Climate Value-at-Risk (VaR)

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Climate Value-at-Risk (VaR)

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Compilation Contents

MSCI Climate Value-at-Risk (VaR) Methodology

MSCI ESG Research

June 2024

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1. Introduction

Climate Value-at-Risk (Climate VaR) provides a forward-looking and return-based valuation assessment to measure climate-related risks and opportunities. Climate VaR is a quantitative assessment calculated at the company and security level. The aggregated company Climate VaR is calculated as a percentage of market value (from -100% to +100%) for multiple climate scenarios and includes the valuation impacts arising from technology opportunities, policy risks and physical risks.

The Climate VaR model uses a data-driven approach, examining a company's positioning within its industry and the regions where it operates. It considers the potential costs and profits associated with different climate scenarios, including the impacts of carbon pricing, regulatory changes, and physical climate events. By simulating these scenarios, the model estimates how climate change could affect a company's financial performance and overall valuation.

Exhibit 1: Pillars of the Climate VaR model

Source: MSCI ESG Research, as of June 2024

Exhibit 1 provides the Climate VaR framework. Climate VaR is composed of the following pillars:

- Policy risk
- Technology opportunities
- Physical risk and opportunities

These pillars are further broken down into the categories listed in Exhibit 1. Cost estimates are made for each pillar under multiple climate scenarios from the Network for Greening the Financial System (NGFS) and Intergovernmental Panel on Climate Change (IPCC). This enables the understanding of climate risk exposure for individual drivers and in aggregate within a consistent and holistic framework.

2. Interpretation of Climate VaR

The Climate Value-at-Risk output is a measure of both a company's potential climate cost exposure and a measure of how climate change may affect a company valuation. This is outlined in the broad calculation steps of the Climate VaR output.

The Climate VaR model estimates annual net climate costs[1] for a company for each scenario and pillar. Climate costs/profits for each pillar are determined separately, allowing for an understanding of the component climate risks and opportunities driving the aggregated result. The high-level steps of the Climate VaR modelling process are as follows:

Step 1: Estimate a time series of forecasted undiscounted net climate costs for a company.

These time series are the most fundamental output of the Climate VaR framework, enabling the assessment of net climate cost exposure of individual companies over time.

Step 2: Calculate the sum of the present value of future net climate costs.

The time series of future net climate costs are discounted back to their present value and then summed. This total represents an estimate of the net climate cost exposure of the company, taking into account the time value of money when assessing costs incurred at different horizons.

Step 3: Revalue the company accounting for the summed present value of future net climate costs.

The company's current valuation (enterprise value including cash or EVIC) reflects current expectations of the discounted sum of its future free cash flows. To understand how new net climate costs may affect this valuation, the present value of these new costs is subtracted from its current valuation. Company Climate VaR output for each scenario and pillar is the percentage devaluation (or appreciation) of the company after these net costs (or net profits) have been accounted for.

The Climate VaR model also provides an output for company equity, company debt, and at the individual bond security level. The split of climate costs between equity and debt holders is based on the assumption that debt holders are only affected by a cost shock to the extent that it increases company default risk. This results in Equity Climate VaR always being equal to or greater in magnitude than Debt Climate VaR. For a company with a high credit worthiness, a relatively large climate cost exposure (and thus a relatively large company Climate VaR) is often accompanied by low debt Climate VaR. The Climate VaR model employs a Merton-type credit model to calculate effects on default risk and thus allocate costs to company equity, company debt, and specific company bond securities.

Key assumptions

Climate VaR output relies on the following key assumptions:

- Current company valuations do not reflect any future climate costs.
- The adjusted valuation reflects the "pricing in" of all future climate costs from a given scenario.

These assumptions are extreme in that they result in the maximum devaluation possible for the company given estimated climate costs.[2]

Due to these assumptions, Climate VaR values are *not a return forecast for a specific horizon*. It is possible and even likely that current valuations reflect some future climate costs, or that scenario-specific future climate costs will not be fully priced in a specific time period.

[1] The output of the transition opportunities pillar are profits, not costs. If these opportunities exceed all other climate costs, sum of all pillars will be net profits (negative net costs). We refer to all time series here as net costs for ease of exposition.

[2] If the present value of climate profits exceeds climate costs, Climate VaR output instead reflects the maximum appreciation of the firm due to climate costs.

Climate VaR is equal to the present value of climate costs as a percentage of the company's current valuation, and thus provides a single number reflecting the climate cost exposure of different companies relative to their scale. Under many reasonable relaxations of the pricing assumptions above, Climate VaR output will still reflect relative valuation shocks across companies.[3]

3. Climate Value-at-Risk cost and profit estimation

The three major pillars of the Climate VaR model, and their underlying categories, are shown in Exhibit 1.

Transition risks and opportunities

- Policy risks: This encompasses costs due to regulatory and governmental factors.
- Technology opportunities: This focuses on business opportunities emerging from innovative clean technology products.

For the policy pillar, costs from direct Scope 1 emissions reduction are calculated by translating NGFS-provided regional and sectoral carbon reduction requirements into firm-level reduction paths; these firm reduction requirements are then multiplied by the scenario's carbon price[4] forecast to estimate total reduction costs incurred by a company. The costs of higher electricity prices and shocks to a company's value chain are also forecasted, with the key drivers of these costs being carbon price forecasts and the firm's Scope 2 and 3 emissions intensities. Indirect costs from Scope 3 emissions, which measure additional transition effects occurring along a company's value chain, are also accounted for. This includes upstream Scope 3 costs, which refer to the rise in input costs due to climate regulation (excluding electricity cost effects mentioned above), and downstream Scope 3 costs, which pertain to changes in product demand resulting from shifting consumer behavior and competitive transitions in downstream markets.

Potentially counterbalancing these new costs are technology opportunities: the technology pillar forecasts firm profits from new revenue streams arising from the development of new technologies serving the transition to a low-carbon economy. Total green revenues by sector are sized, then allocated to firms through forecasts of each firm's future market shares. Market share forecasts are derived from each firm's current green market share and low carbon technology patent share (as a measure of how market shares may change over time).

Physical Risk and Opportunity

- Chronic hazards: These risks manifest slowly over time and may cause business interruptions. MSCI ESG Research considers the various effects of business interruption for five chronic hazards: extreme heat, extreme cold, heavy precipitation, strong snowfall, and severe wind conditions.

[3] Such assumptions include climate costs being partially priced into current valuations and partially priced in further after a shock. For contingencies where future climate costs may only be priced to a short-term horizon, Climate VaR contains a Multihorizon CVaR module which varies the horizon to which the present value of climate costs are calculated. This can also be interpreted as a company's climate cost exposure up to a specific horizon.

[4] NGFS scenarios output carbon emissions prices, which can be interpreted as "a proxy for government policy intensity and changes in technology and consumer preferences", and not necessarily just a simple carbon tax. For more details, see the publication "NGFS Scenarios for central banks and supervisors", Network for Greening the Financial System, September 2022.

- Acute hazards: These risks occur from rare natural catastrophes, such as tropical cyclones, in distinct time intervals. Depending on the hazard type, they may cause business interruption as well as asset damage. MSCI ESG Research considers effects for six acute hazards: tropical cyclones, coastal flooding, fluvial flooding, pluvial flooding, river low flow, and wildfires.

Cash flow estimation begins with MSCI ESG Research's physical hazard models, which project changes in the intensity and frequency of various hazards in specific locations as the scenarios suggest the climate will evolve. These models overlay a firm's physical asset locations and business activity to estimate company assets exposure to specific hazards. Then, damage functions are applied to translate hazard exposures into anticipated physical asset damages and business interruption costs. All physical risk modeling offers global coverage and relies on MSCI ESG Research's Asset Location Database (ALD).[5]

4. Coverage and update processes

4.1 Coverage universe

As of June 2024, the coverage universe includes targeted and tracked indexes – including MSCI ACWI Investable Markets Index (IMI). The Bloomberg Global Aggregate Index is a targeted index for corporate fixed income coverage.

The entity for which data is collected for fixed income issuers may be a different legal entity from the one issuing the bond, in which case MSCI ESG Research's data mapping process is used to map the evaluation to the entity.

4.1.1 Minimum data requirements

MSCI ESG Research minimum data availability requirements must be met for inclusion in the coverage universe. For Climate VaR modeling, essential data include the company's market capitalization, total debt, and Weighted Average Cost of Capital (WACC). Additionally, each Climate VaR subcomponent requires specific input data to ensure coverage and accurately assess a company's risk profile. For Policy Risk Climate VaR, essential data include revenue and Scope 1 and 3 emissions. When companies do not disclose emissions data, MSCI ESG Research uses proprietary methodologies to estimate carbon emissions based on a company's revenue. For Technology Opportunities Climate VaR, clean technology revenue or low-carbon patent data are needed. For Physical Risk Climate VaR, information about the company's asset characteristics is needed, including the geolocations of the assets, their sizes, and business activities. While Policy Risk and Physical Risk Climate VaR are essential for inclusion in the coverage universe, a company can still be considered covered without a Technology Opportunities Climate VaR. In such cases, the aggregated Climate VaR comprises only the sum of the Policy Risk and Physical Risk Climate VaR.

4.1.2 Entity selection & data mapping

ESG Evaluations, including company-level Climate VaR evaluations, may be attributed to related companies. Companies are selected for ESG Evaluations through MSCI ESG Research's Entity Selection process – these are known as Data Entities. To determine which entity or entities within a group of related companies should be evaluated, MSCI ESG Research conducts a review of the

[5] Not all assets and companies in the ALD are covered by the physical risk models, as the physical risk models require company level information regarding at least revenue, market cap, and WACC to calculate physical CVaR.

companies' financing structures. Then, ESG Evaluations are attributed to related companies through MSCI ESG Research's Data Mapping process.

Data Mapping is the process whereby ESG Evaluations for a company (a Data Entity) are attributed to related companies. ESG Evaluations are mapped based on observed parent-subsidiary relationships, subject to certain company and data point requirements.

- Certain companies (such as those classified as financing companies) included in the coverage universe may be covered by data mapping from the relevant Data Entity.
- Bond issuers outside the company-level Climate VaR coverage universe may also have their evaluations mapped from parent entities that are included in the company-level Climate VaR coverage universe.

Note that company-level Climate VaR evaluations are not mapped to:

- Equity issuers; or
- Companies that have already been assessed by MSCI ESG Research.

4.2 Model input data sources

Below is an overview of the data sources used as inputs into the Climate VaR model.

- **Scenario data:** Integrated Assessment Models (IAMs) from sources such as the NGFS provide future transition pathways for assessing economic and environmental impacts of climate change, including carbon emissions pathways, global temperature projections, energy efficiency factors, and policy-related outputs like carbon pricing and mandated emissions reductions.
- **Financial data:** Financial data used in Climate VaR modeling is sourced from Refinitiv and company reporting.
- **Emissions data:** MSCI ESG Research collects greenhouse gas emissions data annually from companies in coverage, using sources like annual reports, CSR reports, company websites, Carbon Disclosure Project (CDP), and government databases. When direct disclosure is unavailable, MSCI ESG Research estimates Scope 1, Scope 2 and Scope 3 emissions using proprietary methodologies.
- **Energy usage:** MSCI ESG Research collects energy consumption data from CDP for companies that report these values. When company disclosure is unavailable, MSCI ESG Research uses an electricity estimation model.
- **Patent data:** MSCI ESG Research's technology opportunities covers patents that have been granted from over 70 patent authorities worldwide. The source for this patent data is LexisNexis IPlytics.
- **Hazard data:** Hazard data is based on observations and reanalysis data as well as on projections from general circulation models and global hydrological models from academic and think tank research organizations. All models are onboarded following MSCI ESG Research's vendor due diligence process. In all cases, the climate data are post-processed to derive hazard specific indicators. Post-processing includes steps such as bias-adjustment of climate projections and overlaying extreme sea level data with a digital elevation model to derive coastal flood inundation depths.

- **Vulnerability data:** Vulnerability factors and damage functions are obtained from various data sources, including historical disaster databases, such as EM-DAT[6] for tropical cyclones, the Munich Re database[7] for recorded wildfires, the European Drought Impact Report Inventory[8] (EDII) for river low flow events, and peer-reviewed scientific publications.[9]
- **Exposure data:** Relevant information about company asset characteristics such as location, size, or business activity are provided by the MSCI ESG Research's ALD. Asset value and revenue are estimated from the company's fixed asset values and total revenue using a disaggregation algorithm.[10]

4.3 MSCI ESG Research methodology governance

The ESG Methodology Committee (EMC) presides over the development, review and approval of all MSCI ESG Research methodologies, including Climate VaR.

MSCI ESG Research may update methodologies and models, including Climate VaR. Methodology update proposals may be subject to market consultation prior to approval for implementation by the EMC.

4.4 Data quality assurance (QA)

MSCI ESG Research considers a broad range of criteria when assessing the quality of input data used in ESG and Climate models. These criteria include completeness, exhaustivity, timeliness, accuracy, and traceability back to sources. The QA processes are designed in an additive setup, consisting multiple layers of automated validation and manual check points.

4.5 Model production cycle

MSCI ESG Research's Climate Risk Center has a quarterly model production cycle where significant code changes to its models, including Climate VaR are introduced, after the methodological changes have been vetted and approved by the EMC. These changes require an extensive and structured QA process that covers both the input data and the generated output data, to assure correctness of the models and their produced data.

All data auditing processes entail quarter-to-quarter statistical comparison of data to identify any possible outliers in the data sets. In case of any anomaly detection or abnormal changes, the issue is flagged and sent back to source for further evaluation and validation. Any model maintenance, methodology updates, and all statistically significant changes are disclosed to clients through quarterly release notes following high-level supervisory checks.

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[6] EM-DAT (2008), 'EM-DAT: The International Disaster Database', Available at: https://www.emdat.be/, Last accessed June 13, 2024.

[7] Munich Re is a German reinsurance and insurance company covering and reporting on damages from a wide range of physical risks, among other risks.

[8] European Drought Centre 2015. "European Drought Impact Report Inventory (EDII) and European Drought Reference (EDR) database"

[9] For example, flood depth damage functions provided in Huizinga, J., Moel, H. de, Szewczyk, W. Global flood depth-damage functions. Methodology and the database with guidelines. 2017. EUR 28552 EN. doi: 10.2760/16510.

[10] More details can be found in the methodology document "Exposure Estimation for Physical Risk Models".

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Notice and disclaimer

Introduction to Climate Value-at-Risk

Methodologies and Tools to Evaluate the Financial Impact of Climate-Related Risks and Opportunities

November 2019

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Carbon Delta estimates the effect of climate change on a company's bottom line

POLICY RISKS

2019 South Africa Carbon Tax

Minerals Council SA says the carbon tax could wipe out 6,000+ mining jobs each year

Eskom's carbon tax liability is projected to be approximately R11.5 billion per year from 2023

TECH OPPORTUNITIES

California – Clean Energy and Pollution Act – 50% Renewables by 2030

Sunrun *(Solar Installer)**:** 1000% revenue growth*

RWE *(German Utility): Analyst-Revision -22.6%*

PHYSICAL RISKS

2015 South Indian floods

Ford Motor Co., BMW AG and Renault SA *halted production at their factories*

TVS Motor Co.'s *stock price dropped 4.9 per cent, saying rainfall adversely affected production and sales.*

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The climate innovation

Transition Risks & Opportunities

Scenario analysis

1.5°C-Scenario — Average Scenario

2˚C Scenarios (7)
- 3 Integrated Assessment Models
- 5 Socioeconomic Pathways

3°C-Scenario / NDC — Worst Case Scenario

Physical Risks & Opportunities

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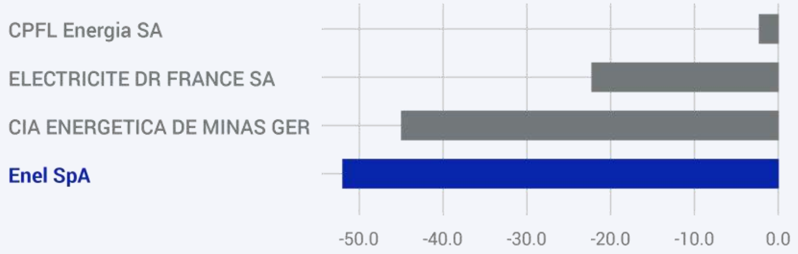
What is Climate Value at Risk (CVaR)?

- Climate VaR aims to assess the potential financial sensitivity to climate risks and opportunities, i.e. what would be the potential financial impact of different climate scenarios (1.5°, 2°, 3° of warming)?
- Estimates of net-present-value impact of climate change on the security pricing
- An aggregate Climate VaR can be broken down into:
  - *Policy* (transition risks)
  - *Technology opportunities* (transition opportunities)
  - *Physical risks & opportunities*
- Asset classes covered: *listed equities, fixed income, real estate assets*

Aggregated Climate VaR

2°C mid-range & average physical climate risk scenarios

The bar chart illustrates how Enel SpA compares to its market peers in terms of the aggregated Climate Value-at-Risk. The Aggregated CVaR combines the Policy CVaR, the Technology CVar, and the Physical CVar into an overall Climate Value-at-Risk metric.



Source: Carbon Delta company report

Climate Value-at-Risk building blocks & risk metrics

Transition Risks & Opportunities

POLICY
15 years until 2100

- Emission Reduction Requirements per year
- Costs to comply with emission reduction targets

+

TECHNOLOGY
15 years until 2100

- Patents deliver deep insights into R&D investments
- 90 million patents
- 10’000+ companies
- > 400 groups of low carbon technologies

+

Physical Risks & Opportunities

PHYSICAL
15 years until 2100

- Extreme Heat
- Extreme Cold
- Heavy Precipitation
- Heavy Snowfall
- Wind Gusts
- Coastal Flooding
- Tropical Cyclones

=

Aggregated Climate VaR

How is Carbon Delta's CVaR calculated?

