion

In this paper, we 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).

Transition risk:

We assess the impact of a hypothetical carbon tax on the portfolios of financial institutions. Following the recommendation of the Task Force on Climate-related Financial Disclosures (TCFD) for financial institutions to implement scenario analysis and stress testing to evaluate the financial risks related to climate change, a stress test is performed to quantify the transition risks related to the implementation of a global carbon tax for financial institutions. An impact ratio is constructed as the costs related to the carbon tax relative to the profits that the financial institutions are exposed to through their portfolios. It thus captures the risks a financial institution faces in terms of potential reductions in portfolio returns when a certain carbon tax is introduced. The method is illustrated through an example for Dutch pension funds.

While the analysis here is performed based on the OECD TiVA model, future research should determine whether an application of (the most recent version of) Exiobase can extend the scope to other greenhouse gases and other environmental pressures. Also, the recent developments of the FIGARO (Full International and Global Accounts for Research in input-Output analysis) model at Eurostat could be explored as another option. The benefit here is that the FIGARO tables will be updated on an annual basis, while Exiobase only receives sporadic updates. Ideally, limitations regarding the setup of emissions in IO-models will be addressed by the financial sector's closer involvement in developing new methodologies. For instance, the GHG protocol Scope 1,2,3 subdivision could be considered to closer match the data that is already available at third-part data providers and would allow for mixed approaches (i.e. substituting aggregated IO-data only when company-level data is unavailable).

Physical risk:

Bridging the damage data gap would lead to physical risk models that can be used as a tool to predict and mitigate the risk for damage due to extreme weather events. 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, respectively. If, for instance, damage data on a more granular level, for example on ZIP-code level, were available, this could improve the fit of the models. We strongly suggest that such data, after being anonymised, should become more publicly available. This directly relates to Network for Greening the Financial System's (NGFS) recommendation to improve data availability in the financial sector. Central banks are advised to try to construct such a damage database and to further research in what way physical risk models can be improved. For instance, the effect of climate change on physical risk could be added to the models.

In more general terms, the label 'physical risks' bunches all types of risks/hazards ((i.e. river and coastal floods, forest fires, landslides, subsidence, windstorms, heatwaves and droughts) together. The goals/tipping points for these risks/hazards are typically less well defined than for carbon emissions. We should thus be aware that we might not be able to deliver very detailed or robust results in this field in the short or medium run, that is compared to what we will be able to do for transition risk. There are of course quite a lot of geographical information system datasets on exposure and the likelihood/occurrence of hazards that we could employ. However, to calculate the risks in monetary terms, we need the factors that translates different hazards to damage ratios for different asset classes and sectors. This paper shows that the historical granular data to model these factors is very much lacking in the public domain. In addition, these factors will also be affected itself by climate change and adaptation and thus differ widely across asset classes sectors.

Green taxonomies:

Our results demonstrate that the current data available at De Nederlandsche Bank (DNB) combined with publicly available data can at best be used to flag investments that can potentially be classified as 'green'. A potential classification allows for a preliminary assessment that includes the sizing of a maximum value of green investments and the generation of preliminary insights about the distribution of these assets across countries, economic activities and bond issuers. Limitations were driven mostly by data availability and the need for further in-depth analysis including data from multidisciplinary fields on the drivers of green financial investments. The methodology suggested in this research, however, represents one step forward in the tracking and assessment of green investments and can help narrow down further research into this field. As green taxonomies move from the development phase into phases of consolidation and maturity, additional information and developments will likely provide elements to extract greater potential from the data and methodologies used in this research.

Our results show that overall, there is substantial scope for financial institutions and central banks to better leverage publicly available data sources and models to develop climate risk proxies. In particular, the results are promising for the transition risk and green taxonomy applications, while for physical risk the performance of the models could be improved if more granular data (e.g. historical damage data on ZIP-code level) were to be made publicly available. For transition risk, a better alignment of IO-models with the GHG protocol could future benefit applications. The three MSc research projects that allowed us to write this paper are available upon request.

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

Justin Dijk, Derek Dirks, Willemijn Ouwersloot, Juan Pablo Trespalacios Miranda

DeNederlandscheBank

EUROSYSTEEM

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 finished April 2022)

   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

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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 emissions 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).

exiobase

OECD
BETTER POLICIES FOR BETTER LIVES
Trade in Value Added

1. TRANSITION RISK – methodology and data

Methodology:

Impact ratio per sector (unit: $\frac{\$}{\$} = \%$): $\frac{Emissions\ (CO_2) * CO_2\ tax\ rate\ (\$/CO_2)}{Profits\ (\$)}$

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.

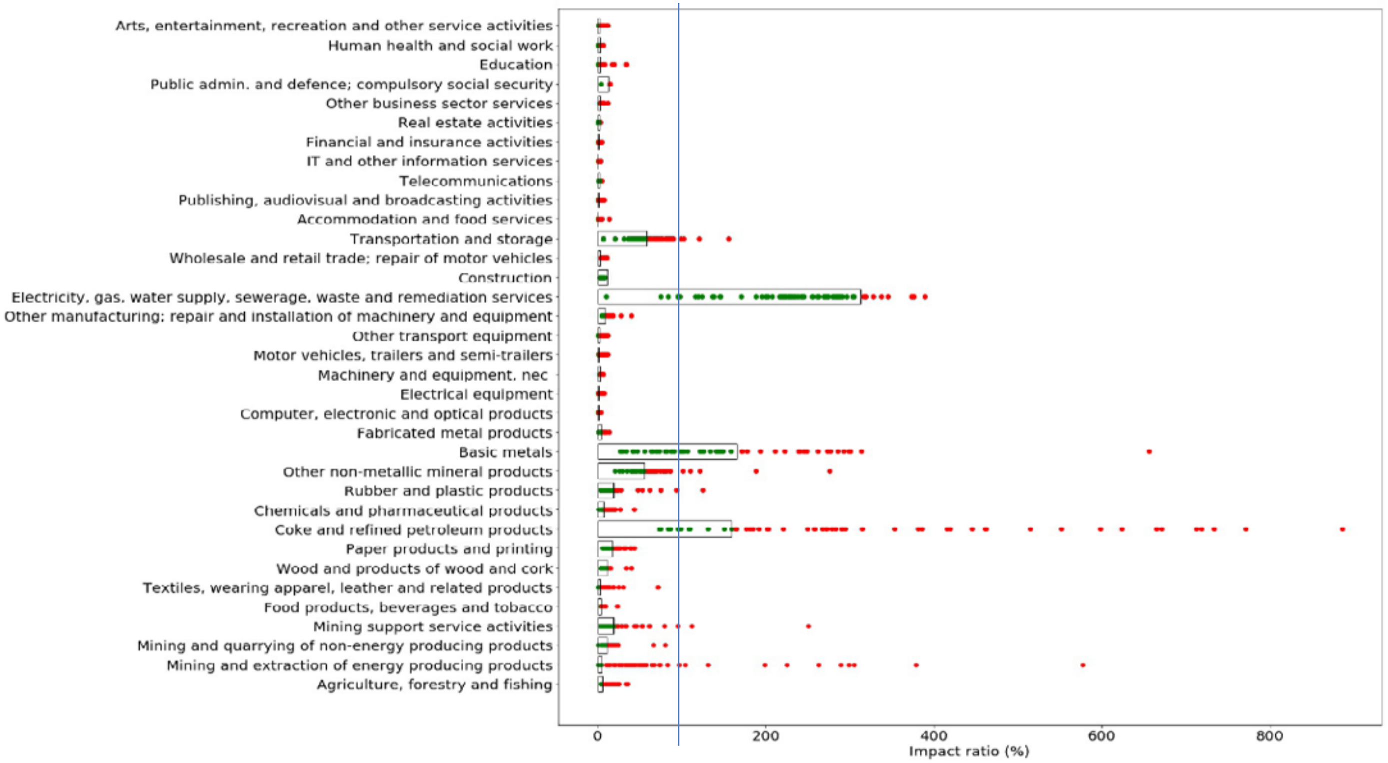
Data:

- 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_2 ($TeCO_2$) 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_2 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)

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EUROSYSTEEM

2. Physical risks

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

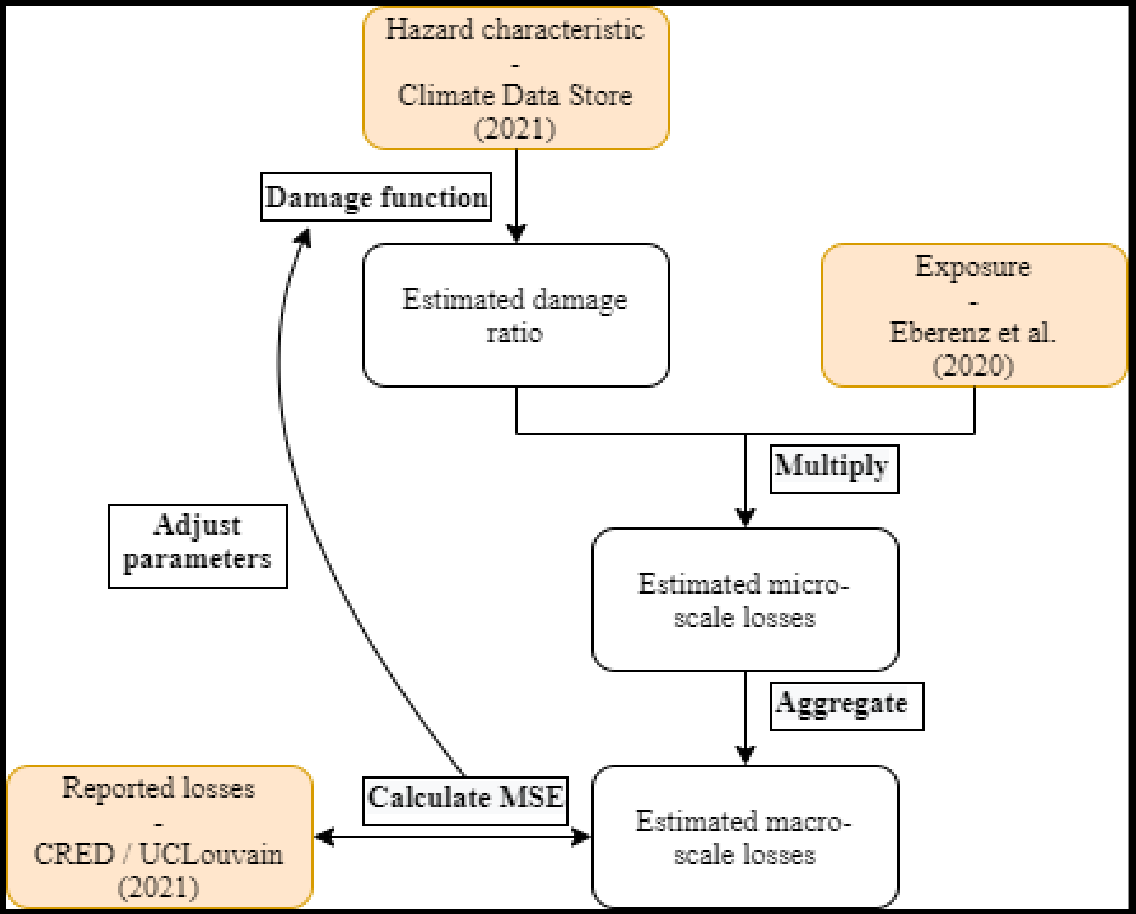
Methodology:

- Calibrate several models to estimate damage due to storms and floods. Use micro-scale damage functions to approximate the available macro-scale hazard damage data for the sample period 1979 through 2019.
- Simulation of storms: Perform a simulation (1000 years of storms) to determine outcome of typical risk measures (e.g. Expected Annual Loss) of a Dutch financial institution's real estate portfolio in Germany.
- Stress test for flood: Estimate the total damages in the district of Ahrweiler, Germany (recently hit by the July 2021 floods).

Data:

- Assets: Survey data of a German real-estate portfolio of 1 Dutch financial institution (incl. location information).
- Assets: Eberenz et al. (2020) "Lit population" (LitPop), an asset exposure dataset using a combination of nightlight intensity and geographical population data (661,392 grid cells (1 square kilometer each) for Germany).
- Damage: Center for Research on the Epidemiology of Disasters' (CRED, Leuven) Emergency Event Database (EM-DAT), an international disaster database; country-lev. data on 35 storms in Germany, duration and total monetary damage.
- Damage: Prapotny et al. (2018) HANZE database of historical damaging floods in Europe; data on 36 floods with the affected NUTS regions, the duration and the total monetary damage.
- Hazard characteristics: Climate Data Store; 1184 locations in Germany with hourly wind gust speed and total precipitation (to model storm damage as a function of wind gust speed & flood damage as a function of precipitation).

2. PHYSICAL RISKS – methodology and data



Methodology:

- Calibrate several mode … unctions to approximate the available macro-sc …
- Simulation of storms: … l risk measures (e.g. Expected Annual Loss) …
- Stress test for flood: E … by the July 2021 floods).

Data:

- Assets: Survey data … n information).
- Assets: Eberenz et al … ation of nightlight intensity and geogra … nany).
- Damage: Center for … Database (EM-DAT), an international disaste … onetary damage.
- Damage: Prapotny et … 36 floods with the affected NUTS region …
- Hazard characteristic … ed and total precipitation (to model storm damage as a function of wind gust speed & flood damage as a function of precipitation).

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

DeNederlandscheBank

EUROSYSTEEM

3. GREEN TAXONOMIES - objective

Research objective	Explore the contribution of two data tools in closing the gap in data availability to track and understand flows of green financial assets : Green taxonomies and Spatial Analysis and Remote Sensing data & analysis
Object	Dutch Investment Funds' (IF) exposures to Corporate Bonds **(Dec 2020)**
Research questions	Can the current collection of **green taxonomic criteria** support the identification of green investments within the portfolio of corporate bonds investments made by Dutch IFs? Are these financial resources aligned with the demand for green investments determined by **spatial observation of environmental conditions** at the destinations where they are being allocated?

Sub-questions	**Taxonomic criteria**	**Supply**	**Demand**	**Gap**
	(i) What is the most consistent taxonomic criteria currently available to identify green economic activities, projects and investments?	(ii) What volume (Euros) of Dutch financial investments in bonds classifies as green investments? Where (country-level) are these investments being allocated?	(iii) Can observation of environmental conditions via GIS/RS at the destinations where investments are allocated, provide insights about the urgency in demand?	(iv) What is the gap in the distribution of green investments versus the demand for green financial resources?