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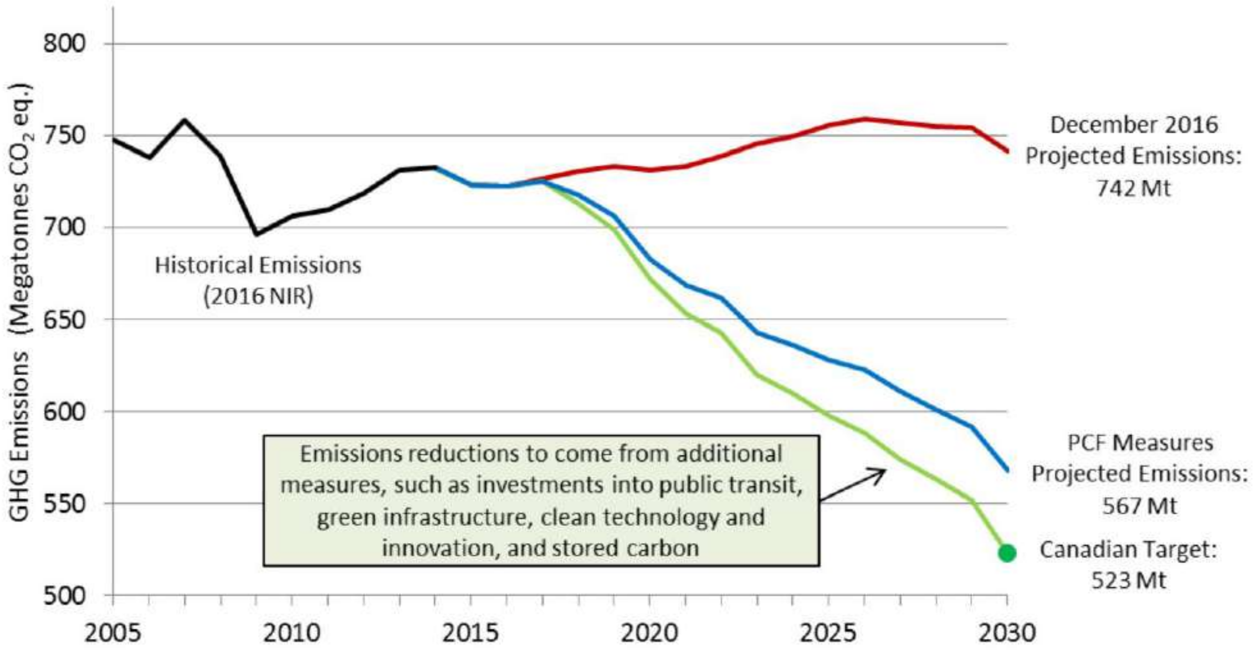
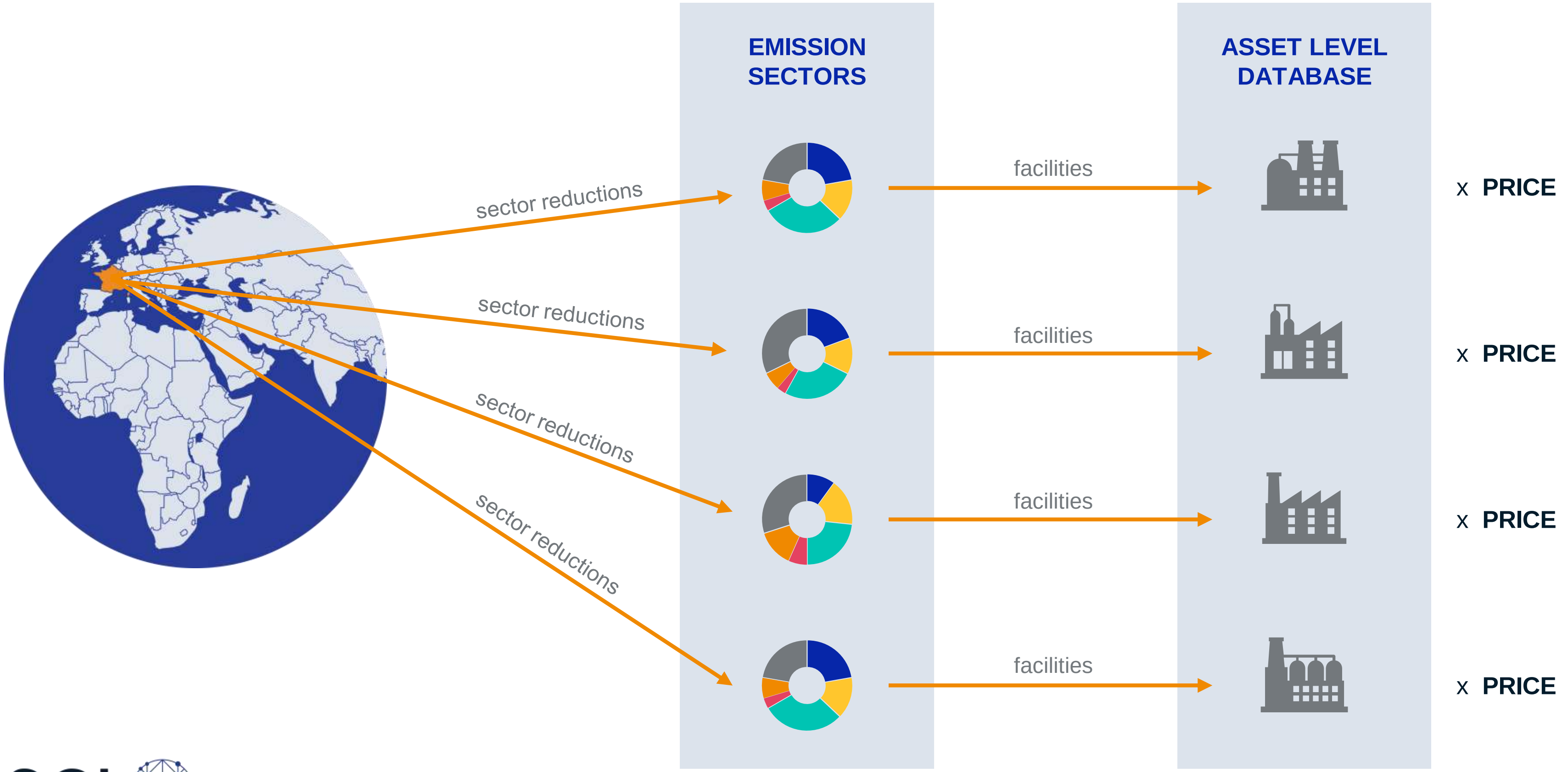
Nationally Determined Contributions (NDCs)

Pathway to Canada's 2030 target



Source: Canada's NDC, Page 4

Overview of Policy Risk Methodology



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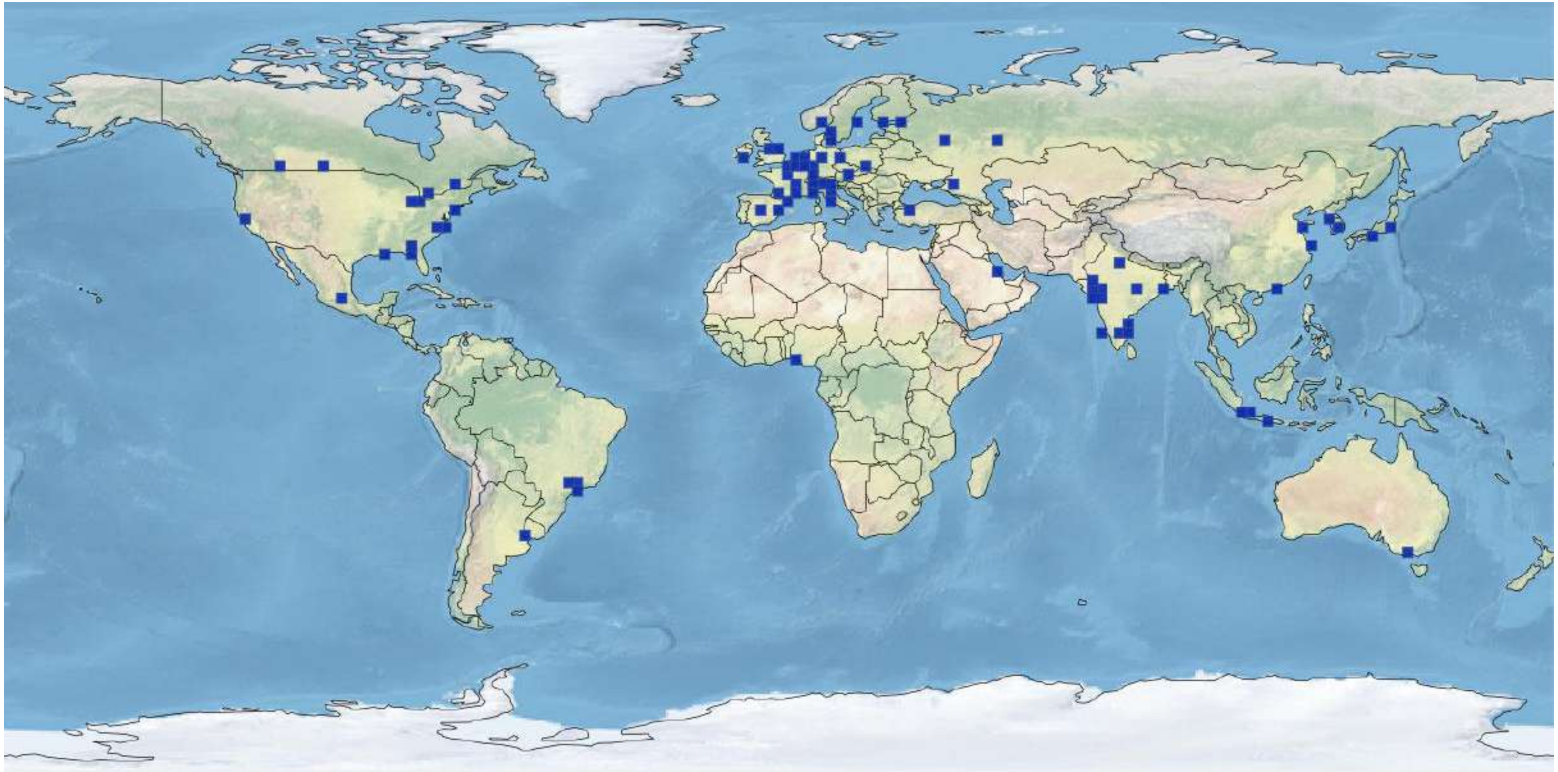
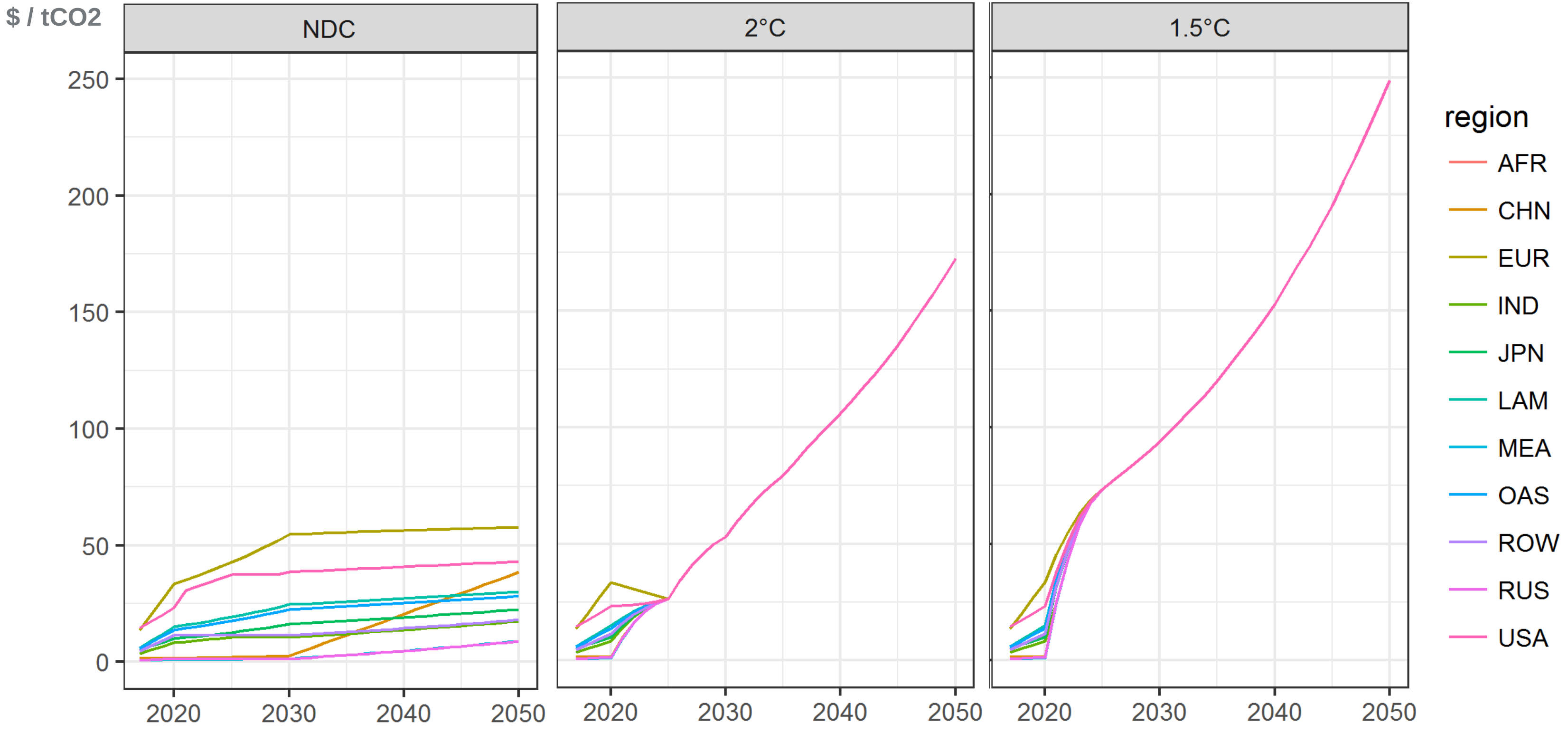
Aggregation Across Company Facilities



Calculate Cost Impact with Carbon Prices



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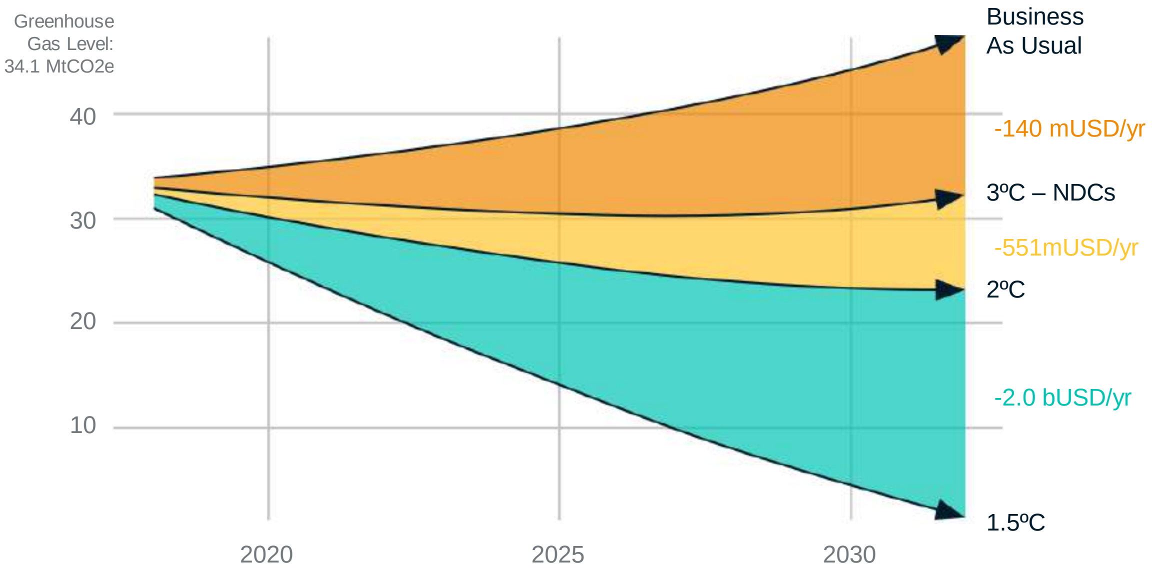
Company-level Scenario Analysis



Emission trajectories for emission scenarios

On a company level, we calculate:

- Current emission level
- Annual emission levels 15 years into the future
- Emission reduction requirements per year
- Costs to comply with emission reduction targets each year under BAU, 3C, 2C and 1.5C scenarios

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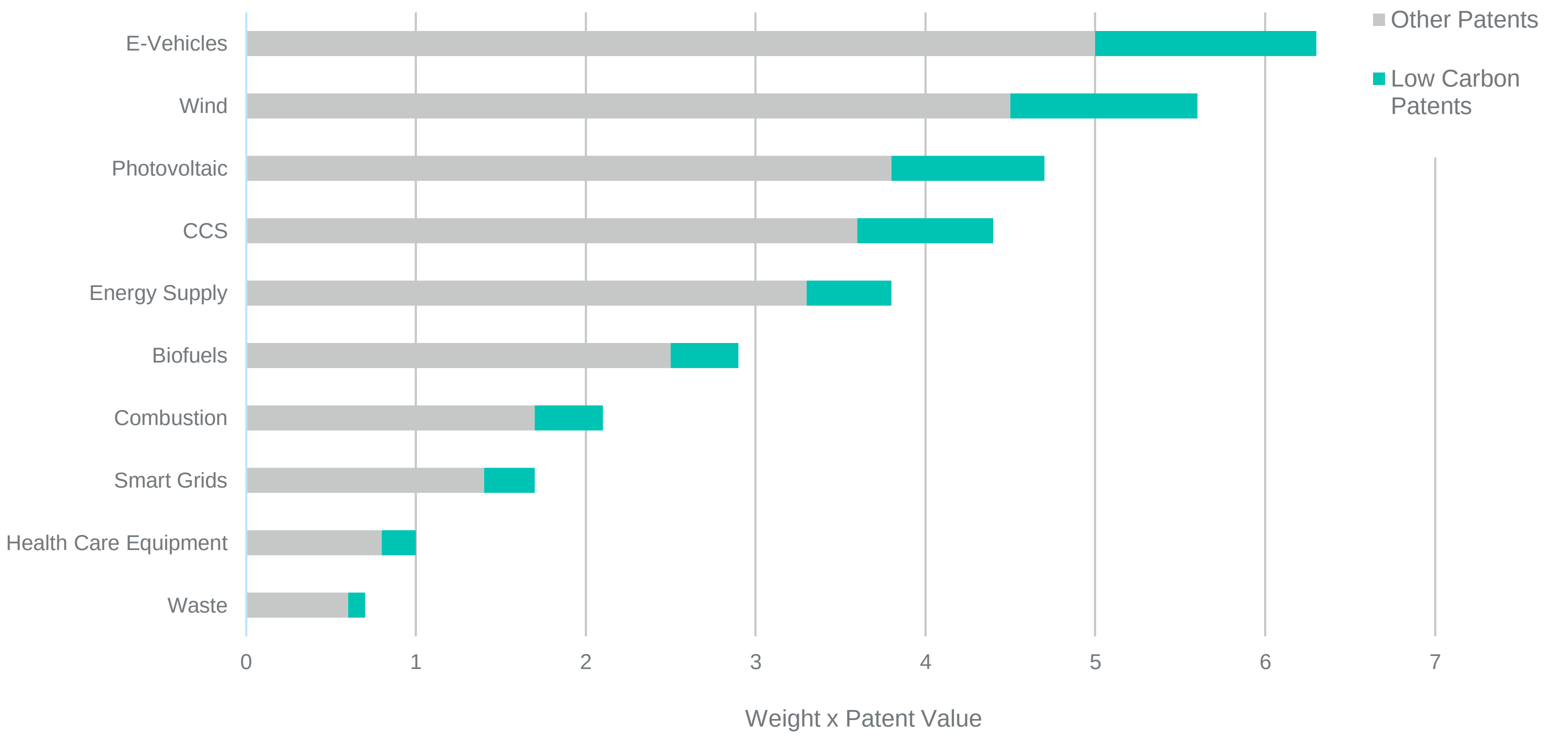
Tech Opportunity: Sector Breakdown of Patents



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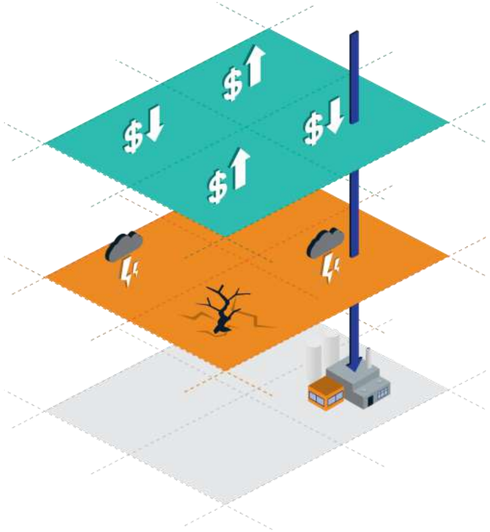
Overview of Physical Risk Methodology



VULNERABILITY Cost function

HAZARD Extreme weather

EXPOSURE Company facility

EXPECTED COST = VULNERABILITY × HAZARD × EXPOSURE

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Hazard: Extreme Weather Types

Extreme heat and cold

Re-analysis

Heavy precipitation and snowfall

Re-analysis

Wind gusts

Re-analysis

Wildfires

Re-analysis, development in progress

Coastal flooding

Climate models

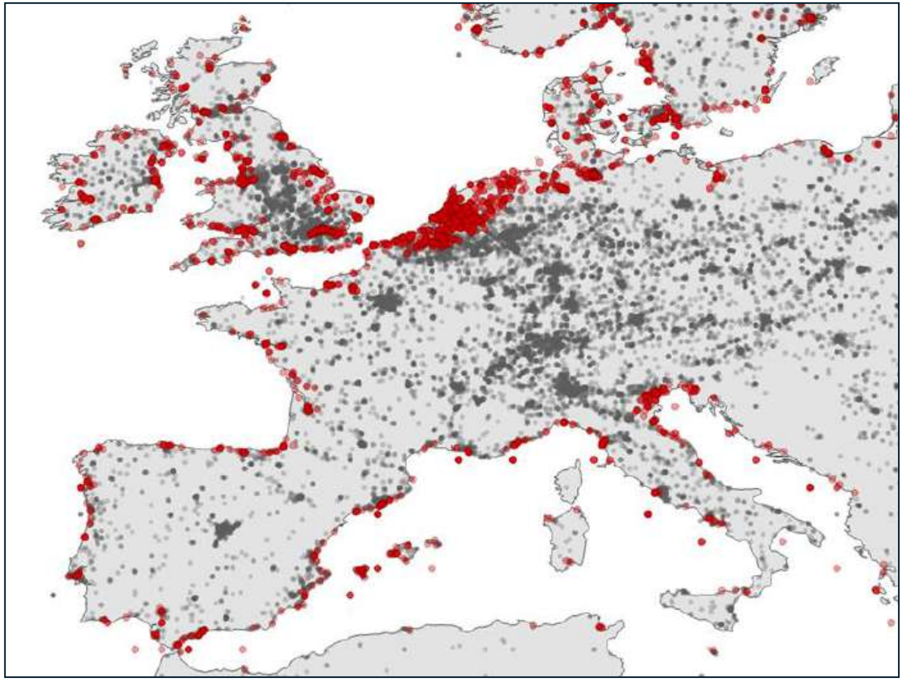
Tropical cyclones

Probabilistic model – Climada

Fluvial flooding

Climate models, development in progress

Exposure: Asset Level Database



Example: European locations within MSCI ACWI and exposure to coastal flooding

- Asset location database with global coverage
- Growing number of enterprise assets (>500k assets)
- Data is obtained from
  - Company analysis
  - Crawling data
  - Industry databases

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Use cases

Regulatory Compliance

CSR and TCFD reporting

Risk Management

Shareholder engagement

2ºC Alignment

Sectoral & regional over- and underweights

New Financial Products

Green Technology Opportunities for Alpha Creation

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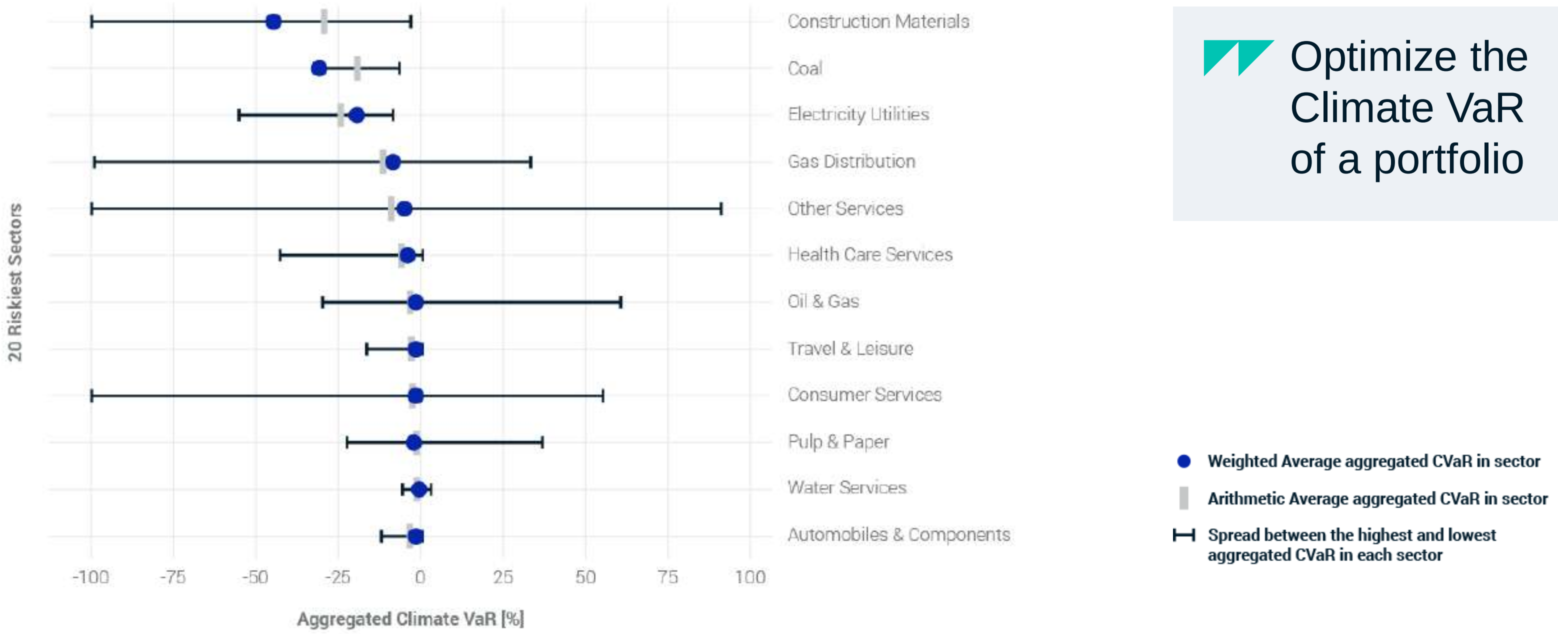
Carbon Delta's existing clients

Carbon Delta has worked with the below organizations to measure and manage climate risk

Which industries are most affected by climate risks?

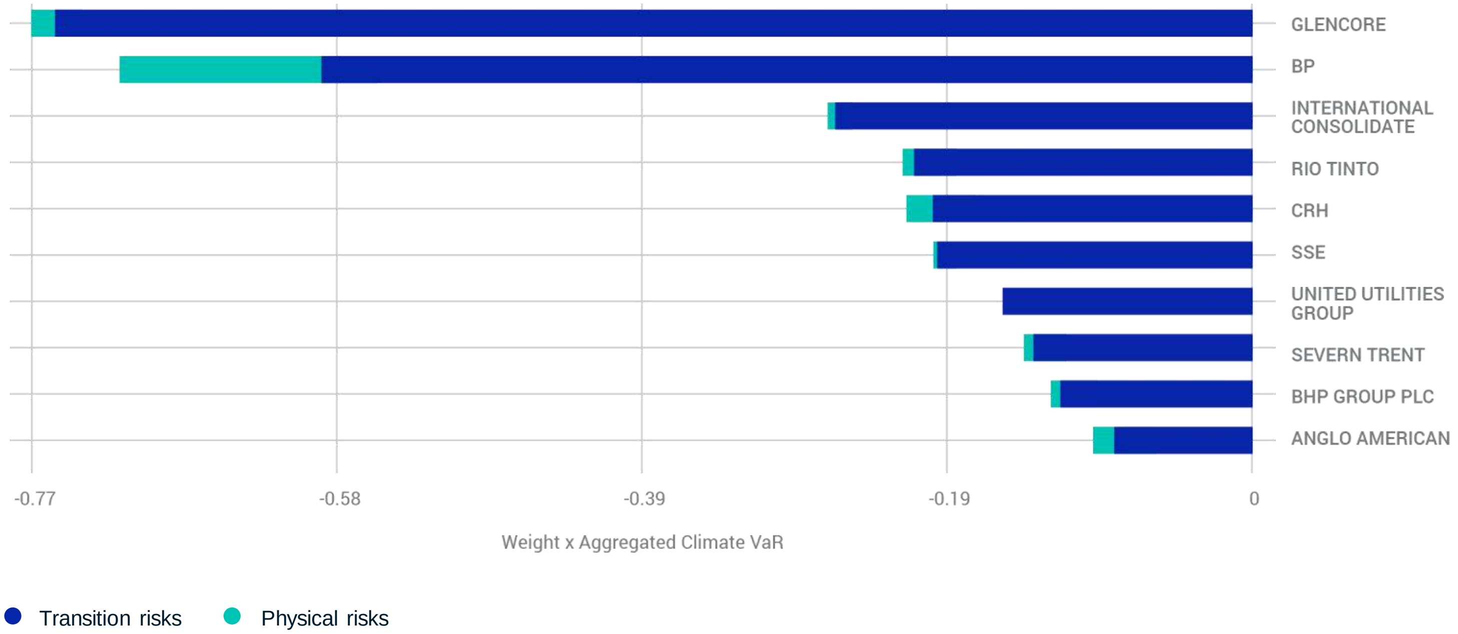
CVaR spread by primary sectors of activity



Optimize the Climate VaR of a portfolio

Climate Risk Contribution

Portfolio CVaR contribution by security



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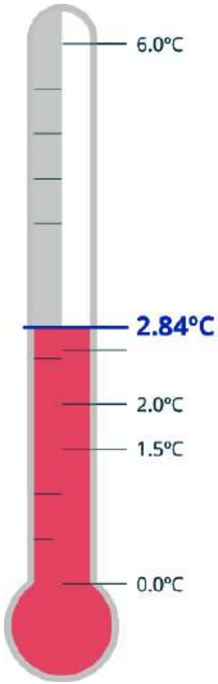
How aligned is a sample portfolio with the Paris Climate Target?

Portfolio Warming Potential



Top 5 High-Warming Potential Securities

Security	Weight	Warming Potential
CANOPY GROWTH CORP	0.03%	6.00°C
HeidelbergCement AG	0.03%	6.00°C
LafargeHolcim Ltd	0.06%	6.00°C
Melco Crown Entertainment Ltd	0.02%	6.00°C
CNMC Health PLC	0.01%	6.00°C

Top 5 Low-Warming Potential Securities

Security	Weight	Warming Potential
Xerox Corp	0.02%	1.30°C
Tokyo Electron Ltd	0.06%	1.30°C
Smith & Nephew PLC	0.04%	1.30°C
Skyworks Solutions Inc	0.04%	1.30°C
Seagate Technology PLC	0.03%	1.30°C

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Research article

Measuring climate-related and environmental risks for equities

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ABSTRACT

Financial regulators and investors are increasingly concerned about the effects of climate change on investments and seek to capture the climate-related and environmental risks of investments. Whilst energy companies have attracted most of the attention due to the contribution of the Energy sector to environmental degradation, climate-related and environmental risks actually affect companies in every sector. In this paper, we propose novel measures termed as climate Value-at-Risk (VaR) and climate Expected Shortfall (ES) that capture the risk attributed to transition risk factors proxied by environmental scores. We compare the average ratio of climate VaR and ES to total risk in various equity sectors, which enables us to identify the sectors in which climate and environmental risk factors contribute most to the total risk. Our analysis considers different risk measurements and various significance levels. Our findings show heterogeneity in sensitivity to climate and environmental risk factors in various sectors. The Health Care sector is the least cost-effective in reducing climate-related and environmental risks, and the Energy sector benefits most from improving the firms' environmental scores.

1. Introduction

As one of the most critical global challenges on this planet, climate change potentially impacts every individual, with health and social implications, but also affecting the economy and the financial system. Fossil fuels are a crucial input to production, and economic growth increases greenhouse gas emissions. The climate change attributes to those emissions and the literature shows that climate change has become a prominent risk that will potentially create substantial costs to the economy (Burke et al., 2015; Dietz et al., 2016; Lesk et al., 2016). Nonetheless, if the economic effects of climate change are as large as some studies have suggested, then, given that financial assets are ultimately supported by economic activities, the impact of climate change on financial assets could also be substantial.

Research on the interaction between climate change and financial economics is termed climate finance (Giglio et al., 2021). In this field, one of the important topics at the moment is to understand the effect of climate on various financial indicators. As highlighted by the Bank of England (2021), there is a research gap in incorporating climate risks into capital requirements. Additionally, the Basel Committee on Banking Supervision (2021) explores how climate-related risk factors arise and impact portfolios as well as levels of risk, providing the theoretical background on climate-related risk drivers and their transmission channels. From an EU perspective, the European Central Bank (2020) expects the financial institutions to continuously monitor the effects of climate-related and environmental risk factors on their holdings and future investments. To act on that, the European Central Bank (2022) put forward a framework for annual climate risk stress test. To address the research gap and meet regulatory demands, our study contributes to the climate finance literature that investigates the impact of climate-related and environmental risks on financial markets and firms.

We introduce new measures of climate-related and environmental risks, specifically *climate Value-at-Risk* and *climate Expected Shortfall* which capture the risk in equities that stems from climate-related and environmental risk factors proxied by environmental scores. Also, we compare the average ratios of climate Value-at-Risk and climate Expected Shortfall to total risk in several equity sectors, and we identify the sectors in which climate-related and environmental risk factors contribute most to total risk.

In this study, we use the terminology "climate-related and environmental risks" following European Central Bank (2020) and Network for Greening the Financial System (2020, 2023) to capture the impact from climate change and environmental degradation in companies, and perform a comparative analysis of the various industry sectors. Climate-related and environmental impact has two main drivers, physical risk and transition risk. The former refers to the mainly negative

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Table 1
Summary statistics.

Sector	*Return* (%)	*Environment*	*Emission*	*Innovation*	*Resource*	*Size*	*M/B**	*ROE**	*Leverage**	*Investment*	*NumComp*
Basic Materials	1.061	42.591	41.739	44.426	44.950	7.837	2.652	0.029	1.423	4.231	62
Consumer Discretionary	1.107	49.103	44.379	45.990	50.110	8.609	4.608	0.050	1.531	4.671	125
Consumer Staples	0.972	48.954	43.753	45.655	53.314	8.873	7.192	0.068	1.690	4.608	61
Energy	0.989	63.171	57.855	53.369	56.901	8.761	1.126	0.001	0.558	5.472	28
Financials	1.403	53.045	52.106	41.627	49.021	9.298	5.905	0.066	1.444	2.895	65
Health Care	1.620	56.791	56.961	46.748	63.459	9.624	7.770	0.020	0.740	4.523	31
Industrials	1.238	43.642	38.535	45.510	42.599	8.258	5.316	0.054	1.764	3.942	188
Real Estate	1.018	51.928	53.844	43.738	51.257	8.467	2.497	0.019	1.374	0.738	74
Technology	2.089	52.050	52.124	52.157	54.933	9.008	4.670	0.032	0.446	4.200	88
Telecommunications	0.617	46.841	48.230	46.677	53.289	8.947	2.424	0.011	1.174	4.968	22
Utilities	1.200	49.931	56.083	44.952	49.158	8.827	2.015	0.025	1.263	6.038	58

Note: This table reports averages (for monthly frequency) of the variables employed in the regressions in this study reported for 11 different sectors listed in the first column. The sample period is from January 2003 to December 2019. *Return* represents average monthly return of the sector (in percentages). *Emission*, *Innovation*, and *Resource* indicate, respectively, the Emission score, Innovation score, and Resource Use score. *Size* is the natural logarithm of market capitalization in $ million. *M/B* denotes the market value of equity divided by its book value. *ROE* is the return on equity. *Leverage* is the total debt (long-term and short-term) divided by the total stockholders' equity. *Investment* is the natural logarithm of the capital expenditures in $ million. *NumComp* represents the number of companies in the sector. Variables followed by * are winsorized at 1%.

Table 2
Panel regression results for returns and environmental scores at various quantiles.

	Quantiles								
Variable	1%	5%	10%	30%	50%	70%	90%	95%	99%
Environment	−0.057***	−0.032***	−0.021***	−0.008***	−0.003**	0.004*	0.013**	0.015	0.021
	(0.011)	(0.006)	(0.005)	(0.002)	(0.001)	(0.002)	(0.006)	(0.010)	(0.018)
Size	3.575***	2.437***	1.794***	0.773***	0.263***	−0.249***	−1.288***	−2.077***	−4.225***
	(0.268)	(0.181)	(0.128)	(0.057)	(0.029)	(0.053)	(0.156)	(0.223)	(0.382)
M/B	0.027***	0.010	0.001	0.002	0.000	0.000	−0.002	−0.001	−0.003
	(0.007)	(0.006)	(0.006)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.015)
ROE	−0.979**	−0.725	−0.037	−0.180	0.034	0.023	0.081	−0.046	−0.606
	(0.420)	(0.584)	(0.375)	(0.226)	(0.188)	(0.165)	(0.132)	(0.236)	(0.514)
Leverage	−0.230**	−0.010	0.001	−0.001	−0.001	0.000	0.010	0.008	0.289*
	(0.101)	(0.028)	(0.013)	(0.008)	(0.005)	(0.003)	(0.013)	(0.034)	(0.168)
Investment	−0.686***	−0.492***	−0.395***	−0.250***	−0.186***	−0.119***	0.024	0.157	0.379**
	(0.144)	(0.112)	(0.098)	(0.047)	(0.030)	(0.031)	(0.076)	(0.100)	(0.193)

Note: This table presents the results of the quantile regression with penalized sector fixed effects for the panel data of returns and environmental pillar under the Refinitiv ESG scores during the sample period from January 2003 to December 2019. The quantiles considered are 1%, 5%, 10%, 30%, 50%, 70%, 90%, 95%, and 99%. All control variables are lagged by one month. The standard errors are reported in parenthesis, *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

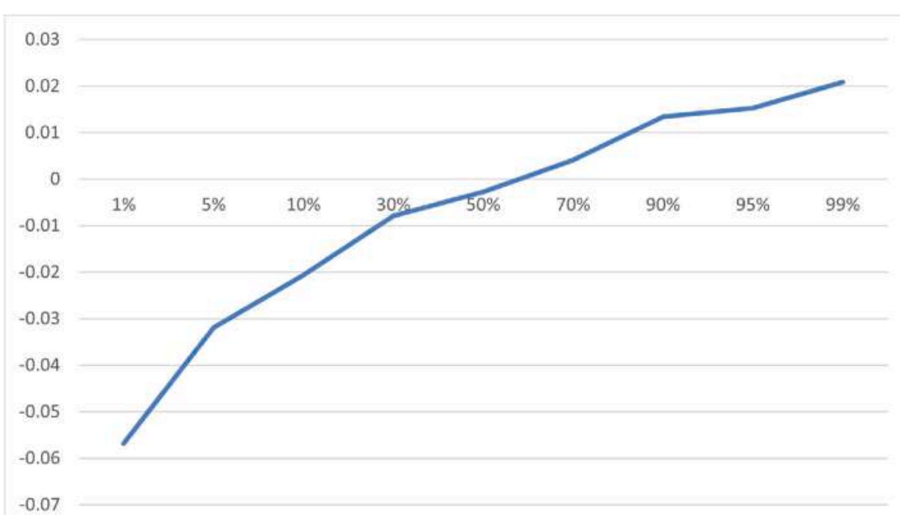

Fig. 1. Effect of the environmental pillar under Refinitiv ESG scores on returns at different quantiles.

impact of climate and weather-related events on business operations, society, and supply chains (Tankov and Tantet, 2019). There are two sub-categories within the class of physical risks: acute risk and chronic risk. Extreme weather events including extreme drought and precipitation, floods, hurricanes, heatwaves, and wildfires are defined as acute risks. Chronic risks are generally considered to include: rising sea levels, rising average temperatures, and ocean acidification. The latter refers to the risk associated with a path to a low carbon economy and all

Table 3
Summary statistics for VaR and ES estimates at 1% level.