3. GREEN TAXONOMIES - methodology

Methodology consists of four phases of analysis

Phases

1. Green taxonomic criteria selection (CRITERIA)
2. Green bonds distribution (SUPPLY)
3. Green investments geolocational demand (DEMAND)
4. Gap in green investments (GAP)

Detail

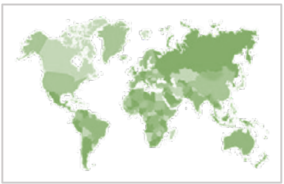
1. Green taxonomic criteria selection (CRITERIA)
   a. Mapping of green taxonomies and sustainable finance definitions globally
   b. Prioritization and selection of most consistent green taxonomic criteria
2. Green bonds distribution (SUPPLY)
   a. Classification of Dutch investments in corporate bonds compliant with green taxonomic criteria
   b. Mapping of potential locational distribution of green investments
3. Green investments geolocational demand (DEMAND)
   a. Analysis of potential demand for green investments according to remote observation of environmental conditions at the destinations where green investments are allocated
4. Gap in green investments (GAP)
   a. Perform a geolocational gap analysis between the supply of green investments and their demand

Data & tools

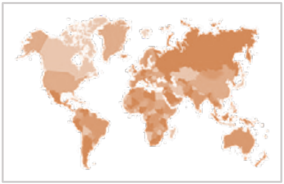
1. EU TAXONOMY, China Green Bond Catalogue, Climate Bonds, The Green Bond Principles – Publicly available pool of Green Taxonomies
2. DeNederlandscheBank EUROSYSTEEM – Dutch Corporate Bonds portfolio; OECD – ADIMA - Database
3. ArcGIS Pro – GIS processing software; WORLD BANK GROUP, ESMAP, SOLARGIS – Public satellite-based imagery
4. ArcGIS Pro – GIS processing software

Outcome

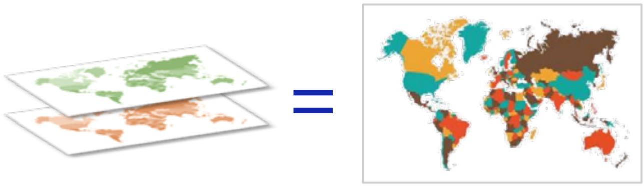
Green taxonomic criteria compilation



Dutch Green Bonds distribution map



Green investment demand distribution map



Gaps in green investment distribution map

3. GREEN TAXONOMIES - methodology

Methodology consists of four phases of analysis

Phases

1. Green taxonomic criteria selection (Criteria)
2. Green bonds distribution (Supply)
3. Green investments geolocational demand (Demand)
4. Gap in green investments (Gap)

Phase #1 seeks to identify all green taxonomic criteria currently available and select the most robust and consistent

a. Mapping of green taxonomies

a.1 **Literature review** to map all green taxonomies and sustainable finance definitions available globally

- **Method:** Scoping (Pham M. et al. (2014)
- **Search query:** **"**Green Taxonomy", "Green Finance Definitions", "Sustainable Finance Definitions"
- **Search engines**: : Web of Science, Google Scholar

b. Prioritization & selection

b.1 Assessment of identified taxonomies and prioritization against 3 criteria:

- **C1. Available published** taxonomy
- **C2.** Provides **taxonomic criteria**
- **C3. Independent development**

b.2 Evaluation of selected taxonomies to **guarantee comparability** using classification framework developed by Ehlers T., et al., 2021)

c. Taxonomic criteria contrasting

c.1 Assessment of criteria of selected green taxonomies. Classification according to **level of consistency** between them

3. GREEN TAXONOMIES - methodology

Methodology consists of four phases of analysis

Phases

1. Green taxonomic criteria selection (Criteria)
2. Green bonds distribution (Supply)
3. Green investments geolocational demand (Demand)
4. Gap in green investments (Gap)

Phase #2 seeks to identify all green taxonomic criteria currently available and select the most robust and consistent

a. Data cleansing, merging & preparation of sample

Dutch Corporate Bonds portfolio (Dec 2020)

ADIMA – Database (2020)

a.1 **Data cleansing:** eliminate errors, duplicates, missing data points

a.2 **Merge locational data** (COUNTRY-LEVEL) from ADIMA into DNB database

- **Attribute**: Legal Entity Identifier (LEI) of TOP **500 MNEs** from the OECD region

b. *Potential* compliance to taxonomic criteria

Bloomberg

Issuer's website

b.1 Evaluation of compliance to taxonomic criteria: **Activity-based (Yes, No, Partial);** not performance or complementing criteria

b.2 **Inspection** on issuers' official **website** (if necessary)

c. Resource allocation & consolidation

c.1 **Regional:** Bond's value of compliant MNEs allocated at country level:

1. **Affiliate:** ADIMA country
2. **MNEs:** Even distribution across ADIMA countries
3. **Affiliate w/subsidiary:** website locations

c.2 **Activity:** Even distribution across taxonomy compliant activities

d. Regional plotting solar investment

d.1 **Country classification per size of investment** [(1)]

Investment	Medium 10MW	Small 5MW
VERY HIGH	+ Than 2	+ Than 2
HIGH	2	2
MEDIUM	1	1
LOW	0,5	0,5
VERY LOW	0,25	0,25

Avg cost [(2)]**: USD**

d.1 **Plotting**

ArcGIS Pro

[(1)] Energy Information Administration USA; [(2)] Solar Energy Industries Association (SEIA, 2020)

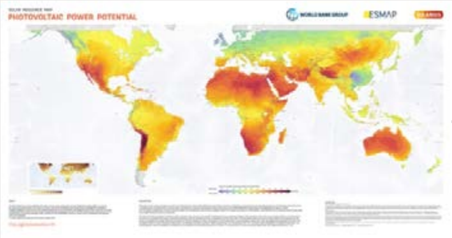
3. GREEN TAXONOMIES - methodology

Methodology consists of four phases of analysis

Phases

1. Green taxonomic criteria selection (Criteria)
2. Green bonds distribution (Supply)
3. Green investments geolocational demand (Demand)
4. Gap in green investments (Gap)

Phase #3



Gobal Photovolotaic Power Potential

WORLD BANK GROUP ESMAP

SOLARGIS

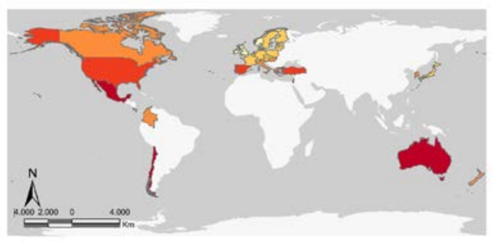
ArcGIS Pro

Clip → **PV Power Potential OECD** (Raster) → Zonal statistics MEAN → Join attribute → **Mean PV Power Potential** (Polygon) → Classify

OECD Political boundaries
(ArcGIS Live Map)

	VERY LOW			LOW		MED		HIGH			VERY HIGH		
Daily totals:	1.8	2.2	2.6	3.0	3.4	3.8	4.2	4.6	5.0	5.4	5.8	6.2	kWh/kWp
Yearly totals:	657	803	949	1095	1241	1387	1534	1680	1826	1972	2118	2264	

Average PV Power Potential
OECD,2020



3. GREEN TAXONOMIES - Methodology

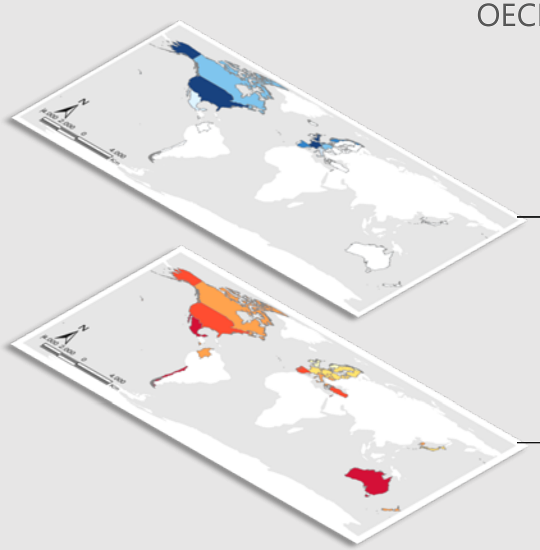
Methodology consists of four phases of analysis