Sector	VaR	ES	Climate VaR	Climate ES
Basic Materials	−27.998	−37.971	0.377	0.577
Consumer Discretionary	−28.306	−39.501	−0.258	−0.784
Consumer Staples	−22.031	−31.454	2.217	3.186
Energy	−30.231	−40.293	6.642	9.346
Financials	−21.000	−27.844	0.372	0.201
Health Care	−21.370	−30.283	−4.928	−7.134
Industrials	−25.150	−34.762	−0.583	−0.684
Real Estate	−17.069	−22.258	−0.329	−0.430
Technology	−27.349	−38.528	2.040	2.797
Telecommunications	−28.696	−41.374	−1.656	−2.368
Utilities	−16.920	−22.357	1.210	1.681

Note: This table reports the average firm-month total VaR and ES as well as climate VaR and ES (in percentages) for 11 sectors during the period from January 2003 to December 2019. In columns 1 and 2, average VaR and ES estimates at 1% level are presented. Average climate VaR and ES calculated using Eq. (6) are reported in columns 3 and 4. The negative coefficients of environmental scores in Tables 4 and 5 may lead to positive Climate VaR or ES estimates. A positive (negative) Climate VaR or ES means that the environmental scores contribute to a reduction (increase) in the total risk.

related implications of fossil fuels and dependent sectors (Curtin et al., 2019).[1]

Climate-related and environmental risks are growing concern for the financial sector, and they are affecting the prices of various assets, including stocks, bonds, real estate, and more (see Bernstein et al., 2019; Goldsmith-Pinkham et al., 2019; Hong et al., 2019; Baldauf et al., 2020; Painter, 2020; Bolton and Kacperczyk, 2021; Giglio et al., 2021). Also, they are long-term risks that pose significant challenges to investors, as it is often not effectively priced in financial markets (Andersson et al., 2016; Bansal et al., 2016). To mitigate these risks, investors need to consider the potential impact of climate change on the returns of assets. The implementation of carbon pricing can play an important role in reducing CO_2 emissions (Best et al., 2020), but it is also important to consider other factors, such as firm-level risk exposure to climate regulation (Seltzer et al., 2022), to climate change news shocks (Ardia et al., 2023), to the attention paid by market participants in earnings calls related to a firm's climate risks (Sautner et al., 2023), and the effects of weather conditions with abnormal temperatures (Anttila-Hughes, 2016; Kumar et al., 2019; Choi et al., 2020). On the one hand, companies with high carbon emissions are more likely to be exposed to climate-related and environmental risks, and their stock prices may be more likely to be affected by climate-related factors (Bolton and Kacperczyk, 2021). On the other hand, companies with higher environmental scores on ESG scores are likely to perform better when climate-related events occur (Engle et al., 2020; Huynh and Xia, 2021). Furthermore, climate policy uncertainty is reflected in the option price and can influence the social cost of carbon, as well as affecting the stock prices of firms with high exposure to climate policy (Barnett, 2023; Barnett et al., 2020; Ilhan et al., 2021). The hot debate of the climate change also arises the concerns of the impact of climate change on the financial risk management. Dietz et al. (2016) propose a climate risk measure by taking into account effects of climate damages on the present value of global assets. Acharya et al. (2023) provide a climate risk measure exploring a climate stress testing characterization of risk for financial firms and banks.

Risk measures such as Value-at-Risk (VaR) and Expected Shortfall (ES) have been widely used in academics and practice. VaR is one of the most popular tail risk measures that is employed to assess and manage financial risk. VaR is an estimate of the quantile of the distribution of profit and losses, and it can be measured at different levels. Due to its conceptual simplicity, VaR has become a popular risk measure of market risk and is frequently investigated (see Duffie and Pan, 1997; Dowd, 1998; Jorion, 2000; Dempster, 2002; Allen, 2012). However, since VaR ignores the shape and structure of the tail of the returns' distribution and is not a coherent risk measure (i.e. it is not subadditive), ES, as an alternative, has been proposed (Artzner, 1997; Artzner et al., 1999). It measures the expected value of the observations provided that they exceed VaR and is a coherent risk measure (Roccioletti, 2015). Due to its favourable properties, ES has consistently increased in popularity (see e.g. Chen et al., 2012; Patton et al., 2019; Taylor, 2019; Gerlach and Wang, 2020). However, the measurement of ES is inherently dependent on the value of the VaR estimate. As such, ES is not elicitable by itself, and only the (VaR, ES) tuple is elicitable (Ziegel, 2016). There is no doubt that in recent years climate-related and environmental risks have become some of the most important components of total financial risks, as highlighted by the European Central Bank (2020) and the Network for Greening the Financial System (2020, 2023). One important question that arises is to what extent climate-related and environmental risks contribute to the total financial risks, and this is the central research question we address here. Additionally, it has been well documented that different sectors have heterogeneity in the climate and environmental-factors (e.g. Giese et al., 2021). Thus, we extend our analysis by investigating the relationship between market risks and climate-related and environmental risk factors in various sectors.

This paper makes three main contributions. First, we pioneer in investigating the relationship between stock returns and transition climate-related and environmental risk factors in different return quantiles. The existing literature focuses on the link between environmental risk factors and the stock returns in the mean (Giese et al., 2019; Cornell, 2021; Luo, 2022), without paying attention to possible variations in the different quantiles of the stock returns. Based on firm-level environmental scores constructed by the ESG ("Environmental, Social, and Governance") scores data provided by Refinitiv to proxy the firms' climate-related and environmental risk exposure, we find a significant negative relationship between them in the lower quantiles of stock returns, implying that companies that face financial difficulties are affected negatively by the costs of improvements made to their environmental scores.

Our second contribution is to propose novel measures (climate VaR and climate ES) that capture the market risk attributed to climate-related and environmental risk factors proxied by environmental scores. Some institutions have proposed risk measures that they labelled "Climate Value-at-Risk" (e.g. MSCI, 2020). However, there is no publicly available documentation on how their measure is computed.[2] In addition, we introduce climate risk ratios for VaR and ES, which show the proportion of market risk which is due to climate-related and environmental risk factors. These novel measures can be useful tools for other researchers, investors and policymakers.

Our third contribution is to highlight how companies in various sectors respond to climate-related and environmental risks. As far as we know, there is no literature on sectoral analysis for climate VaR/ES. Our results indicate the heterogeneity in the sensitivity of different sectors to climate-related and environmental risk variables. In particular, companies in the Energy sector gain the most from improving environmental scores, whereas companies in the Health Care sector are the least cost-effective in decreasing their climate-related and environmental risk. Our results are robust to changes to the models used to capture risk and to the levels of risk significance.

The rest of the paper is organized as follows. Section 2 discusses the methodology to estimate the climate-related and environmental risk

[1] Also see Basel Committee on Banking Supervision (2021) for a regulatory perspective on climate-related risk drivers in the banking system.

[2] The commercial product illustrated by MSCI (2020) reports the climate VaR spread by different sectors of activity found within a portfolio, whereas our study provides a new measure on climate VaR/ES based on the relationship between market risks and climate-related and environmental risk factors.

Table 4
Environmental scores and VaR.

Variable	(1) Basic Materials	(2) Consumer Discretionary	(3) Consumer Staples	(4) Energy	(5) Financials	(6) Health Care	(7) Industrials	(8) Real Estate	(9) Technology	(10) Telecommunications	(11) Utilities
Emission	−0.028***	0.014**	0.002	0.014	0.009	−0.053***	0.015***	−0.016***	0.044***	0.050***	0.006
	(0.007)	(0.006)	(0.005)	(0.014)	(0.014)	(0.010)	(0.004)	(0.006)	(0.007)	(0.011)	(0.006)
Innovation	−0.004	−0.001	0.014***	0.031***	−0.030***	−0.006	−0.017***	0.020***	0.004	0.018**	0.016***
	(0.006)	(0.005)	(0.003)	(0.008)	(0.010)	(0.011)	(0.004)	(0.005)	(0.006)	(0.008)	(0.004)
Resource	0.038***	−0.017***	0.028***	0.074***	0.023**	−0.026***	−0.010**	−0.007	−0.008	−0.092***	0.003
	(0.007)	(0.006)	(0.005)	(0.013)	(0.011)	(0.010)	(0.004)	(0.005)	(0.008)	(0.018)	(0.005)
Size	4.273***	5.801***	4.236***	6.510***	7.632***	6.602***	5.479***	3.670***	2.477***	1.030**	8.209***
	(0.657)	(0.290)	(0.382)	(0.575)	(0.808)	(0.704)	(0.353)	(0.582)	(0.269)	(0.448)	(1.915)
M/B	0.527***	−0.022**	0.003	−0.016	−0.007	0.053***	−0.005*	1.681***	−0.039***	0.531***	−0.352
	(0.080)	(0.011)	(0.003)	(0.081)	(0.017)	(0.012)	(0.003)	(0.196)	(0.012)	(0.112)	(0.223)
Leverage	−0.518***	0.014	−0.019	0.047	−0.575***	−0.910***	0.003	−3.456***	0.102**	−1.494***	0.434
	(0.07)	(0.031)	(0.020)	(0.091)	(0.106)	(0.142)	(0.003)	(0.378)	(0.045)	(0.254)	(0.430)
ROE	1.866**	0.869*	0.211***	1.429	4.752***	4.809***	0.103	0.481	−0.521	4.957***	4.229**
	(0.861)	(0.524)	(0.071)	(1.281)	(1.646)	(1.287)	(0.203)	(3.705)	(0.321)	(1.679)	(1.970)
Investment	−0.543***	0.061	−0.115	0.775**	−0.251**	−0.742***	0.074	0.571**	−0.160	−1.754***	−0.519**
	(0.189)	(0.112)	(0.097)	(0.344)	(0.098)	(0.183)	(0.094)	(0.272)	(0.098)	(0.338)	(0.259)
Constant	−59.430***	−79.160***	−60.890***	−104.100***	−98.490***	−76.470***	−71.030***	−49.790***	−51.450***	−23.140***	−89.160***
	(5.229)	(2.614)	(3.639)	(5.858)	(8.051)	(6.659)	(3.040)	(5.204)	(2.289)	(4.267)	(17.830)
Observations	4009	8590	5092	1789	4699	2125	13,280	3680	7574	1742	5489
Adjusted R-squared	0.766	0.738	0.792	0.871	0.866	0.800	0.761	0.870	0.711	0.793	0.619
Year-Month F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table provides panel regression estimates for the impact of environmental scores on VaR. Regressions are estimated at sector level. The independent variables are *Emission*, *Innovation*, and *Resource*. All control variables are lagged by one month. The sample duration extends from January 2003 to December 2019. All regressions include the year-month fixed effect and firm fixed effect. Huber-White robust standard errors are used in the regression and reported in parentheses. ** and *** denote statistical significance at 5% and 1% levels, respectively.

measures. Section 3 introduces the firm-level data used in the empirical analysis. Section 4 presents the estimation results from panel data regressions. Section 5 reports the results of several robustness checks. Section 6 concludes. The online Supplemental Appendix contains additional results.

2. Methodology

2.1. Risk measures

The downside risk is captured by the left tail of stock returns' distribution. Two prevalent measures are employed to identify such risk. The first measure, VaR, is an estimate of the quantile of the distribution of profit and losses and it can be measured at different levels. Due to its conceptual simplicity, VaR has become a popular risk measure of market risk. However, VaR ignores the shape and structure of the tail of the returns' distribution and is not a coherent risk measure (i.e. it is not subadditive) (Artzner et al., 1999). Thus, a second risk measure has been introduced, ES, which measures the expected value of the observations provided that they exceed VaR; this is a coherent risk measure (Roccioletti, 2015).

VaR provides banks and financial institutions with an estimate of the minimum loss level that occurs in the worst outcomes at a given level $\alpha \in (0,1)$. Let $F_Y(\cdot|\Omega_{t-1})$ denote the cumulative distribution function of asset return Y_t over a time horizon (such as one day or one week) conditional on the information set Ω_{t-1}. The VaR at level α can be written directly in terms of the inverse cumulative distribution function (Duffie and Pan, 1997):

$$VaR_t^\alpha = F_Y^{-1}(\alpha|\Omega_{t-1}), \tag{1}$$

where VaR_t^α denotes the α-quantile of the underlying return distribution at time t. As such, Following Ziegel (2016), Nolde and Ziegel (2017), and Chen (2018), the VaR at level α at time t can be defined as:

$$VaR_t^\alpha = \inf\{Y_t | F_Y(Y_t|\Omega_{t-1}) \geq \alpha\}. \tag{2}$$

ES measures the expectation of return conditional on its value being less than VaR. As a coherent risk measure and due to its superior properties, ES has become increasingly popular in the risk management of banks and financial institutions. Recently, the Basel Committee on Banking Supervision (2013) proposed a transition from VaR at 1% level to ES at 2.5% level motivated by the global financial crisis in 2008. ES at level α at time t can be formally defined as (see Acerbi and Tasche, 2002):

$$ES_t^\alpha = \mathbb{E}\left[Y_t \middle| Y_t \leq VaR_t^R, \Omega_{t-1}\right]. \tag{3}$$

Since the generalized autoregressive conditional heteroskedastic (GARCH) model of Bollerslev (1986) and its variants (Nelson, 1991) capture the time-varying volatility feature, they are widely used to forecast VaR and ES in the literature. We also employ the GARCH model with skewed t distribution of Hansen (1994) for our estimation of risk measures. The model is specified as follows:

$$v_t = \mu_t + a\sigma_t, \quad \text{where} \quad a = F_\eta^{-1}(\alpha),$$

$$e_t = \mu_t + b\sigma_t, \quad \text{where} \quad b = \mathbb{E}[\eta_t|\eta_t \leq a],$$

$$Y_t = \sigma_t\eta_t, \quad \eta_t \sim iid\, F_\eta(0,1),$$

$$\sigma_t^2 = \omega + \delta\sigma_{t-1}^2 + \gamma Y_{t-1}^2 \tag{4}$$

where σ_t^2 is the conditional variance which follows a GARCH(1,1) process, η_t is the standardized residual that follows the skewed t distribution $F_\eta(0,1)$ and Y_t is the de-meaned daily returns. This model is based on a strong link between VaR/ES and equity returns, which has been widely discussed in the early literature (e.g. Duffie and Pan, 1997; Dowd,

Table 5
Environmental scores and ES.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Basic Materials	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Real Estate	Technology	Telecommunications	Utilities
Emission	−0.037***	0.019**	0.004	0.025	0.006	−0.072***	0.021***	−0.022***	0.064***	0.072***	0.009
	(0.010)	(0.008)	(0.008)	(0.019)	(0.020)	(0.014)	(0.006)	(0.007)	(0.010)	(0.016)	(0.008)
Innovation	−0.004	−0.007	0.020***	0.036***	−0.042***	−0.010	−0.021***	0.026***	0.007	0.026**	0.022***
	(0.008)	(0.007)	(0.004)	(0.010)	(0.015)	(0.016)	(0.005)	(0.006)	(0.00844)	(0.012)	(0.006)
Resource	0.052***	−0.026***	0.039***	0.105***	0.033**	−0.040***	−0.013**	−0.008	−0.016	−0.133***	0.004
	(0.010)	(0.008)	(0.008)	(0.018)	(0.015)	(0.014)	(0.006)	(0.007)	(0.011)	(0.026)	(0.006)
Size	5.879***	8.120***	6.145***	8.632***	9.975***	9.500***	7.557***	4.942***	3.538***	1.629**	11.000***
	(0.908)	(0.409)	(0.555)	(0.789)	(1.104)	(1.010)	(0.500)	(0.773)	(0.394)	(0.645)	(2.560)
M/B	0.690***	−0.031**	0.005	−0.026	−0.013	0.076***	−0.006	2.199***	−0.056***	0.780***	−0.458
	(0.107)	(0.015)	(0.005)	(0.111)	(0.027)	(0.018)	(0.004)	(0.257)	(0.017)	(0.161)	(0.298)
Leverage	−0.675***	0.018	−0.030	0.069	−0.702***	−1.295***	0.004	−4.562***	0.150**	−2.200***	0.564
	(0.097)	(0.042)	(0.028)	(0.123)	(0.137)	(0.204)	(0.005)	(0.495)	(0.066)	(0.368)	(0.576)
ROE	2.338**	1.230*	0.304***	1.837	6.250***	6.865***	0.148	1.137	−0.750	7.183***	5.675**
	(1.129)	(0.728)	(0.0994)	(1.732)	(2.196)	(1.846)	(0.279)	(4.693)	(0.476)	(2.400)	(2.631)
Investment	−0.686***	0.020	−0.162	0.916**	−0.306**	−1.042***	0.071	0.738**	−0.266*	−2.474***	−0.757**
	(0.253)	(0.153)	(0.140)	(0.465)	(0.130)	(0.256)	(0.125)	(0.354)	(0.141)	(0.478)	(0.351)
Constant	−81.600***	−109.700***	−87.650***	−137.700***	−128.900***	−109.100***	−97.620***	−66.050***	−72.420***	−34.640***	−118.60***
	(7.205)	(3.663)	(5.280)	(8.005)	(10.99)	(9.527)	(4.307)	(6.914)	(3.321)	(6.094)	(23.840)
Observations	4009	8590	5092	1789	4699	2125	13,280	3680	7574	1742	5489
Adjusted R-squared	0.770	0.767	0.812	0.882	0.863	0.816	0.770	0.872	0.716	0.813	0.631
Year-Month F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table provides estimates of the effect of environmental scores on ES based on panel regressions. Regressions are estimated at sector level. The independent variables are *Emission*, *Innovation*, and *Resource*. All control variables are lagged by one month. The sample period is from January 2003 to December 2019. All regressions include the year-month fixed effect and firm fixed effect. Huber-White robust standard errors are used in the regression and reported in parentheses. ** and *** denote statistical significance at 5% and 1% levels, respectively.

1998). We transform the daily VaR and ES to monthly estimates by multiplying average daily risk measures in the given month by the square root of 21. There are many other ways to estimate VaR and ES. We provide the robustness checks using alternative estimation of VaR and ES in Section 5.

2.2. *Climate VaR and ES*

We employ the Environmental component (denoted as E-score) of the ESG score in our study, given that it is related to the environmental factors and captures the effects of climate-related issues on companies. The E-score is comprised of three sub-scores: the *Emission* score, the *Innovation* score, and the *Resource Use* score. Specifically, the *Emission* score reflects the extent to which a firm is committed to reducing environmental emissions in its production and operational processes; the *Innovation* score measures a firm's capacity to create new market opportunities through environmental technologies and processes, or eco-designed products; the *Resource Use* score reflects a firm's performance and capacity to reduce the amount of natural resources it uses and improve its supply chain management. Taken together, these sub-components provide a comprehensive view of a firm's environmental performance and can help investors make informed decisions about the long-term sustainability and financial performance of a company. Thus, instead of directly revealing the link between this environmental pillar and the downside risks, we consider these three sub-components of the E-score in order to quantify the market risks attributed to the climate-related and environmental risk factors.