Phases

1. Green taxonomic criteria selection (Criteria)
2. Green bonds distribution (Supply)
3. Green investments geolocational demand (Demand)
4. Gap in green investments (Gap)

ArcGIS Pro

Investment Solar energy
OECD,2020

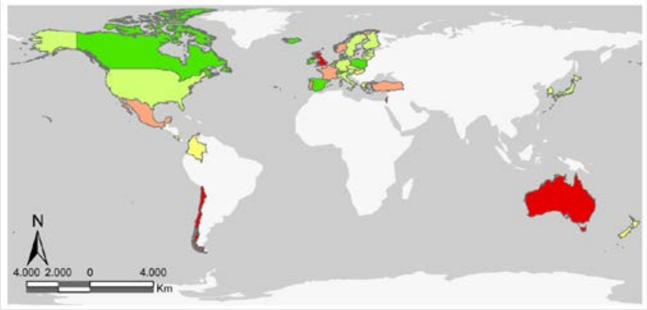


Average PV Power Potential
OECD,2020

PV POWER POTENTIAL \ LEVEL OF INVESTMENT	1 Very Low	2 Low	3 Medium	4 High	5 Very High
Very High 1	2	3	4	5	6
High 2	3	4	5	6	7
Medium 3	4	5	6	7	8
Low 4	(4 + 1 =) 5	6	7	8	9
Very Low 5	(5 + 1 =) 6	(5 + 2 =) 7	8	9	10

Country classification – Level of alignment

- 6 Totally aligned
- 5 7 Aligned
- 4 8 Potentially misaligned
- 3 9 Misaligned
- 2 10 Totally misaligned



Gaps in investment vs PV potential
OECD,2020

3. GREEN TAXONOMIES - Results – Phase #1

21 taxonomies and sustainable finance definitions are identified globally. 3 provide the best reference of green taxonomic criteria

Taxonomies / SF Definitions	C1. Publicly available	C2. Provides taxonomic criteria	C3. Independent development	Prioritized	Detail
1. EU Green Taxonomy	✓	✓	✓	✓	Most sophisticated official-sector taxonomy; to be applied on relevant financial market
2. China's Green Catalogues	✓	✓	✓	✓	Independent development; to be applied on relevant financial market
3. CBI Green Taxonomy	✓	✓	✓	✓	Globally recognized market-based taxonomy
4. Bangladesh Green Taxonomy	✓	✓	✗	✗	Based on previous taxonomies (EU GT); adaptations to local reality
5. Colombia Green Taxonomy	✓	✓	✗	✗	Based on previous taxonomies (EU GT, CBI, GBP); adaptations to local reality
6. Indonesia Green Taxonomy	✓	✓	✗	✗	Based on previous taxonomies (EU GT, China GC); adaptations to local reality
7. Mongolia Green Taxonomy	✓	✓	✗	✗	Based on previous taxonomies (China GT); adaptations to local reality
8. South Africa Green Taxonomy	✓	✓	✗	✗	Based on previous taxonomies (EU GT); adaptations to local reality
9. France Green Inv. Definitions	✓	✗		✗	Definitions of green investments
10. ICMA Green Bond Principles	✓	✗		✗	Pioneering instrument of green finance; provides guidelines to identify eligible project categories
11. Japan Green Taxonomy	✓	✗		✗	Provides guidelines to identify environmental objectives and eligible project categories
12. Malaysia CC Taxonomy	✓	✗		✗	Provides a framework for financial institutions to classify assets in terms of climate friendliness
13. MDBs-IDFC Principles	✓	✗		✗	Pioneering instrument of green finance; provides guidelines to identify eligible activities
14. Netherlands Green Schemes	✓	✗		✗	Range of financial instruments mostly in the form of grants and tax reliefs for green investments
15. OECD Rio Markers	✓	✗		✗	Tool to track finance aid for CCM, CCA, biodiversity and desertification from developed to developing countries
16. Australia Green Taxonomy	✗			✗	Initiative remains under discussion
17. Canada Green Taxonomy	✗			✗	Initiative under construction (delayed)
18. ISO 14040 – 1	✗			✗	Preview circulated for discussion and approval. Final version to be published in 2022
19. Kazakhstan Green Taxonomy	✗			✗	Initiative under construction
20. Mexico Green Taxonomy	✗			✗	Initiative under construction
21. Singapore Green Taxonomy	✗			✗	Initiative under construction

3. GREEN TAXONOMIES - Results – Phase #1

21 taxonomies and sustainable finance definitions are identified globally. 3 provide the best reference of green taxonomic criteria

	Energy												Buildings	
	Nuclear	Natural gas	Clean fossil fuels (CCS)	Hydropower	Solar	Wind	Biofuels (biogas, biomass)	Marine renewables	Geothermal	Power transmission & distribution	Power storage	Heat pumps	Green buildings / energy	Urban development
EUGT	Y	Y	D	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
CGBC	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
CBIT	Y	D	D	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N

	Transport						Water			Land & sea			
	Private passenger	Public passenger	Freight rail	Road freight	Aviation (infrastructure)	Waterborne transport	Water supply	Waste water management	Flood prevention	Forestry	Agriculture	Fisheries and aquaculture	Ecosystems & biodiversity
EUGT	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	N	Y
CGBC	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
CBIT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

	Pollution						Industry							Services		
	Preparation & storage	Re-use	Recycle	Treatment	Waste to energy	Landfill	Manufactory key components	Manufactory energy efficient eq.	Clean steel	Clean aluminum	Clean cement	Hydrogen	Clean up (CCS)	Information & communication	Research, development, innovation	Consulting, auditing, monitoring
EUGT	N	N	N	N	N	N	Y	Y	Y	Y	Y	Y	D	Y	Y	Y
CGBC	Y	Y	Y	Y	N	N	Y	Y	Y	N	Y	Y	Y	N	Y	Y
CBIT	Y	Y	Y	Y	Y	Y	Y	Y	D	D	D	D	Y	Y	N	N

FULL CONSENSUS

Activity or asset is signaled as aligned to environmental objectives by all taxonomies

23 activities/assets

PARTIAL CONSENSUS

Activity or asset is signaled by at least one taxonomy. Other taxonomies do not signal

13 activities/assets

CONTROVERSY

At least one taxonomy signals as contrary to environmental objectives or requiring further research

7 activities/assets

Y Signaled as compliant · N Not mentioned / Pending · D Discarded / Requiring research · C In consultation / validation

DeNederlandscheBank EUROSYSTEEM

3. GREEN TAXONOMIES - Results – Phase #2

From the totality of investments made by Dutch IFs on Top 500 Corporate Bonds (Dec 2020), EUR6,40 Bi are compliant with green economic activities

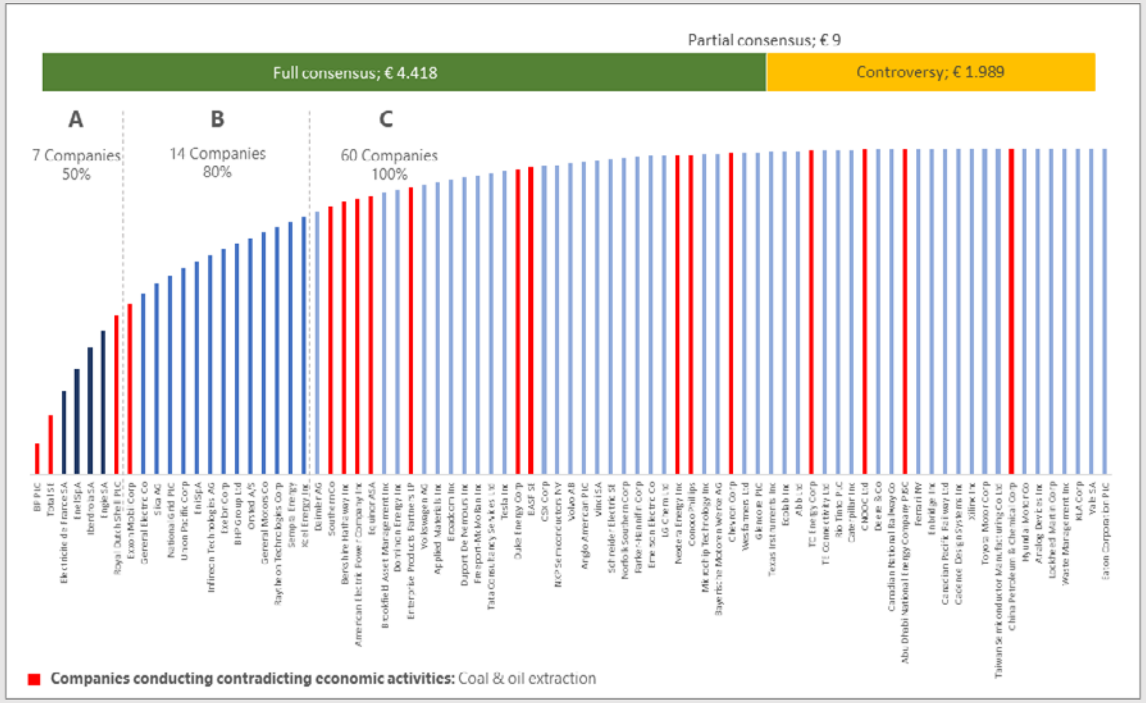
	Total Corporate bonds Dec 2020	Total localized Corporate bonds Dec 2020	Total potentiallly Green Corporate bonds Dec 2020
Issuer legal entities (LEI)	3,608	617	166
Issued security (ISIN)	13,620	5,441	2,281

MNE: Multi National Enterprise

3. GREEN TAXONOMIES - Results – Phase #2

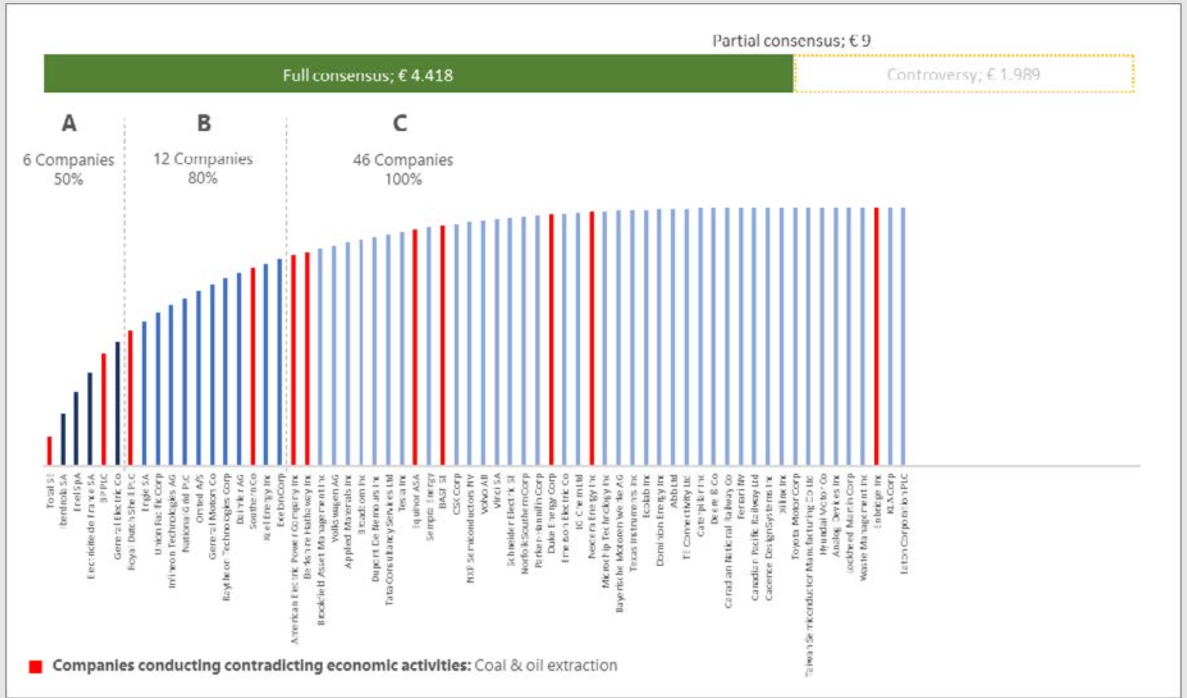
At the MNE level, 7 companies concentrate 50% of *green* investments

Investment per issuer *All Green* economic activities
(100% = EUR €6,4 Bi); 2020



- **High concentration of investments**: 7 companies make up for 50% of investments; 14 companies 80% (81 in total)
- When including Controversial Green activities, **4 major fossil fuel companies appear within the TOP bond issuers**: BP, Total, Shell and ExxonMobil

Investment per issuer *Full & Partial Green* economic activities
(100% = EUR €4,4 Bi); 2020