To determine the extent to which the risk presented by climate-related and environmental factors affects the VaR and ES of the equity returns, we begin our analysis by investigating the link between market risk measures and environmental scores in various sectors. For every sector, we estimate the following panel data regression:

$$\begin{aligned} \mathit{Downside\ Risk}_{i,t} &= \beta_0 + \beta_1 \mathit{Emission}_{i,t} + \beta_2 \mathit{Innovation}_{i,t} + \beta_3 \mathit{Resource}_{i,t} \\ &\quad + \beta_4 \mathit{Controls}_{i,t-1} + \delta_i + \gamma_t + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where the $\mathit{Downside\ Risk}_{i,t}$ represents one of the two risk measures ($VaR_{i,t}$ and $ES_{i,t}$) of the firm i in month t at 1% level; $\mathit{Emission}_{i,t}$, $\mathit{Innovation}_{i,t}$ and $\mathit{Resource}_{i,t}$ measure the Emission, Innovation and Resource Use scores, respectively, of firm i in month t; $\mathit{Controls}_{i,t-1}$ is a vector of control variables that may affect downside risk, including size, M/B, leverage, ROE, and investment.[3] We include firm fixed effect (δ_i) and year-month fixed effect (γ_t). We obtain $\widehat{\beta}_1$, $\widehat{\beta}_2$, and $\widehat{\beta}_3$, and these capture the effects of the climate-related and environmental risk factors on VaR and ES. Also, we report the heteroskedasticity-consistent standard errors of White (1980).

In the following, we provide the definition for Climate VaR and ES, which are the VaR and ES of the stock returns of a firm, attributed to environmental scores. Based on Eq. (5), the Climate VaR and ES of firm i in month t are calculated as:

$$\mathit{Climate\ Downside\ Risk}_{i,t} = \widehat{\beta}_1 \mathit{Emission}_{i,t} + \widehat{\beta}_2 \mathit{Innovation}_{i,t} + \widehat{\beta}_3 \mathit{Resource}_{i,t}. \tag{6}$$

If the β is negative (positive), an increase in the Emission score, Innovation score, or Resource Use score increases (decreases) the risk.[4] Additionally, we define the portion of VaR or ES attributable to environmental scores as follows:

[3] Following the approach in Bolton and Kacperczyk (2021), we run these regressions for firm-months observations. The firm-level control variables are updated quarterly, so in our regressions, we use the most recent observation for these variables. The emission score variables are updated annually, and for these as well we use the most recent observations in our regressions.

[4] The environmental scores are between 0 and 100, and the risk is typically expressed as a negative number.

Fig. 2. Heatmaps of the Statistical significance (left) and Economic significance (right) of the Emission score, Innovation score, and Resource Use score for VaR from 11 sectors during the sample period from January 2003 to December 2019. The statistical significance is represented by the coefficients of environmental scores in Table 4. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Economic significance is defined as the percentage change in total VaR associated with an increase of one standard deviation in the specified environmental score. In both heatmaps, red (green) boxes indicate that an improvement in the specified environmental score increases (decreases) risk.

Table 6
Summary statistics of climate risk ratio for VaR and ES at 1% level.

Sector	Mean		Std		Max		Min	
	(1) VaR	(2) ES	(3) VaR	(4) ES	(5) VaR	(6) ES	(7) VaR	(8) ES
Basic Materials	−1.703	−1.861	3.090	3.081	3.825	3.791	−10.870	−10.268
Consumer Discretionary	1.026	2.249	1.301	1.744	6.161	9.259	−1.092	−0.679
Consumer Staples	−12.382	−12.771	7.997	8.515	−1.240	−1.217	−32.989	−36.480
Energy	−26.996	−29.397	18.960	21.607	−4.905	−5.120	−76.727	−86.979
Financials	−1.896	−0.805	4.032	4.084	6.510	9.748	−11.419	−10.604
Health Care	26.499	27.671	15.638	16.909	69.415	75.364	1.987	2.130
Industrials	2.585	2.223	2.139	2.020	9.570	8.892	−2.476	−2.753
Real Estate	1.879	1.900	3.590	3.660	10.070	10.118	−8.939	−8.909
Technology	−8.086	−7.954	4.949	4.972	−0.410	−0.264	−23.312	−23.123
Telecommunications	7.141	7.382	8.882	9.614	29.765	33.169	−9.396	−9.684
Utilities	−7.776	−8.314	3.672	3.997	−1.459	−1.606	−15.918	−17.169

Note: This table presents the summary statistics of the climate risk ratio for VaR and ES (in percentages) for 11 sectors from January 2003 to December 2019. The mean values and standard deviations of the ratio appear in columns 1–2 and 3–4, while the maximum and minimum values of the ratio appear in columns 5–6 and 7–8.

$$\mathit{Climate\ Risk\ Ratio}_{i,t} = \frac{\mathit{Climate\ Downside\ Risk}_{i,t}}{\text{Downside Risk}_{i,t}}. \tag{7}$$

When the sign of the ratio is negative, the effort spent on the improvement of these three environmental scores reduces the riskiness of the firm. When it is positive, the cost associated with the improvement of the environmental scores leads to an increase in the firm's downside risk.

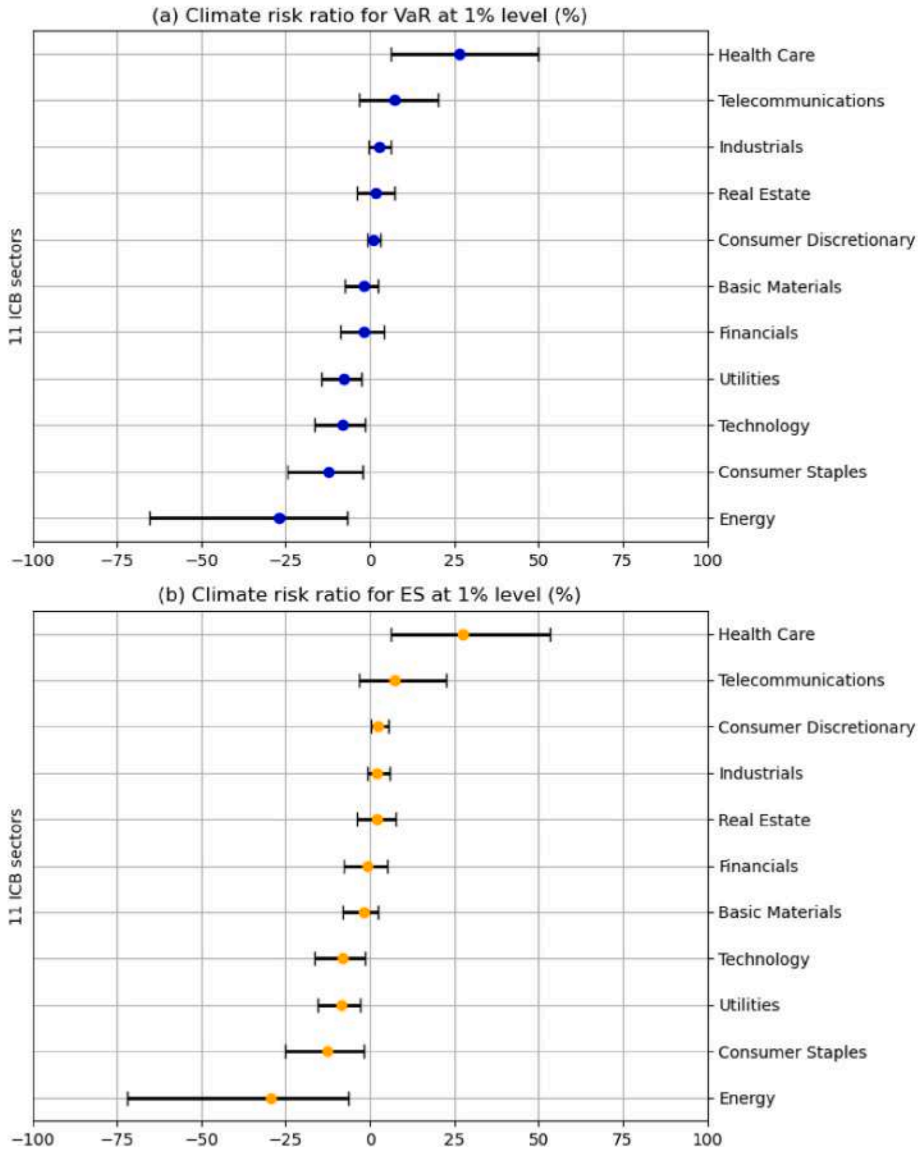

Fig. 3. Climate risk ratio (in percentages) for 11 sectors at 1% level. The ratios for Var and ES are displayed in (a) and (b), respectively. The left and right boundaries of the error bar for each sector are the 5 percent and 95 percent quantiles of the ratio, while the coloured marker represents the mean value. The sectors in the panel are ordered in descending order of the average climate risk ratio.

2.3. *Quantile regression with penalized fixed effect for panel data*

In the recent literature, several environmental proxies have been shown to affect stock returns (Engle et al., 2020; Bolton and Kacperczyk, 2021; Hsu et al., 2023). Here we employ the quantile regression proposed by Koenker (2004) using panel data to discover the relationship between stock returns and environmental scores at various quantiles. To determine how environmental scores influence returns at different quantiles of their distribution, we first investigate the following standard linear panel regression model:

$$y_{i,t} = x_{i,t}^{\top}\beta + \delta_i + \epsilon_{i,t}, \quad t = 1, \ldots, T_i, \quad i = 1, \ldots, n, \tag{8}$$

where $y_{i,t}$ indicates the firm's stock return, $x_{i,t}$ is a vector of variables including the environmental pillar of the ESG score and the lagged one-month size, M/B, leverage, ROE, and investment. δ_i represents the firm fixed effect, and $\epsilon_{i,t}$ is the error term. The subscript i indexes the firm, while the subscript t indexes the time. The following model is then considered for the conditional quantile functions (at quantile) of the returns in month t of the i^{th} firm $y_{i,t}$:

$$Q_{y_{i,t}}(\tau|x_{i,t}) = x_{i,t}^{\top}\beta(\tau) + \delta_i, \quad t = 1, \ldots, T_i, \quad i = 1, \ldots, n, \tag{9}$$

To simultaneously estimate Eq. (9) for several quantiles, we perform the following optimization:

$$\min_{(\beta,\delta)} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T_i} w_k \rho_{\tau_k}\left(y_{i,t} - x_{i,t}^{\top}\beta(\tau_k) - \delta_i\right), \tag{10}$$

where $\rho_\tau(\epsilon) = \epsilon(\tau - I(\epsilon < 0))$ denotes the piecewise linear quantile loss function of Koenker and Bassett Jr (1978). The weights w_k control the relative impact of the q quantiles $\{\tau_1, \ldots, \tau_q\}$ on the estimation of the parameters.

The estimation of β and the firm fixed-effect δ_i can be improved by reducing the unconstrained δ_i's toward a common value. To achieve that, we employ the ℓ_1 penalty, $P(\delta) = \sum_{i=1}^{n} |\delta_i|$ in addition to Eq. (10). Then, we obtain the estimators by solving the penalized version of Eq. (10):

Table 7
The climate risk ratios and ratio rankings.

Sector	Climate risk ratio				Rank			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	G-SKT	GJR-G-SKT	G-FZ	CARE	G-SKT	GJR-G-SKT	G-FZ	CARE
Basic Materials	−1.703	−0.410	1.351	3.031	6	6	7	7
Consumer Discretionary	1.026	1.951	1.265	2.361	7	7	6	6
Consumer Staples	−12.382	−16.257	−11.202	−10.786	2	2	2	3
Energy	−26.996	−28.556	−27.457	−17.976	1	1	1	1
Financials	−1.896	−1.355	−3.521	−5.484	5	5	5	5
Health Care	26.499	27.649	20.652	17.795	11	11	11	11
Industrials	2.585	4.126	2.018	3.790	9	9	8	8
Real Estate	1.879	1.964	2.149	4.630	8	8	9	9
Technology	−8.105	−8.248	−7.668	−7.601	3	3	4	4
Telecommunications	7.141	8.699	12.404	5.460	10	10	10	10
Utilities	−7.776	−6.516	−8.355	−11.218	4	4	3	2

Note: This table presents the average climate risk ratios (in percentage) and the rankings for 11 sectors (the model with the lowest ratio is ranked 1 and the model with the highest ratio is ranked 11) based on the climate risk ratio for VaR estimates at 1% level from January 2003 to December 2019 for 3 risk model specifications. The negative (positive) ratio refers to a reduction (increase) in the total risk due to environmental scores. G-SKT, GJR-G- SKT, G-FZ, and CARE correspond to the GARCH model with skewed *t* distribution, the GJR-GARCH model with skewed *t* distribution, the GARCH model estimated with the FZ0 loss function from Fissler and Ziegel (2016), and the CARE model based on Taylor (2008), respectively.

$$\min_{(\beta,\delta)} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T_i} w_k \rho_{\tau_k} \left(y_{i,t} - x_{i,t}^{\top} \beta(\tau_k) - \delta_i \right) + \lambda \sum_{i=1}^{n} |\delta_i|, \quad \lambda > 0, \tag{11}$$

where λ is the penalty term. For $\lambda \mapsto 0$ we obtain the fixed effects estimator described in Eq. (10), while as $\lambda \mapsto \infty$ the $\widehat{\delta} \mapsto 0$ for all $i = 1, \ldots, n$ and we obtain an estimate of the model with the fixed effects eliminated.

3. Data

In this section, we describe all datasets used in the empirical analysis. Detailed definitions of the variables are provided in Table SA.1 of the Supplemental Appendix. We focus on U.S. companies in this study. To avoid the potential structural break during the COVID-19 period, our primary database ranges from January 2003 to December 2019 and is primarily comprised of three datasets obtained from Refinitiv, Compustat, and CRSP. Refinitiv provides data on environmental scores, Compustat provides data on corporate fundamentals, and CRSP provides data on stock returns. We implement the matching using CUSIP as the main identifier, and the ultimate matching produces 802 unique firms and 58,290 firm-month observations.[5]

According to Section 2.2, we measure firm-level environmental performance using the *Emission* scores, the *Innovation* scores, and the *Resource Use* scores under the environmental pillar of the Refinitiv ESG scores. Calculated at the firm-quarter level, our control variables are defined as follows. *Size* is the natural logarithm of the firm's market capitalization. *M/B* is the firm's market capitalization divided by its book value. *Leverage* is the book leverage of the firm. *ROE is* the firm's earning performance. *Investment* is the natural logarithm of the firm's capital expenditure plus one (to avoid the natural logarithm of zero). To mitigate the impact of outliers, *M/B*, *Leverage*, and *ROE* are winsorized at 1% level. We note that firms in various sectors have diverse responses to environmental scores. Hence, we report the summary statistics of the sample with respect to the FTSE/DJ Industry Classification Benchmark (ICB) in Table 1. Telecommunications has the lowest average return with a value of 0.617%, while Technology has the highest average return (2.089%), followed by Health Care (1.620%). The Energy sector has the greatest overall environmental score, Emission score and Innovation score, with respective values of 63.171, 57.855 and 53.339. The Health Care sector has the highest Resource Use score (63.459), but the lowest Innovation score (41.626). The lowest Emission and Resource Use scores are reported for Industrials, which are 38.535 and 42.599, respectively.

4. Results

4.1. Quantile regression results

We begin our analysis by investigating the relationship between stock returns in different quantiles and the environmental pillar of the Refinitiv ESG scores, by employing the quantile regression described in Section 2.3. Table 2 reports the panel regression results for quantiles $\tau \in \{1\%, 5\%, 10\%, 30\%, 50\%, 70\%, 90\%, 95\%, 99\%\}$, where all quantiles are assigned with equal weights when estimating using Eq. (11). For the quantiles below 95%, significant coefficients are observed for the environmental score.

The overall trend is that the effect is negative for lower quantiles and positive for higher quantiles and is more pronounced for lower quantiles. The signs of the control variables are generally consistent with the literature. Fig. 1 illustrates the values of the coefficient of the environmental score, for the above quantiles between $\tau = 1\%$ to $\tau = 99\%$. At the 1% quantile, the environmental scores have the most negative effect on the stock returns. This effect diminishes when the quantile reaches the 50% quantile, at which point this effect switches to positive. When companies struggle, then the costs associated with improving their E-score bring additional burdens and so improving the E-score reduces overall returns. The effect is opposite when companies do well, in such instances improving the E-score increases company returns.

4.2. Climate VaR and ES results

The quantile regression results of Section 4.1 show that there is a differential effect of the environmental scores on the returns, depending on which quantile the returns falls into. This subsection examines the relationship between downside risk (VaR and ES) and environmental scores. We collect daily stock returns from January 2003 to December 2019 using CUSIP from CRSP as described in Section 3. Then, the firm-month VaR and ES at 1% level are estimated using the specification in Section 2.1. We present the average monthly VaR and ES across several sectors in columns 1 and 2 of Table 3. Real Estate and Utilities are the sectors with the lowest average VaR and ES, whereas Energy is the sector with the highest total risk.

To reveal the effects of environmental scores on downside risk, we regress the VaR and ES at 1% level on the *Emission* score, the *Innovation* score, the *Resource Use* score, along with firm-level control variables. The results are presented in Table 4 and Table 5 for VaR and ES,

[5] The correlations of the environmental scores and control variables are reported in the Supplemental Appendix.

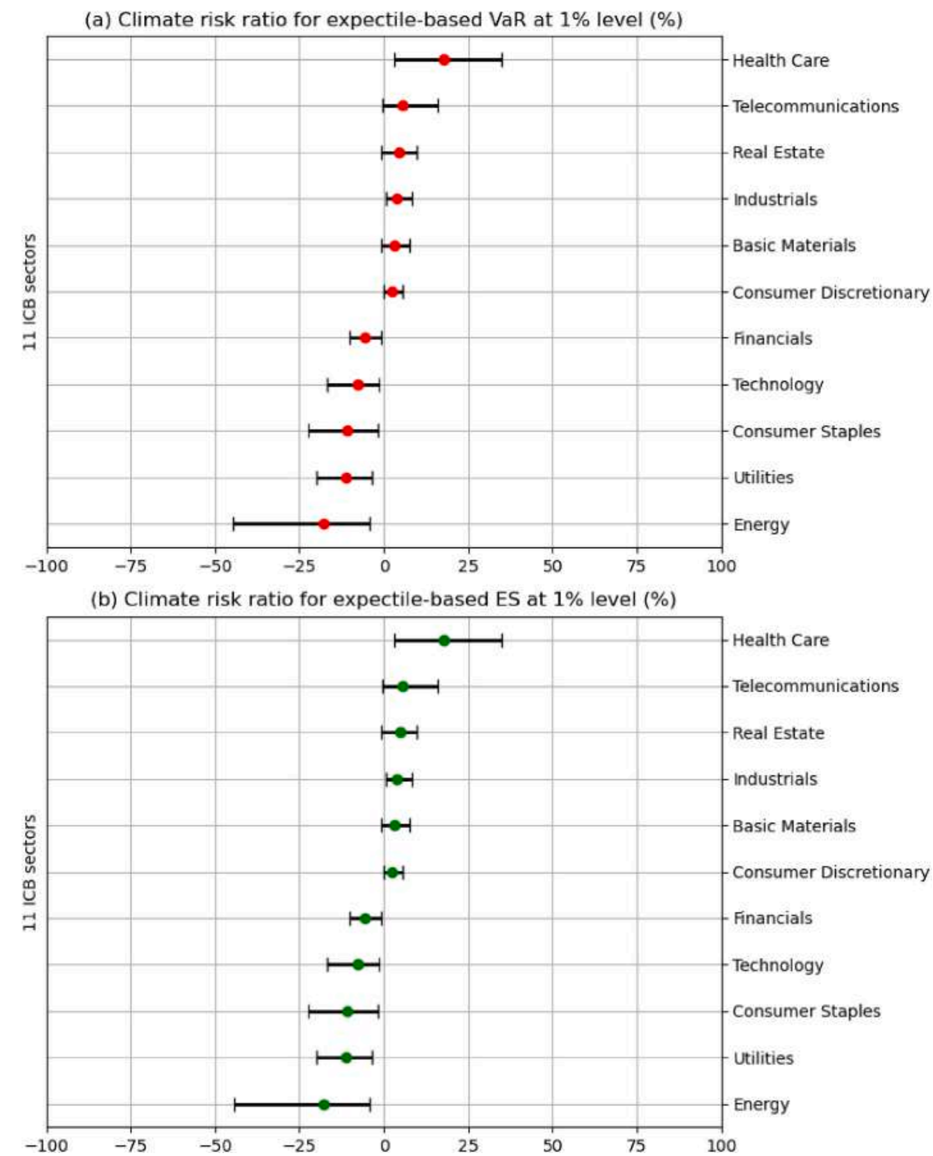

Fig. 4. Expectile-based climate risk ratio (in percentages) for 11 sectors at 1% level. The ratios for expectile-based Var and ES are displayed in (a) and (b), respectively. The left and right boundaries of the error bar for each sector are the 5 percent and 95 percent quantiles of the ratio, while the coloured marker represents the mean value. The sectors in the panel are ordered in descending order of the average expectile-based climate risk ratio.

respectively. The Energy and Utilities sectors have only positive coefficients across all scores, indicating that an improvement in any one of these environmental scores of firms in these two sectors leads to a reduction in the total risk of the firms. Health Care, however, has solely negative coefficients on the environmental scores, which indicates that as the environmental scores increase, the firms' total risks increase proportionally. In other words, the companies' investments in improving their environmental scores reduce their total risk in the Energy and Utilities sectors, whilst it increases their total risk in the Health Care sector. This might be related to the link between medical services and emissions, as also argued by Pichler et al. (2019). Building low carbon strategies requires considerable effort, given the complexities of medical supply chains and health treatments, and can be very costly for health companies, which makes emission reductions hard to achieve. Other sectors have coefficients with mixed signs associated with the three environmental scores. Due to the differences of sectors, some sectors benefit from increases in the individual scores but are negatively affected by others. For instance, firms in the Industrials sector have their risk affected positively by their Emission score but negatively by their Innovation score and Resource Use score.