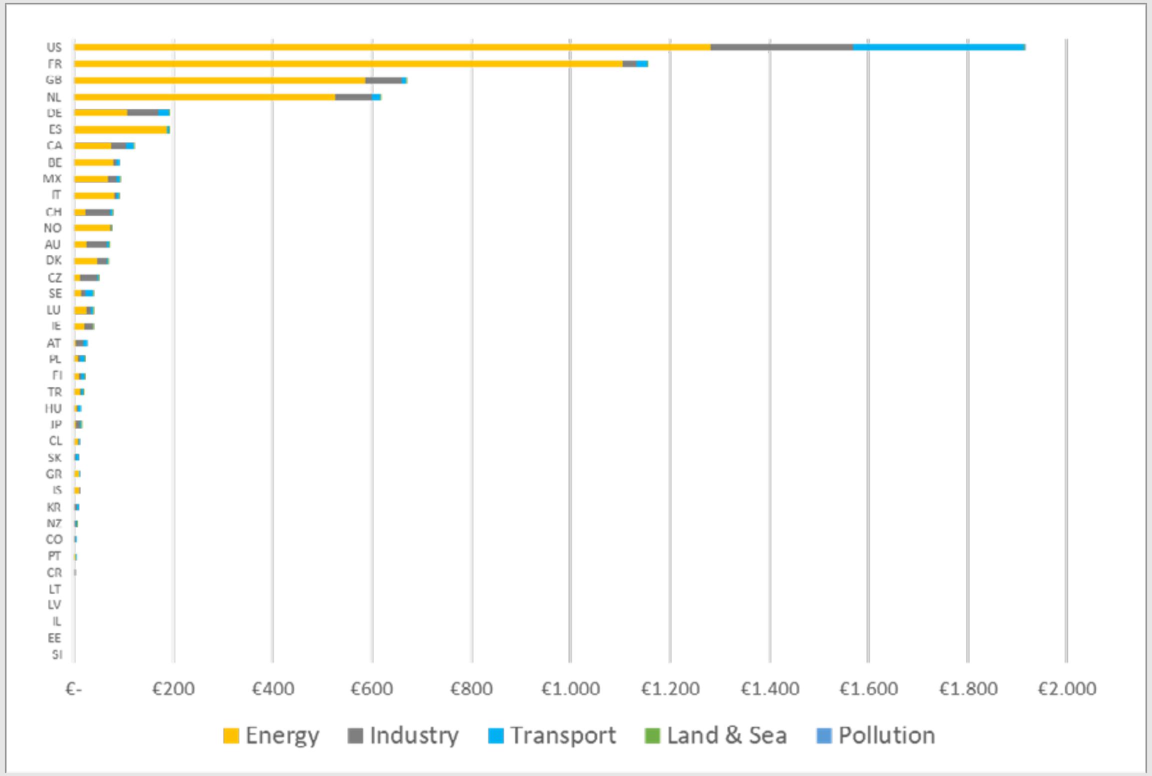


- **Higher concentration of investments**: 6 companies make up for 50% of investments; 12 companies 80% (17 issuers less)
- When including Full or Partial Green activities, the list of major fossil fuel extractors sees a reduced relevance. **Total & BP remains as top issuers;** European Oil & Gas companies show a more aggressive transition towards renewables

3. GREEN TAXONOMIES - Results – Phase #2

At country level concentration is even higher. Energy is the green economic activity consolidating the most green investment

Regional distribution of *green* investments in Corp Bonds
(100% = EUR €6,4 Bi); 2020



- At country level, concentration of investments is higher: 2 countries concentrate 50% of investments, while 4 make up for 80%
- Top 10 countries (90% of investments) are distributed across EU countries and North America (CA, US, MX)

Breakdown of *green* investment per economic activity
(100% = EUR €6,4 Bi); 2020

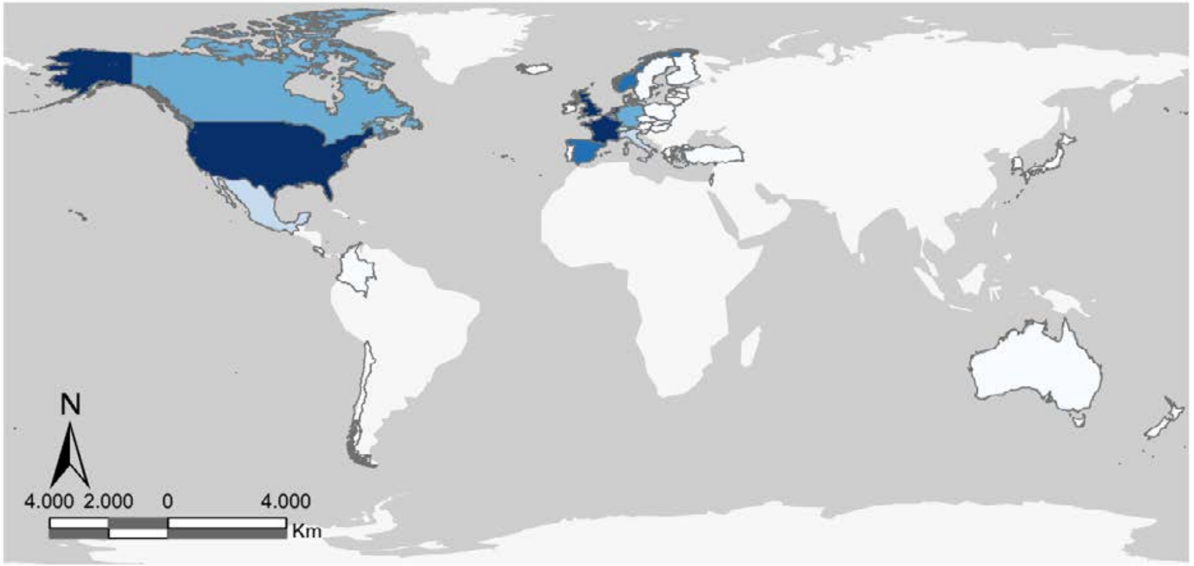
- Economic activities related to generation, distribution & transmission of clean energy, are the ones consolidating the highest investments
- Natural gas (controversy) is the category with the highest level if investment

DeNederlandscheBank
EUROSYSTEEM

3. GREEN TAXONOMIES - Results – Phase #3

Investments in solar are concentrated in northern countries. PV power potential is higher in desertic regions closer to the equator

Regional distribution of *green* investments on solar energy
2020



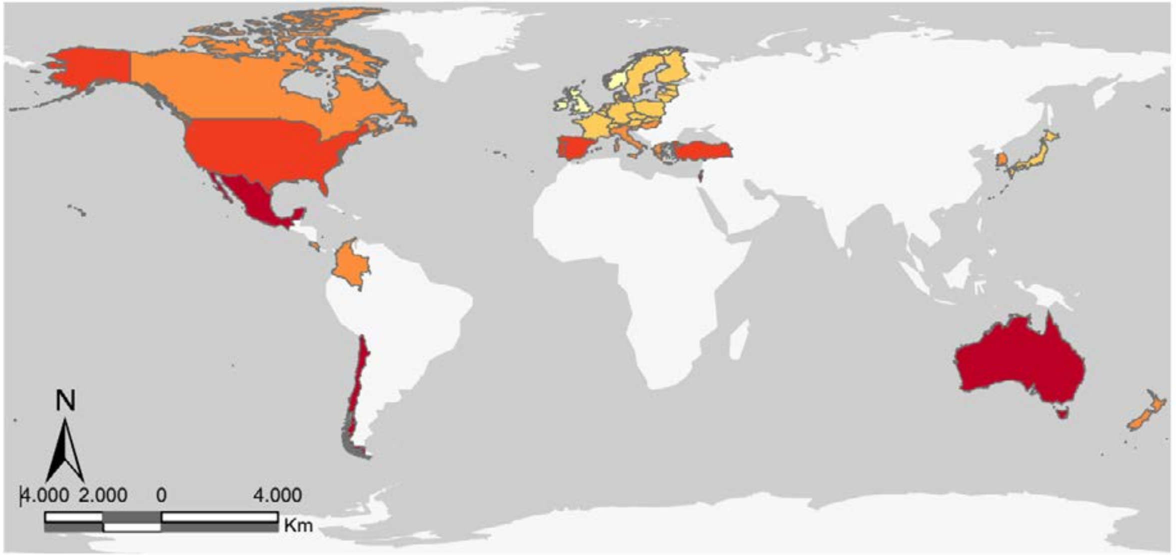
Investment solar (OECD, 2020)

SOLAR_INV

- Very low investment (€ 0,00 - € 3.75 Mi)
- Low investment (€ 3.75 - € 7.50 Mi)
- Medium investment (€ 7.50 - € 15.00 Mi)
- High investment (€ 15.00 - € 30.00 Mi)
- Very high investment (€ 30.00 - € 85.00 Mi)

- 5 countries consolidate +85% of total investments directed at producing electric power from PV technology. France is the major destination for investment (EUR 84 Mi)
- Countries with major investment are located in western Europe. US is the only Top 5 country outside this region

PV Power Potential (MEAN) per country
2020



PV Potential (OECD, 2020)

MEAN

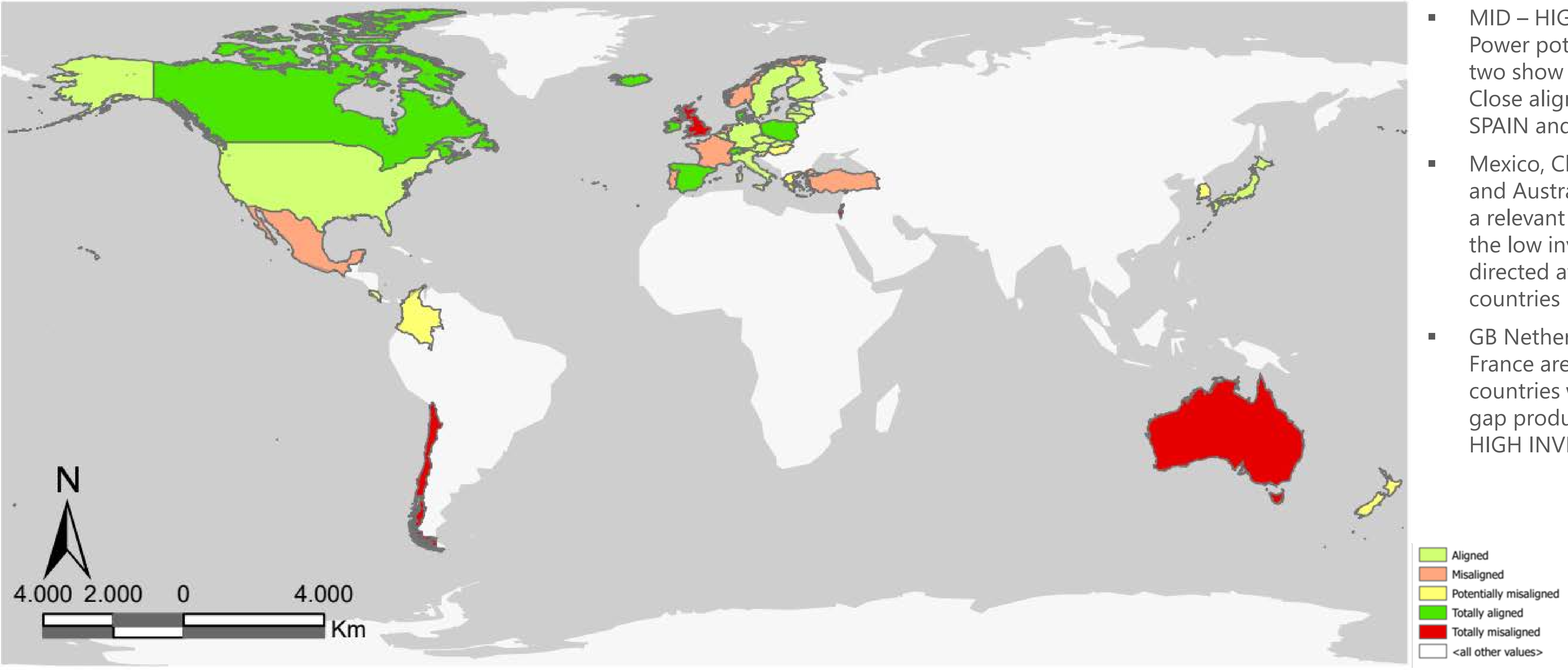
- Very low potential (0,0 - 2,8 kWh/m2)
- Low potential (2,8 - 3,4 kWh/m2)
- Medium potential (3,4 - 4,2 kWh/m2)
- High potential (4,2 - 4,8 kWh/m2)
- Very high potential (4,8 - 8,0 kWh/m2)

- Top values of solar resource and PV power potential are found in South America: Northwest Argentina, Bolivia, **Chile**
- Mexico: opportunity due to high PV potential and proximity of population
- Favorable mid rage: USA, Canada
- Low range: European countries

3. GREEN TAXONOMIES - Results – Phase #4

Important gaps between investments in solar energy and PV power potential are identified in the area of study

Regional alignment between investments and potential for electricity generation from solar
2020

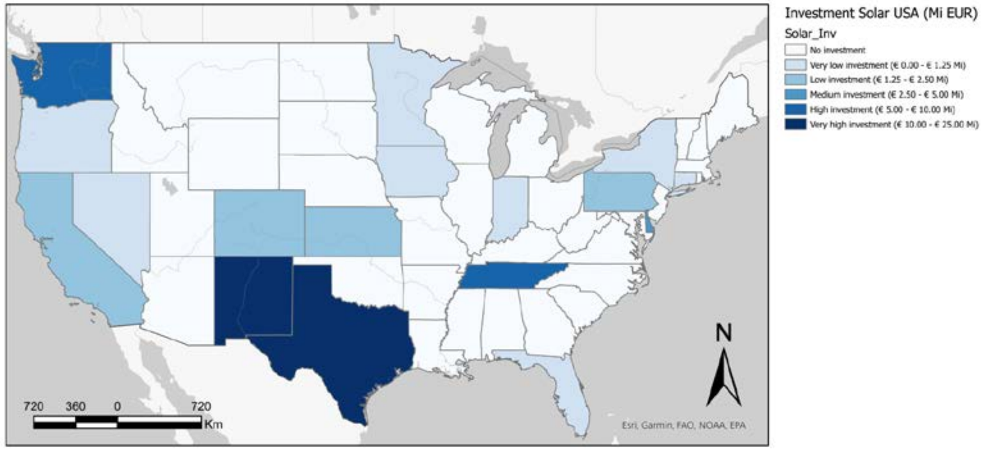


- MID – HIGH PV Power potential, only two show a Total or Close alignment SPAIN and USA
- Mexico, Chile, Israel and Australia there is a relevant gap due to the low investments directed at these countries
- GB Netherlands and France are top the countries with a big gap produced from HIGH INVESTMENTS

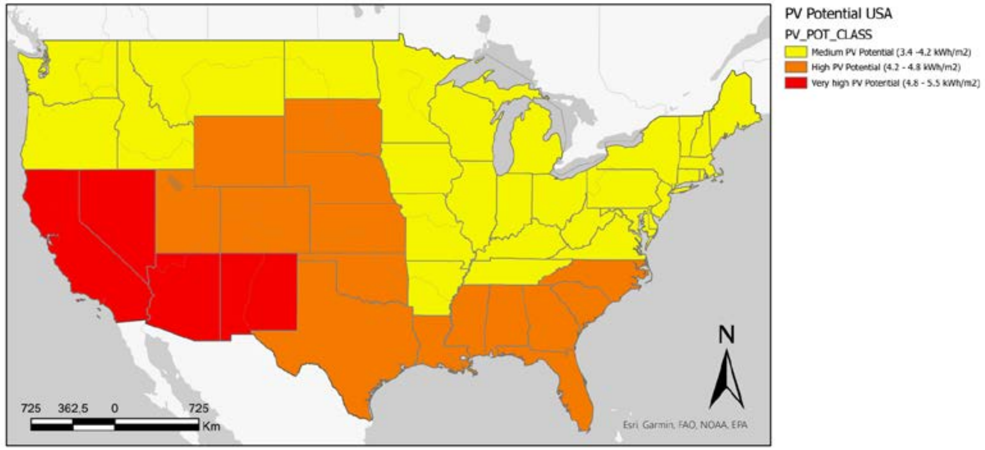
3. GREEN TAXONOMIES - Results – Phase #4

Methodology was replicated to provide more granularity for the USA (EUR €63 Mi, 2020), given data availability