The left panel of Fig. 2 displays the heatmaps of the statistical significance of VaR with respect to the three environmental scores. According to the value of the coefficients, sectors including Consumer Staples, Energy, and Utilities benefit from the improvement in all of the three environmental scores. The Innovation score has a positive and statistically significant effect on the total risk of the companies in these three sectors. This effect is also observed for Resource Use Score in the Consumer Staples and Energy sectors. However, the negative signs of the coefficients of the three environmental scores in the Health Care sector indicate that the additional expenditures made by companies to improve their environmental scores raise their total risk. The right panel of Fig. 2 reports the economic significance of the results. Several key observations are worth noting.[6] First, an one-standard-deviation increase in the Resource Use score of companies in the Energy sector leads to a worsening of 2.042% in their total risk. Second, companies in the Health Care sector suffer a deterioration of 1.490% in their total risk due to an one-

[6] To our knowledge, there is no existing literature of performing such a sectoral analysis to compare our results against.

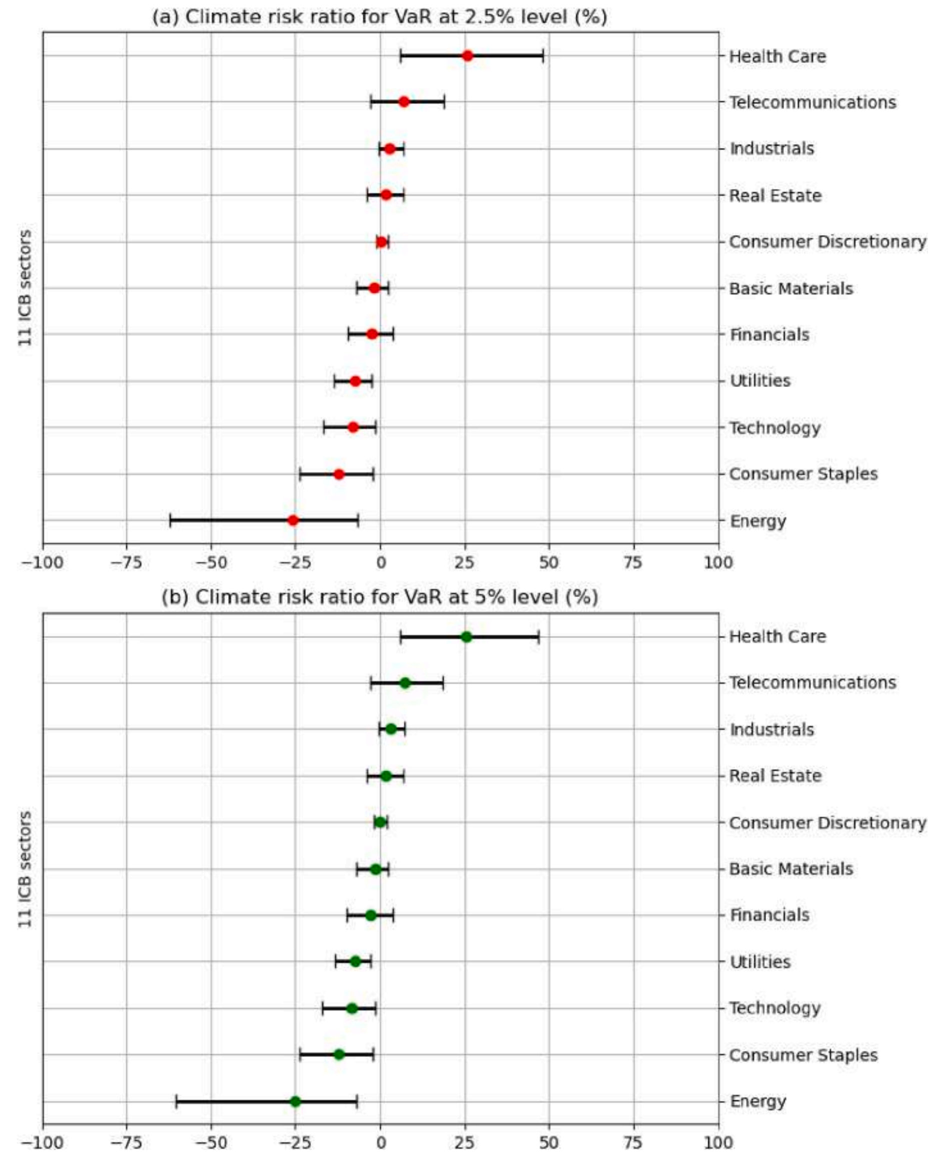

Fig. 5. Summary statistics of the climate risk ratio (in percentages) for VaR at 2.5% (a) and 5% (b) levels for 11 sectors. The left and right boundaries of the error bars are the 5 percent and 95 percent quantiles of the ratio, while the coloured marker represents the mean value. The sectors in both panels are ordered in descending order of the average climate risk ratio.

standard-deviation increase in the Emission score. Third, an one-standard-deviation increase in the Resource Use score of companies in the Telecommunication sector is associated with a 2.392% improvement in their total risk. Lastly, companies in the Technology sector benefit an improvement of 1.159% in their total risk via an one-standard-deviation increase in the Emission score.

Climate VaR and ES are computed[7] based on Eq. (6), and the results are presented in columns 3 and 4 in Table 3. In the Energy sector, the average Climate VaR (ES) is the most positive at 6.642% (9.346%), which implies that the environmental scores lead to a reduction of total VaR (ES). On the contrary, the VaR and ES of firms in Health Care attributed to environmental scores are the highest in absolute value. The cost associated with improving the environmental scores leads to an increase in the firms' downside risk in this sector. A similar effect can be seen in the Telecommunication sector.

We employ the climate-related and environmental risk measure proposed in Eq. (7) to demonstrate the extent to which the environmental scores affect the total downside risk of the firms. The summary statistics of the climate risk ratio for VaR and ES for different sectors are reported in Table 6. A negative (positive) sign in the mean value of the climate risk ratio indicates that, on average, improvements in the environmental scores reduce (increase) the total risk of the firm. Sectors including Basic Materials, Consumer Staples, Energy, Financials, Technology, and Utilities benefit from the effort spent on increasing the companies' environmental scores, and the proportion of total VaR reduced by environmental scores ranges from 1.703% to 26.996%. Sectors such as Consumer Discretionary, Health Care, Industrials, Real Estate, and Telecommunications are negatively affected by the increases in the companies' environmental scores, but the effect on their total VaR is less than 7.2%, with the exception of Health Care, which is characterized by VaR increases of 26.499% on average, due to the companies' environmental scores. Similar results can be found for ES.

To visually illustrate the fraction of VaR and ES that is attributable to the environmental scores, we display summary statistics of the climate risk ratio of VaR and ES in Fig. 3, and sort the climate risk ratio of different sectors in descending order in both panels. We would like to highlight three points. First, in four sectors (particularly the Energy

[7] As far as we know, there is no backtest for climate VaR/ES developed yet.

sector), the climate risk ratio is negative, as expected, showing that climate-related and environmental risks are reduced when companies improve their environmental performance. In the Energy sector, the climate-related and environmental risk factors can reduce VaR or ES by about 28% on average and the 5% quantile of the ratio for VaR is −65.294% and for ES it is −71.872%. Second, the climate risk ratio in six sectors is not significant on average. The ranking of sectors including Health Care, Telecommunication, Consumer Staples, and Energy are the same in both Fig. 3(a) and (b). Third, the only outlier is the Health Care sector where the effect is inversed, which means by improving environmental performance, the VaR and ES of the companies increases.

In the Health Care sector, the climate-related and environmental risk factors contribute approximately 27% on average to the total VaR and ES, the 95% quantile of the ratio for VaR is 49.956% and for ES it is 53.454%. In this sector, emissions can result from medical treatments and low emission alternatives are often expensive, making it difficult to reduce emissions, the priority being improvements in health and reducing the risks to the patients; see Pichler et al. (2019) for further deliberation.

5. Robustness checks

5.1. Asymmetric VaR and ES models

To account for the possibility of asymmetry in the volatility, we repeat our previously presented climate-related and environmental risks estimation methodology using the GJR-GARCH model (Glosten et al., 1993) with skewed *t* innovations. Table 7 (column 2) depicts the climate risk ratios for the GJR- GARCH model. We notice that it yields similar but slightly different values for the climate risk ratio. When it comes to the ranking of the sectors based on the climate risk ratios (Table 7, column 6), there is a high degree of consistency, with the ratios remaining mostly unaffected.

5.2. Semi-parametric VaR and ES models

Recently, Patton et al. (2019) introduced semi-parametric models for VaR and ES. In the following, we check whether our results are affected if the risk measures are obtained via one of the semi-parametric models, namely the GARCH-FZ model. Table 7 (columns 3) shows the climate risk ratios obtained with this model, which is similar to the previous results. The ranking of the sectors based on the GARCH-FZ model (Table 7, column 7) is consistent with our earlier rankings.

5.3. Expectile-based climate VaR and ES

In this section, we explore expectile-based climate risk measures as an alternative. This is motivated by the fact that expectiles have a different dependence on the form of the distribution, as compared to quantiles. Whilst a change in the shape of the distribution will not alter the quantile, it will modify the expectile. Taylor (2008) developed the Conditional Autoregressive Expectile (CARE) model to compute expectile-based risk measures. Using the CARE model, we obtain the expectile-based VaR and ES, which is further used to calculate climate VaR and ES (as well as risk ratios). Fig. 4 shows the expectile-based climate risk ratios for various sectors. Table 7 (columns 4 and 8) provides the expectile-based climate risk ratios as well as sector ranks. It can be noted that the results obtained from the expectile-based measures are in line with the quantile-based values reported in Section 4.2, demonstrating the robustness of our findings to expectile-based risk measures.

5.4. Alternative risk levels

After the 2007–2008 financial crisis, the Basel Committee on Banking Supervision (2013) proposed a transition from 1% VaR to 2.5% ES. In addition to VaR and ES at 1%, different risk levels are therefore explored in this robustness check. We employ VaR at 2.5% and 5% levels estimated from the GARCH model with skewed *t* distribution, as dependent variables in Eq. (5).[8] Fig. 5 presents the summary of the climate risk ratio for VaR at 2.5% and 5% levels for the 11 sectors previously considered. Figs. 3 and 5 are similar, in that the ranking position of all sectors corresponds between the two figures. The 5% (95%) quantile of the climate risk ratio for companies in the Energy (Health Care) sector at 1% risk level is on average −65.293 (49.956), and at the 5% risk level, it is −60.268 (46.893). By shifting 1% risk levels to less extreme risk levels, the influence of environmental scores on downside risk is reduced, with the exception of companies in the Financials, Industrials, and Technology sectors, which have 5% risk levels on average more impacted by the companies' environmental scores.

6. Conclusion

In this study, we propose new measures of climate downside risk that reveal to what extent the firm-level environmental scores influence the downside risk of the firms. We reveal the statistically significant negative relationship between stock returns and environmental pillar of the Refinitiv ESG scores at low quantiles of the returns. We employ the Emission score, Innovation score, and Resource Use score of the environmental pillar to explain the downside risk of the firms in various sectors. Our definitions of climate VaR and ES capture the market risk components associated to climate-related and environmental risks. We document that there is heterogeneity in the sensitivity of the firm-level risk to environmental scores. Our framework shows that firms in some sectors, notably Energy and Utilities, can reduce their downside risk by improving their firms' environmental scores, while for companies in sectors such as Health Care, improving the environmental scores is not cost-effective. These results are consistent with various risk assessments and levels of risk. These findings have important implications for investors and business managers to capture sensitivities to climate-related risk factors. Future research could consider a more nuanced decomposition of climate-related and environmental risks, in addition to the investigation of the relationship between downside risks and physical risk factors (e.g. rising sea levels or hurricane-prone regions).

CRediT authorship contribution statement

Emese Lazar: Writing – review & editing, Methodology, Conceptualization. **Jingqi Pan:** Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Shixuan Wang:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.123393.

Data availability

Data will be made available on request.

[8] Analogous results for ES are available in the Supplemental Appendix.

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Incorporating climate risk in to Strategic Asset Allocation

Scenario Analysis is a key pillar of climate-aware Strategic Asset Allocation

The systemic nature of climate change drives variations in the risk and return of a portfolio through its impact on the future time paths of macroeconomic and market parameters, such as GDP, inflation, interest rates, and equity risk premium. Climate scenario analysis and stress testing are important tools to assess/quantify the financial impact of climate change on the portfolio. They are a key component of climate-aware strategic asset allocation (SAA), asset and liability management (ALM), and overall risk management, especially for asset owners who also have a stream of future liability payments – such as insurance companies.

Important today, more than ever

An increasing number of investors across the globe are adopting a net zero investment framework. While the path towards net zero involves various steps including setting targets around emissions. Investments in aligned assets, incorporating climate scenario analysis and stress testing within SAA allows investors to systematically consider the risks and opportunities from climate change in the risk and return expectations of assets, especially of long-term assets.

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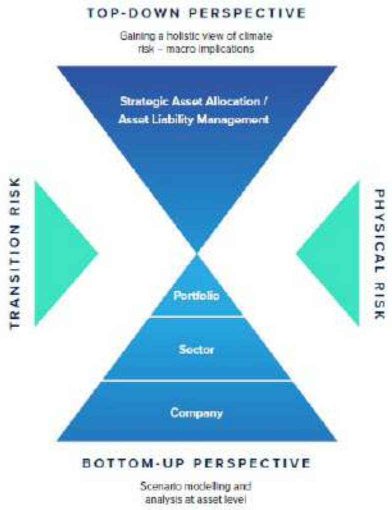
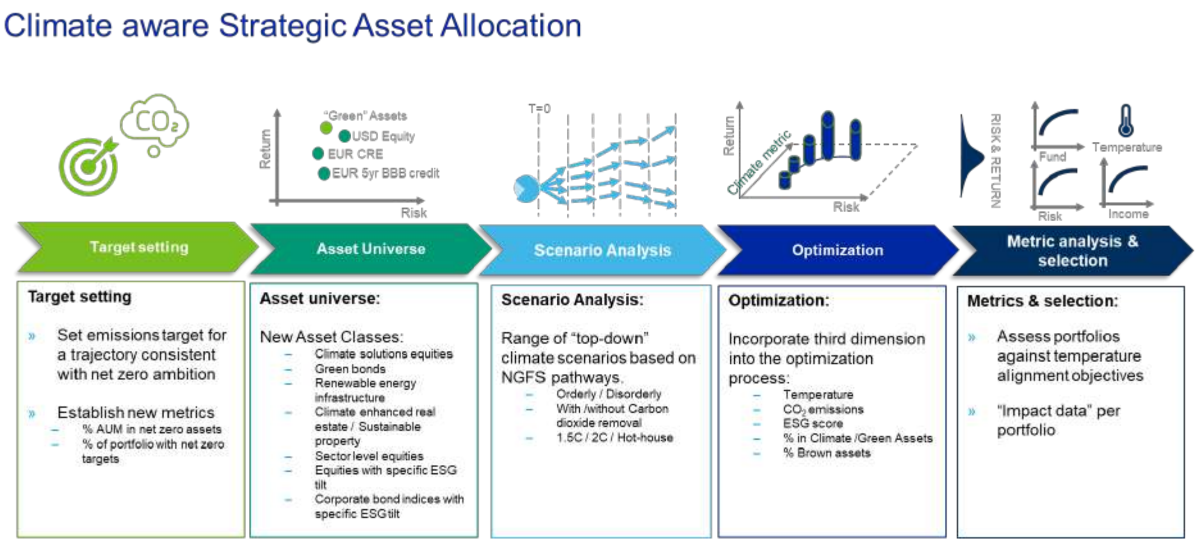
The Institutional Investors Group on Climate Change (IIGC) has published a framework which was developed through discussions with its members. This emphasizes the role of integrating climate scenario analysis in to asset allocation.



Source: IGCC Navigating climate scenario analysis – a guide for institutional investors[1]

Climate-aware Strategic Asset Allocation

Asset allocation must evolve to incorporate climate-related risks and the impact from any constraints imposed as insurers target their climate. A top down approach which looks at how climate change related drivers affect returns of asset classes. The analysis should ideally combine a top-down mapping at the macroeconomic level and a bottom-up analysis at the sector and company level. Creating an understanding of the risks and opportunities within the existing asset allocation structure and through evolving the asset mix over time. In a top-down-only analysis, some regional and sectoral impacts might be netted out, especially in a diversified portfolio. A combination of top-down and bottom-up approaches, although data- and resource-intensive, will achieve broad coverage. In addition, the depth of analysis required to make key investment decisions in sectors where these risks are most material.



1 Institutional Investors Group on Climate Change

1. Target Setting

As with traditional asset allocation, the process starts with assumption setting. This takes place at both the portfolio level and the asset class level. At the portfolio level, the insurer must set emissions targets, based on science-based pathways such as, temperature-growth target trajectories, aligned to their net zero commitment. Following COP26 we have seen a wave of net zero announcements from financial institutions. These company-wide objectives now need to be translated in to more granular metrics for example,% of assets under management (AUM) in net zero assets. In their recent paper[2], the UK Prudential Regulatory Authority states that "their analysis found significant variation between firms in translating climate science in to targets and scenarios, on modeling climate-related market risk and capital modeling".

For insight in to the types of metric which an insurer may establish, we can look to the regulation in the pensions world, where new climate risk reporting requirements came in to effect for large schemes on 1 October 2021. Trustees must select and report on at least three metrics, including an absolute emissions metric, an emissions intensity metric and one additional climate related metric[3]. The additional climate change metrics includes a portfolio alignment metric and climate value at risk (VaR). The temperature alignment metric compares the implied warming potential of the portfolio to established indices and indicates how the portfolio is positioned compared to a particular climate pathway or global warming outcome. The Moody's temperature alignment data[4] assesses the forward-looking trajectory of companies' emissions. Based on their greenhouse gas emissions reduction targets and covers approximately 4,400 large publicly listed companies. The climate VaR provides a forward-looking valuation assessment to quantify climate risks and may provide a metric to help adjust the investment portfolio to limit exposure to climated-related risks.