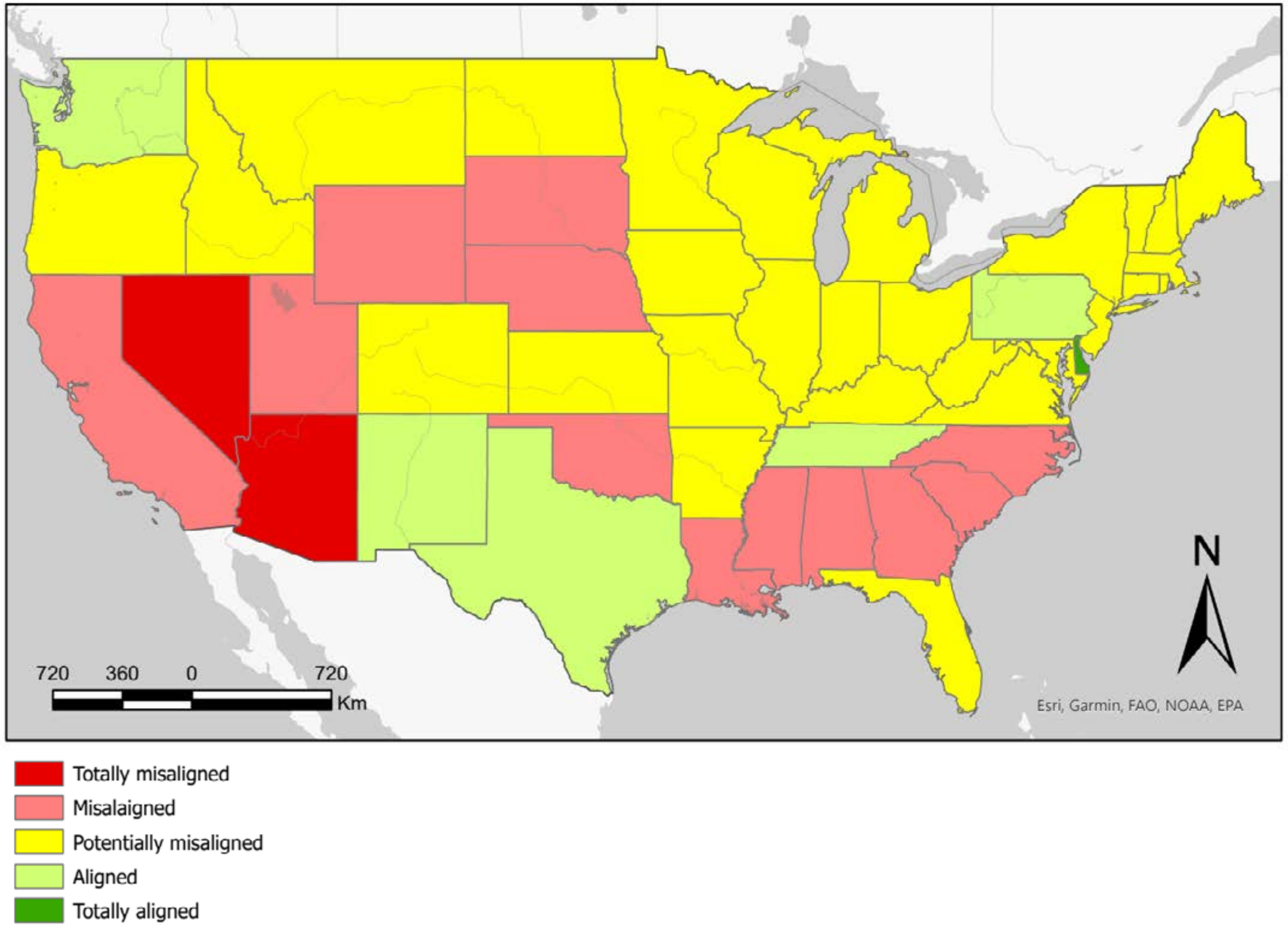
Regional distribution of investments on solar energy
USA 2020



PV Power Potential (MEAN) per country
USA 2020



Regional alignment in investments towards solar energy development
USA 2020



3. GREEN TAXONOMIES - Discussion

1 Out of ≥20 identified green taxonomies (GT), **3 provide the most robust set of taxonomic criteria** : EU Green Taxonomy, China Green Bonds Catalogue, Climate Bond Initiative Green Taxonomy. In line with literature (Ehlers T. et al, 2021)

- **a** Activities/assets, that can be clustered into **43 comparable clusters**. Important discrepancies are identified: **8 clusters show direct contradictions between GTs ("Controversies")** ; 13 clusters do not appear across the 3 GTs ("Partial consensus")

2 When applied to a sample of the Dutch Investment Funds' portfolio on Corporate Bonds (Top 500 enterprises within OECD in 2020 - with LEI code identifier in ADIMA database) **a total of EUR €6,40 Bi** (total sample value of EUR €35,60 Bi – 18% representativeness) **can be potentially flagged as *green investments (GIs)***

- **a** **Represents only a potential value; to vary as data gaps are minimized**: Value to reduce as full taxonomic criteria is applied **Current benchmark reported at 3,0-3,5% of total bond issuance** (European Commission)
- **b** **Outcomes can be used to signal potential trends**. High concentrations against all perspectives: Issuer level – 7 companies consolidating 50% of GIs ; Country level – 2 countries (US, FR) consolidating 50%; Economic activity level – Energy consolidating over 70% of GIs. Results in line with reported by Green Bonds Reports by CBI
- **c** **Discrepancies in taxonomic criteria cause significant variation in potential GIs.** EUR 1,99 Bi (30%) are associated to controversial economic activities/assets, natural gas consolidating the biggest share

3 **Power generation from solar energy has one of the highest concentration of GIs**, with potential tied to characteristics recorded through spatial observation (e.g. Solar radiation, temperature, cloudiness, etc. – contained in the PV Power Potential index)

- **a** **2 high PV power potential countries being receptors of high levels of investment** (US, ES); **relevant potential is being lost** however in countries with the highest PV power potential within OECD region (MX, CL, IL, AU). Gaps can be explained through understanding of local regulatory outlook (IEA Renewables Report 2020)

3. GREEN TAXONOMIES - Conclusions

1 **Green Taxonomies and Remote Sensing data are useful mechanisms for the identification and assessment of CBIs** directed at economic activities that deliver objectives on environmental objectives. Complete potential cannot be extracted due to current **limitations in data availability** and **complementary mechanisms**

2 **Green Taxonomies can be used to track Green CBIs, however,**

- **a** **Current available information (DNB) only serves for a potential *flagging*:** With current data disclosed to DNB, compliance to taxonomic criteria can only be established at level of economic activity/asset of issuer
- **b** **Additional data required:** Need to **for data on the performance indicators** of economic activity/assets (*Significant contribution criteria*); data to assess **complementary criteria** (*Do no significant harm, Minimal social safeguards criteria*)
- **c** **Need for harmonization**; the issues on **Natural Gas**, Nuclear energy, CCS, Hydrogen, Clean Al, Steal, Cement generate significant variability. Discrepancies generate uncertainty on the financial assets' capacity to deliver on green objectives

3 Remote sensing data provides a relevant tool to **follow and analyze the effectiveness in the allocation of these resources**

- **a** This research demonstrates this tool's utility to assess investment potential of **power generation from solar energy.** Other applications can be explored for economic activities with relation to observable environmental conditions: wind, mining, natural gas, agriculture, biodiversity, among others
- **b** **By itself it cannot completely explain the distribution of green investments**; needs to be complemented with political, regulatory, sociodemographic & market outlook information

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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