2. Asset Universe

To impose Economic Social Governance (ESG) criteria as constraints in the optimization, it is necessary to have ESG classification data, ideally at individual security level. It may be sourced from the external asset manager and the insurer may wish to incorporate their own views on top of this. Ideally the ESG classification should explicitly categorize the E, S, and G considerations. Vigeo Eiris, part of the Moody's ESG solutions, evaluates the efforts of corporates to pursue a sustainable business and attributes a score relative to 38 environmental, social, and governance criteria.

3. Scenario Analysis

Scenario modeling is an essential component of the framework and the scenarios should consider both the chronic physical and transition effects of climate change:

» Physical risks arise from increasing severity and frequency of climate and weather-related events, such as sea-level rises and floods.

» Transition risks arise from the adjustment towards net-zero emissions, which will require significant structural changes to the economy and technologic advancements.

Scenario analysis is a key feature of insurer's risk management and, unsurprisingly, features heavily in an insurer's approach to modeling climate risk. The financial risks posed by climate change are also high on the regulator's agenda.For example, in the UK the Bank of England carries out a biennial stress testing exercise, launched in June 2021. These scenarios built on the reference scenarios developed by the Network For Greening the Financial System (NGFS) and the set includes three scenarios:

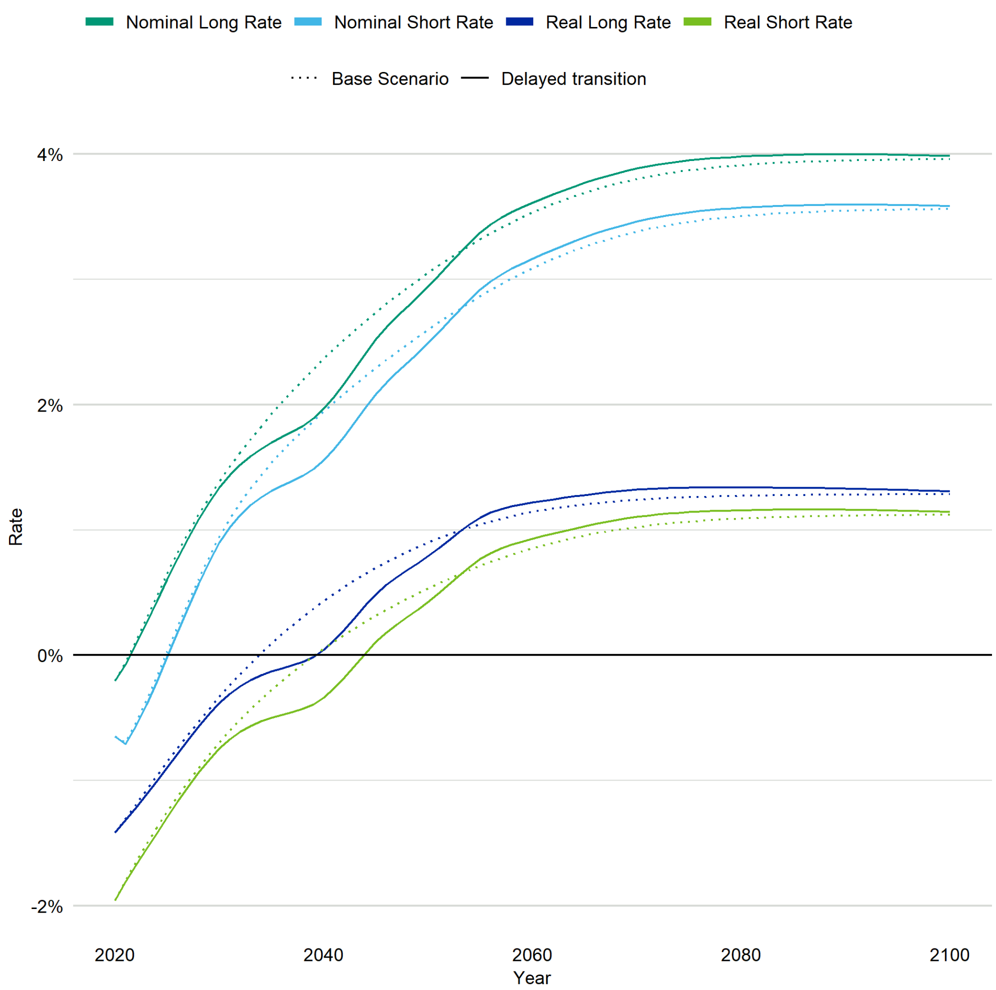
» Orderly: early, ambitious action to a net zero CO_2 emissions economy

» Disorderly: action that is late, disruptive, sudden and/or unanticipated

» Hot house: limited action leads to a hot house world with significant global warming and, as a result, strongly increased exposure to physical risks

[2] *Climate-related financial risk management and the role of capital requirements*, PRA, October 2021
[3] *Governance and reporting of climate change risk: guidance for trustees of occupational schemes*, DWP, June 2021
[4] For more details, please refer to esg.moodys.io/climate-solutions

The Moody's Analytics Climate Pathway Scenario Service, built on our award-winning scenario generation software, can translate climate pathways into an insurer's financial risk variables to help them assess their climate-related risks and anticipate the future impact of climate change on asset and liability projections. Climate pathways can be specific to the NGFS criteria, Moody's Analytics economic climate assumptions, or the client's own input. The climate pathways explore the impact of carbon tax and how these costs get passed through in to different industry sectors. As an example, the chart below shows the model's projection of nominal and real rates under the disorderly transition scenario:



4. Optimization

The investment portfolio optimization will incorporate a third climate dimension, which may be specified as an additional objective or there may be additional constraints introduced. The optimization will aim to satisfy the targets specified in the first step such as meeting the climate glidepath and targets specified for the allocation to green asset classes and /or ESG tilted funds.

5. Metric analysis

After reviewing the output from the SAA process, the insurer will consider the practicalities of implementation including the transaction costs involved. For example, if significant changes in the sector split of the portfolio are required, then fund mandates need to be updated. Where assets are allocated to funds with a specific ESG tilt then benchmark indices will need to be established to monitor performance. If the output proposes investment in new asset classes, then approval for the new asset classes will likely be required and the time horizon should allow for the necessary governance.

In addition to analyzing the metrics, it is important to understand the narrative such as, why the climate the pathways have impacted the existing portfolio and how the proposed investment strategy meets the objective while still satisfying the insurer's internal hurdle rate.

Conclusion

The insurance industry has an important role to play in the transition to net zero. Towards the end of 2021, there was significant momentum behind the transition to a low carbon economy, with many financial institutions announcing their plans to become a net zero emissions company. To achieve these plans insurers, now have to align their investment strategy with these targets. Climate scenario analysis is likely to feature heavily in the insurer's approach to strategic asset allocation, and to guide their decision around asset class and sector preferences.

This is part of a series of papers on climate risk topics for insurers. Read the others here:

» Climate change – The biggest risk multiplier for the insurance industry

» Constructing Climate Pathway Scenarios to Assess the Financial Impact of Climate Risk

» Incorporating ESG into P&C underwriting

» Climate aware Own Risk Solvency Assessment

» Exploring the impact of IFRS Sustainability Disclosure Standards on Insurers

CLIMAFIN handbook: pricing forward-looking climate risks under uncertainty Part 1

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Abstract

Aligning finance to sustainability requires methodologies to price forward-looking climate risks and opportunities in financial contracts and in investors' portfolios. Traditional approaches to financial pricing models cannot incorporate the nature of climate risk (i.e. deep uncertainty, non-linearity and endogeneity), and of financial risks (interconnectedness and complexity). To fill this gap, we developed a transparent, science-based framework to assess and price climate financial risks under uncertainty, the CLIMAFIN tool. It embeds climate scenarios adjusted financial pricing models (for equity holdings, sovereign and corporate bonds), climate scenarios conditioned risk metrics (such as the Climate Spread and the Climate Value-at-Risk). These allow us to introduce forward-looking climate risk scenarios in the valuation of counterparty risk, in the probability of default and largest losses on investors' portfolios. This handbook is intended to support investors in the assessment of forward-looking climate risks in their portfolios and in the identification of portfolios' risk management strategies, and financial supervisors in the analysis of risk exposures that could have implications for systemic risk and in the design of prudential measures to mitigate such risk.

Keywords: CLIMAFIN, forward-looking climate transition risk, climate deep uncertainty, financial contracts, financial pricing models, Climate Spread, Climate Value at Risk

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*This is a first version of a work in progress. The aim is report and discuss in a single document the

[The aim of this report is to discuss in a single document the results of works on the pricing of climate risk in financial instruments and markets that have been published in form of articles and working papers. As such, it should be quoted whenever used as "Battiston S., Mandel A., Monasterolo I. (2019): CLIMAFIN handbook: pricing forward-looking climate risks under uncertainty". Working Paper, Climate Finance Alpha.]

1. Introduction

There is growing awareness among academics, practitioners and financial supervisors of the fact that unmitigated climate change and a disorderly transition to a low-carbon economy could affect the profitability of several economic activities and cause relevant losses for investors' portfolios (Carney 2015, NGSF 2018, Battiston et al. 2017).

Nevertheless, recent research highlighted that investors are not pricing yet climate-related risks in their portfolios (Monasterolo and de Angelis 2019, Morana and Sbrana 2019, Ramelli et al. 2018).

Since financial investors take decisions based on what they can measure, and their decisions do influence (and are influenced by) the benchmark in their respective markets, evaluating climate risks in financial contracts is crucial from an investors' risk management perspective, and for financial supervisors whose mandate is about preserving financial stability.

Main barriers that investors face in pricing climate-related financial risks are represented by (i) the nature of climate risks (physical, transition), (ii) the poor understanding of existing classifications to assess financial exposures to climate risks, (iii) the need to move from the backward-looking nature of traditional financial risk assessment and of investors' benchmarks to the forward looking nature of climate risks, and (iv) the integration of forward looking climate shocks in financial risk metrics and management approaches.

In this handbook, we show how the CLIMAFIN tool can guide a risk averse investor in integrating climate risks considerations in her counterparty credit and financial risk valuation

results of a stream of scientific works on the pricing of climate risk across financial instruments and markets.

and probability of default, including new climate scenarios adjusted risk metrics (Climate Value-at-Risk, Climate Spread). CLIMAFIN provides a transparent, science-based framework to assess investors' exposure to forward-looking climate risks and to price climate risks in the value of their financial contracts and portfolios. This allows investors to align to the recommendations of the Network for Greening the Financial System (2019) on climate financial risk assessment and climate stress-testing, and financial regulators to identify the drivers of climate-related financial instability and to design prudential measure to mitigate it.

In this first part of the handbook we focus on the following CLIMAFIN's characteristics:

- The information set that a rational risk averse investor should use to assess financial risk under climate transition scenarios;
- The forward-looking climate transition risk scenarios and shocks and the transmission channels through which they hit economic activities (low-carbon and carbon-intensive) and firms' profitability;
- The climate financial pricing models for climate scenarios adjusted counterparty risk valuation for individual contracts (equity, corporate and sovereign bonds, loans);
- Climate scenarios conditional financial risk metrics such as the Climate Value at Risk (Battiston et al. 2017) and the Climate Spread (Battiston and Monasterolo 2019);
- Climate Stress-testing models (see Battiston et al. 2017, Roncoroni et al. 2019). The presentation of the Climate Stress-test and its applications to investors' portfolios is included in the second part of this Handbook.

The CLIMAFIN Handbook is organized as follows. Section 2.3 describes the information set of a risk averse investor that aims to minimize climate risks in her portfolio. Section 3 describes the climate scenarios adjusted financial risk evaluation model for equity holdings. Section 4 and Section 5 present the climate scenarios adjusted credit risk evaluation models for corporate and sovereign bonds respectively. Section 6 introduces the Climate Spread while Section 7 introduces the Climate Value-at-Risk.

2. Model component, investors' information set and risk management strategy

2.1. Climate risk: not a Normal type of risk for financial actors

In this section we introduce the concepts of climate **physical** and **transition** risks, and we discuss the main differences between the properties of climate risks and of the risks usually considered in finance.

2.1.1. Climate physical risks

Climate change physical risk refers to risk of damages to physical assets, natural capital and/or human lives resulting into output losses, as a result of climate induced weather events. Based on the available scientific information, the Greenhouse Gases (GHG) emissions trajectory currently followed by UN countries would lead to severe socio-economic consequences, resulting in particular from sea level rise, icesheet and permafrost melting, and the increased frequency of extreme weather events such as drought, floods and heatwaves. These events will have economic consequences both at the firm and macroeconomic level, and include:

- The destruction of immobilized productive capital, with negative implications on firms' profitability, investments, employment and eventually on Gross Domestic Product (GDP) (Burke et al. 2015, 2018, Hsiang et al. 2017);
- Drops in properties' values (see e.g. the example of luxury coastal properties in Florida and South Carolina, that would eventually become not insurable anymore, US 4th Climate Assessment Report), with implications for banks and insurance companies;
- Loss of arable land productivity, with implications on food commodities' production and prices, and thus on famine and social unrest, and eventually the relocation of millions of people currently living in areas particularly exposed to climate physical risks, even within developed countries (FAO SOFA 2018, IPCC 2014).

2.1.2. Climate transition risks

Climate change transition risk refers instead to the risk arising from sudden assets' values adjustments and repricing as a result of coordination of expectations of market participants about the implementation of climate policies (e.g. a carbon tax, or the revision of the Emissions Trading Scheme (ETS) scheme in Europe). These adjustments are expected to negatively impact the value of fossil fuels related assets (the so-called carbon stranded assets, see e.g. Leaton et al. 2012). They are also expected to impact indirectly the value of assets in other sectors that use fossil fuel energy and electricity as a production input, or that are involved in the value chain of companies that do it, thus generating cascading losses. In addition, in today's interconnected business and financial sectors, a shock generated from an economic activity could cascade on the investor who is exposed to the financial contracts issued by that activity. However, the sign of the impact can be positive or negative, depending on whether firms are able to anticipate the policy and adapt their business to alternative sources of energy (e.g. in certain scenarios, renewable-based utilities or energy-intensive processes that manage to diversify their energy sources away from fossil-fuels are expected to grow in market share).

Complexity of climate risks and limits of traditional financial pricing models

Climate risks are characterised by deep uncertainty, non-linearity, fat tailed distributions, path-dependency and endogeneity. These characteristics, that we briefly outline below, cannot be easily embedded in traditional financial pricing models that stand on assumptions of Normally distributed shocks, perfect information, complete markets, absence of arbitrage and short term valuation.

Non-linearity. Climate shocks probability distribution can't be inferred from historical data being forward-looking in nature. In addition, recent studies showed that past temperature data are not normally distributed. For instance, Western European summer of 2003 was 5.4 above mean temperature for 1864-2000. Within a Normal distribution, 5.4 summer would occur once every 30 million years. But Eastern Europe had similar heat wave in 2010. Thus, if such events happen every 7 years, temperatures are not normally distributed (Ackerman 2017).

Deep uncertainty. The forecasts of climate change and its impact on humans and ecosystems contain irreducible uncertainties because of the nature of the earth system, including the presence of tail events (Weitzman 2009) and tipping points (Solomon ea. 2009), which cannot be overcome by model consensus (Knutti 2010). This means that largest shocks expected to occur in mid-to long-term but their exact localization and magnitude is unknown.

In addition, uncertainty characterises the costs and benefits estimates in each scenario that vary substantially with the assumptions on agents' utility function, future productivity growth rate, and intertemporal discount rate. These assumptions, sometimes implicit or given for granted in the mathematical treatment of economic agents' behavior, ultimately imply fundamental philosophical and ethical considerations (Nordhaus 2007; Stern 2008, Ackerman et al. 2009, Stern 2013, Pyndick 2013).

Complexity. Even if costs and benefits could be predicted precisely, the likelihood of the realization of a given pathway depends on the assumptions on agents' rationality and on the ability of countries to coordinate on international policies. The political economy of the actors involved is complex and plays a fundamental role. However, this is not accounted for by the literature on the social cost of carbon nor by the literature on Integrated Assessment Models (IAMs). **Endogeneity of risk**. On the one hand, the likelihood of achieving climate targets and the mitigation of climate risks in financial markets and investors' portfolios depends from the orderly introduction of climate policies and the scaling up of financial investments in low-carbon sectors. However, the endogeneity between uncertainty of policy decisions and annoucements and investors' expectations on the financial risk deriving from the policies generates the possibility of multiple equilibria. In this context, a rational agent cannot identify a preferred investment strategy.

In this context, the standard approach to financial risk analysis, consisting of: identifying the most likely scenario, computing expected values, and estimating financial risk based on backward looking metrics and historical values of market prices, is not an adequate approach (Battiston 2019).

2.2. Model components

We define and implement a model that is composed of the following:

- Definition of the investor's portfolio of risky financial contracts;
- A discussion on the nature of climate risks considered;
- Macro-economic trajectories and climate transition risk at issuer/counterparty level;
- A valuation model to price equity risk;
- A structural model to price credit risk;
- A model of forward-looking climate transition risk using the Climate Policy Shock Scenarios from the Investor Information Set
- The definition of *Climate Spread* and *Climate VaR*
- The assessment of impact of Climate Policy Shocks on bonds default probability, Climate Spread, Portfolio Climate Value at Risk (VaR).

2.3. Investors' information set

Building on Battiston and Monasterolo (2019) we consider a risk averse investor that aims to assess the exposure of her portfolio to forward-looking climate transition risk in a context of incomplete information and deep uncertainty (Keynes 1973, Knight 1921, Greenwald and Stiglitz 1986, Nalebuff and Stiglitz 1983).

We identify an $Information\ Set$ relevant to climate transition risk, suitable for investor that does not necessarily have a greening mandate but who does need to implement a financial valuation (risk) of its portfolio. We want to identify the properties of portfolio's risk management strategy accounting for investor's risk aversion, counterparty risk, Probability of Default (PD), Spread and Value-at-Risk (VaR) adjusted for forward-looking climate transition risk scenarios. In this context, implementing the strategy requires to adjust the traditional Probability of Default (PD), the Spread and VaR, conditional to forward-looking Climate Policy Shock Scenarios (i.e. happening in the future).

The information set of the risk averse investor is composed of:

- A set of *Climate Policy Scenarios* P_l corresponding to GHG emission reduction target across regions (B = Business-as-Usual):

$$\mathbf{ClimPolScen} = \{B, P_1, ..., P_l, ..., P_{n^{\text{Scen}}}\}$$

- A set of economic output trajectories for each country j, sector k under each scenario P_l, estimated with each climate economic model M_m:

$$\mathbf{EconScen} = \{Y_{1,1,1,1}, ..., Y_{j,k,P_l,M_m,...}\}$$

- A set of **forward-looking** *Climate Policy Shock Scenarios* (disorderly transition $B \rightarrow P_l$):

$$\mathbf{TranScen} = \{B \rightarrow P_1, ..., B \rightarrow Pl, ..., B \rightarrow P_{n^{\text{Scen}}}\}$$

- A set of *Climate Policy Shocks* on economic output for j, k under transition scenario $B \rightarrow P_l$, estimated with model M_m

$$\mathbf{EconShock} = \{..., \frac{Y_{j,k,P_l,M_m} - Y_{j,k,B,M_m}}{Y_{j,k,B,M_m}}, ...\}$$

By defining the information set we want to:

- Include the current available knowledge about transition risk factors related to climate change and climate change mitigation that can affect the investment value. We consider the climate policy scenarios developed by the International Scientific Community and reviewed by the Intergovernmental Panel on Climate Change (IPCC). Then, we translate the economic trajectories for both low-carbon and carbon-intensive economic activities obtained from climate economics models (e.g. Integrated Assessment Models (IAM) as well as other models) into climate policy shocks on the Gross Value Added (GVA) of those activities and firms.

- Cover a time horizons that is relevant both for investment strategies and for the low-carbon transition, and ideally covers several decades, from 2020 to 2050 and possibly beyond that.
- Include varying investor's risk aversion preferences. We consider multiple scenarios that account for different risk aversion and allow to go beyond the inadequate notion of "most likely scenario" and include the notion of "worst case scenarios".
- Compatible with the hypothesis of the possibly incomplete information and incomplete markets (Greenwald and Stiglitz 1986), the economic shocks led by a disorderly low-carbon transition allow to model to be temporary out-of-equilibrium.
- Be relevant for institutions with a focus on financial risk valuation and financial stability mandate (thus, we do not assume financial actor's mandate beyond risk).

2.4. Investors' Climate Risk Management Strategy

The investor risk management strategy is based on the VaR and aims to minimize climate risk in its portfolio by:

- Accounting for investor-specific **risk aversion** level (i.e. varying subsets of investor information set InfoSetClimRisk).
- Accounting for **counterparty risk** adjusted for **climate policy shock** scenarios (e.g. probability of default, spread)
- Accounting for metrics relevant for financial regulation e.g. *risk measure* such as **VaR**.

In this context, the risk averse investor aims to minimize her Climate Value-at-Risk (*Climate VaR*) under the investor information set *InfoSetClimRisk* i.e. the forward-looking climate policy shocks, the scenarios of economic trajectories for low-carbon and carbon-intensive economic activities' GVA, and the climate models (e.g. the IAM) used to estimate the economic shock on GVAs.

The Climate VaR Management Strategy that aims to minimize the worst-case losses of the portfolio across the forward-looking Climate Policy Shock Scenarios can be written as:

$$\textbf{ClimVaRStr} = \min_{\text{Portfolios}} \{ \max_{\text{Shocks}} \{ \text{VaR}(\text{Ptfolio,Adj.PD} \,|\text{Policy Shock}) \} \}$$

In this context, future asset prices are subject to shocks that depend on the issuer's future economic performance, the risk premia demanded by the market, as well as the timing and magnitude of the climate policy introduced and the outcome of the energy transition of individual firms and countries. The investor considers different feasible climate policy scenarios (but has no information on the probability associated) for which she can calculate the impacts (negative or positive) on the market share of carbon-intensive or low-carbon economic activities and firms.

The investor is subject to incomplete information on her (and competitors') exposure to risk stemming from a disordered transition from a climate policy scenario to another one, uncertainty on the outcome of the firms and country's energy transition, and no information on the probability distribution. Thus, her risk management strategy is to consider a set of feasible climate transition scenarios that her portfolio should withstand, and then compute the VaR conditional to those scenarios.

2.5. Climate policy scenarios

With the aim to assess the impact of a disorderly low-carbon transition, i.e. forward-looking climate policy shocks on the value of contracts of the investor's portfolio, we consider the climate policy scenarios of the IPCC 2014 report, described in .

Scenario Name	Scenario Type	Near-term Target / Fragmented Action	Fragmented Action until	Long-term Target, in 2100	Burden-sharing
Base	Baseline	None	N/A	None	None
RefPol	Reference	Weak	2100	None	None
StrPol	Reference	Stringent	2100	None	None
450	Benchmark	None	N/A	450 ppm CO2e (2.8 W/m²)	None
500	Benchmark	None	N/A	500 ppm CO2e (3.2 W/m2)	None
RefPol-450	Climate Policy	Weak	2020	450 ppm CO2e (2.8 W/m²)	None
StrPol-450	Climate Policy	Stringent	2020	450 ppm CO2e (2.8 W/m²)	None
RefPol-500	Climate Policy	Weak	2020	500 ppm CO2e (3.2 W/m2)	None
StrPol-500	Climate Policy	Stringent	2020	500 ppm CO2e (3.2 W/m2)	None

(Source: IIASA, Kriegler et al. 2013) Characteristics of the mild and tight climate policy scenarios considered in the LIMITS project

In particular, we select four climate policy scenarios aligned to the 2°C target from the LIMITS database of IAM and a baseline of no climate policy, described in Table 1. We use the LIMITS project database (Kriegler et al. 2013) to compute the trajectories of the market shares for several variables including the output of primary energy from fossil fuel and the output of secondary energy in the form of electricity both from fossil fuel sources and renewable energy sources. Then, we estimate the effect of the introduction of market-based climate policies (i.e. a carbon tax). The two emissions concentration targets chosen under milder and tighter climate policy scenarios (i.e. 500 and the 450 ppm), determine the amount of CO2 to be emitted in the atmosphere by 2100 consistently with the 2°C aligned IPCC scenarios (IPCC 2014). The 500 and 450 ppm scenarios are associated to a probability of exceeding the 2°C target by 35-59% and 20-41% respectively (Menishausen et al. 2009). Thus, the choice of specific emissions concentration targets could be considered as a proxy for the stringency of the global emission cap imposed by potential climate treaty.

A change in climate policy (i.e. in the value of the carbon tax every 5-years time step) implies a change in the sectors' macroeconomic trajectory, and thus a change in the market share of primary and secondary energy sources. The shock in the market share could differ

Climate policy shock scenario	Climate policy scenario	Scenario Class	Target by 2020	Target between 2020 and 2100
Not applicable	Base	No climate policy	None	None
Disorderly switch from Base to RefPol-450	RefPol-450	Countries Fragmented, Immediate Action	Lenient	450 ppm: 2.8W/m2 in 2100, overshoot allowed
Disorderly switch from Base to StrPol-450	StrPol-450	Countries Fragmented, Immediate Action	Strengthened	450 ppm: 2.8W/m2 in 2100, overshoot allowed
Disorderly switch from Base to RefPol-500	RefPol-500	Countries Fragmented, Immediate Action	Lenient	500 ppm: 3.2W/m2 in 2100, overshoot allowed
Disorderly switch from Base to StrPol-500	StrPol-500	Countries Fragmented, Immediate Action	Strengthened	500 ppm: 3.2W/m2 in 2100, overshoot allowed

Table 1: Selected climate policy scenarios from the LIMITS database. The table shows the four climate policy scenarios considered (plus the Base scenario), i.e. RefPol-450, RefPol-500, StrPol-450, StrPol-500.

in sign and magnitude depending on the scenario S, the region R, the model M used and the sector S. We consider a shock occurring in 2030, affecting the market shares of the economic activities and firms (low-carbon and carbon-intensive, see Figure 2.1) to which the investor's portfolio is exposed via financial contracts (equity, corporate and sovereign bonds, loans).

2.6. Climate Policy Shocks

In the model,the climate and energy targets of each countries are assumed to be known by the investor. These targets translate in a share of energy and electricity produced by renewable energy sources.

However, for each country, the investor does not known if and when the country will introduce climate policies to foster the alignment of the economy to its targets. She also does not know along which economic trajectory, which means, the change in energy mix of the economy that leads to a change in the market share of different renewable/fossil sub-sectors of the economy and thus the revenues of the firms in those sectors.

The investor does not have priors on the probability of these events and assumes that if a country implements the low-carbon transition, then it does so by switching from its BAU scenario to one of the climate policy scenarios described by the scientific community (i.e. the energy and economic scenarios based on IEA roadmap and IPCC climate scenarios, see Kriegler et al. 2013, IPCC 2014). This assumption is motivated by the fact that there is policy and scientific consensus on these climate policy scenarios and their trajectories.

The transition of a country from the Business as Usual B to a climate policy scenario P can occur orderly or disorderly.

Orderly, means here that the introduction of a climate policy is carried out timely enough for the country to achieve its renewable energy targets and with a public and predictable schedule. In this scenario, investors can anticipate it and discount the effects on asset prices of the economic activities affected. For instance, the phasing out of coal-based electricity plants is announced to happen with a certain schedule, which is maintained and the market players know that it will be maintained. Thus, they can discount the future value of investments in assets that have these plants as underlying, accordingly, and they can price the risk associated to their exposure to financial contracts related to those plants.

In contrast, **disorderly** means that the transition is carried out at a schedule that is not predictable by markets and investors, e.g. the government introduces the climate policy in a late and sudden way, or retroactively revise its policies. In this case, we assume that the climate policy shock stemming from a disordered transition is not anticipated (despite potentially expected) by the investor. This is due to the backward looking nature of the benchmark considered by asset managers and on which asset managers' performance (and thus remuneration) is assessed. It is common knowledge that asset managers take investment decisions based on the benchmark in their respective markets (Greenwald and Stiglitz 1986). Recent research shows that the market benchmark is carbon intensive (see e.g. Battiston and Monasterolo 2019 for the case of corporate bonds market benchmark against which the European Central Bank's corporate bonds purchase (CSPP) has been assessed).

If the investor cannot anticipate the policy shock, then we can assume that she cannot discount correctly the effect of a climate policy on the change in asset prices of the economic activities affected by the transition. A failure to anticipate the climate policy shock leads to a failure in pricing it correctly. In turn, this has potentially severe implications on price volatility, on portfolio's performance and financial stability.

It is important to notice that the assessment of the policy shock could be incorrect even on average across market participants. The motivation for considering this possibility is due to the fact that several recent policy events (achievement of Paris Agreement, outcome of US elections, the US withdrawal from Paris Agreement, Brexit, the outcome of 2018 Italian elections) have been incorrectly forecast by most observers and investors. Nevertheless, these events and their incorrect pricing are having long-lasting economic effects (see e.g. the spread on Italy' sovereign bonds). This implies that these effects could not be priced in by market participants, and this possibility should be considered in financial pricing models of sovereign bonds. Since the experience shows that the possibility that markets do not anticipate correctly policy events and their economic impact is material, we assume that the investor wants to include this possibility among her scenarios. For instance, the phasing out of coal based electricity plants could occur late on the policy agenda, behind the initially announced schedule (e.g. in Poland), in a situation where market players are thinking that it won't happen any longer. This implies that they do not discount correctly the future value of investments in the assets that have these plants as underlying.

Today, the information available to policy makers and market players on the trajectories of future values of economic sectors' market share comes mostly from Integrated Assessment Models (IAM). These are (partial or general) equilibrium models, calibrated on the recent state of the economy and climate targets, and provide trajectories in which the economy remains in equilibrium along any given trajectory. Thus, moving from a BAU to a climate policy scenario implies jumping from an equilibrium condition to another one. Moreover, the levels of output of the sectors of the economy must be consistent one with each other to reach again equilibrium conditions. The latter feature means that, for instance, a decrease in electricity generation based on coal has to be compensated by an increase in generation based on other sources to be consistent with the internal demand. This, in turn, affects the relative prices. Each trajectory is also consistent with a specific target in terms of GHG by 2050, and with a specific scenario on the status of international coordination on climate efforts. The trajectories integrate also the estimates of climate change damages to physical assets in the economy by means of a climate module. There exists only a limited number (less than 10) of established IAM in the world, run by independent and internationally recognized scientific institutions. The models consider a common set of internationally agreed climate policies and emissions scenarios but differ in the way they define certain output variables and in the data used for the calibration (e.g. Kriegler et al. 2013). There is a consensus in considering the IAMs' set of trajectories as the information set available today about the future economic impact of climate change. Nevertheless, it is increasingly recognized that such models have some limitations (e.g. in the computation of the trajectories and outputs) that relate to the model structure and behaviour, and can affect the policy relevance of the outcomes (see e.g. Battiston and Monasterolo 2018).

2.7. Composition of the economy

We consider n countries j whose economy is composed of m economic sectors S. Economic activities included in S are based on a refined classification of the Climate Policy Relevant Sectors (CPRS), which was originally introduced in Battiston et al. (2017). NACE codes (4 digits) are mapped to CPRS (2017), which identifies the main sectors that are relevant for climate transition risk (fossil-fuel, electricity, energy-intensive, transportation, buildings). CPRS classification departs from the NACE classification of economic sectors (at 4 digit level) in so far, it catches the energy and electricity technology of the economic activity. Its refinement (i.e. CPRS Rev2 2019) provides a more granular classification of the economic activities in terms of technologies (utility—electricity—wind, solar, gas).

Within S, we focus on the fossil fuel and renewable energy primary and secondary sectors and subsectors, due to the main role thy play in the low-carbon transition via the energy and electricity supply along the value chain. Firms that compose economic sectors S are considered as a portfolio of cash flows from fossil fuel and renewable energy activities. The classification of countries and regions affected by the climate shock is based on the LIMITS/CD-LINKS aggregation, see Kriegler et al. (2013), McCollum et al. (2018).

CPRS 2017	CPRS 2019
1-fossil	1-fossil|coal
	1-fossil|oil
	1-fossil|gas
2-utility	2-utility|electricity|coal
	2-utility|electricity|gas
	2-utility|electricity|solar
	2-utility|electricity|wind
	2-utility|electricity|biomass
	2-utility|electricity|marine
	2-utility|electricity|nuclear
	2-utility|other
	2-utility|water&sewerage
	2-utility|waste
3-energy-intensive	3-energy-intensive

Figure 2.1: Climate Policy Relevant Sectors. The figure shows the classification of economic activities by different degrees of granularity by technology

In particular, we can define a set of issuers $\{1, ..., j, ...n\}$ from economic sectors $\{1, ..., s, ..., n^{\text{Sect}}\}$, where the issuers' GVA in a country is the sum of sectors' contributions: $\text{GVA}_j = \sum_s \text{GVA}_{j,s}$

2.8. Impact of climate policy shock on economic activities' GVA and profitability

We consider the contribution of issuer j's to the sector S's GVA and fiscal assets and how this can be affected by changes in its economic performance, either negatively or positively. We then relate the performance of the economic activity to the change in its market share as a result of a disorderly climate policy transition scenario.

In a disorderly transition, a climate policy shock affects the performance of issuers in sectors S via a change in economic activities' market share, cash flows and profitability, eventually affecting the GVA of the sector. The climate policy shock is calculated at the sector, country and regional level. The country's GVA composition is available at NACE 2 digit level from official statistics (e.g. Eurostat). Negative shocks result from the policy impact on the GVA of sectors based on carbon-intensive (i.e. fossil fuels) technologies, while positive shocks result from the impact on the GVA of sectors based on low-carbon (i.e. renewable energy) technologies.

We consider macroeconomic trajectories of output over time for sector s consistent with climate policy scenario $P \in \{..., P^{\text{RefPol}}, P^{450}, ...\}$ The **Climate Policy Shock Scenario** consists in the transition from a trajectory Business-as-usual (B) to trajectory with climate policy P. Forward-looking climate policy shock arises from investors that are not fully anticipating the introduction and impact of the climate policy (as an analogy, we can consider the introduction/impact of Brexit). We focus on shocks on the GVA of 3 Climate Policy Relevant Sectors (CPRS):

- primary energy fossil (**PrFos**)
- electricity fossil (**ElFos**) / renewable (**ElRen**)

$$u_j^{\text{GVA}}(P) = u_{j,\text{PrFos}}^{\text{GVA}}(P)\, w_{j,\text{PrFos}}^{\text{GVA}}(B)) + \\ u_{j,\text{ElFos}}^{\text{GVA}}(P)\, w_{j,\text{ElFos}}^{\text{GVA}}(B)) + u_{j,\text{ElRen}}^{\text{GVA}}(P)\, w_{j,\text{ElRen}}^{\text{GVA}}(B))$$

We assume that a % shock on output ≈ % shock on GVA, u_j^{GVA}, for each sector of j

$$u_j^{\text{GVA}}(P) = \frac{\text{GVA}_j(P) - \text{GVA}_j(B)}{\text{GVA}_j(B)} = \sum_s \left(\frac{\text{GVA}_{j,s}(P) - \text{GVA}_{j,s}(B)}{\text{GVA}_{j,s}(B)} \quad \frac{\text{GVA}_{j,s}(B)}{\text{GVA}_j(B)} \right)$$
$$u_j^{\text{GVA}}(P) = \sum_s \left(u_{j,s}^{\text{GVA}}(P) \quad w_{j,s}^{\text{GVA}}(B) \right)$$

where then $u_{j,s}^{\text{GVA}}(P)$: GVA shock on sector s; $w_{j,s}^{\text{GVA}}(B)$: share of GVA of sector s

From an accounting perspective, at the level of an individual firm, it holds true that a decrease (increase) x in the market share translates in a relative decrease (increase) x in its sales, as long as market conditions are the same[1]. Indeed, a body of empirical literature has found a strong and positive relation between firms' market-share and profitability (Szymanski et al. 1993; Venkatraman et al. 1990). At similar argument can be made at the level of countries' economic sectors, such as their utility sectors. A decrease (increase) x in the market share in a given region of countries competing on the energy market translates in a relative decrease (increase) x in its sales. As a result, there is a decrease (increase) in the tax revenues that the sovereign issuer j collects from the firms operating in that sector in its country.[2] In the case of the energy and utility sectors, this argument is corroborated by the fact that ownership is very concentrated in both fossil and renewable business. Indeed in most EU countries there is just a major energy firm (e.g. OMV in Austria, ENI in Italy) and one major utility firm.

The net effect of the change in energy mix on the profit of a given sector depends on the pre-shock energy mix and the post-shock energy mix. For instance, sector S_{j_1} will have a larger post-shock profit compared to S_{j_2}, denoted as $\pi(S_{j_1}, P) > \pi(S_{j_2}, P)$, because it starts from a larger pre-shock share of renewable-based power (everything else being equal). Moreover, S_{j_2}'s profit (summed over the two business lines) could decrease after the policy

[1]More precisely, it holds under the conditions that total demand and prices remain unchanged in the period considered, and that returns to scale are constant.

[2]Notice that while the tax rate may vary in principle with firms' size (e.g. total level of pre-tax profits), in many cases large firms are subject to similar tax rates than smaller firms. Hence, agents assume that an x% drop in firm's profits implies the same x% drop in revenues.

shock, denoted as $\pi(S_{j_2}, P) < \pi(S_{j_2}, B)$, if it is not possible for S_{j_2} to more than compensate on the renewable business line the losses on the fossil business line.

The final impact of the climate policy shock on the net fiscal assets of an issuer j depends not only on the tax revenues from sector S_j and thus on its profit $\pi(S_j, P)$, but also on the expenses that the issuer incurs. If we consider j as a sovereign issuer, the consideration discussed earlier in this section lead us to make the assumption that a relative change in the market share of sector S within the country j, implies a proportional relative change in the net fiscal assets of issuer j from sector S.

In the case of a sovereign issuer, we define the *net fiscal assets related to sector* S, denoted as $A_j(S)$, as the difference between accrued fiscal revenues from sector S and public investments and subsidies granted by j to the same sector.

The impact of the market share shock (resulting from the policy shock P) on net fiscal assets of sector S is thus assumed to imply a change $\Delta A_j(S, P, M)$, estimated under model M, as follows:

$$\frac{\Delta A_j(S, P, M)}{A_j(S)} = \chi_S \, u_j(S, P, M),$$

where χ denotes the elasticity of profitability with respect to the market share.

The forward-looking trajectories of sectors' market shares are taken from the LIMITS IAM scenario database (Kriegler ea. 2013), considering combinations of IAM M and four climate policy scenarios P, characterized by different Greenhouse Gases (GHG) emissions targets and way to achieve them [3].

Because, in general, the policy shock affects at the same time several sectors in the economy of the issuer j, we have to consider the total net effect on the issuer's net fiscal assets as follows:

$$\frac{\Delta A_j(P, M)}{A_j} = \sum_S \frac{\Delta A_j(S, P, M)}{A_j(S)} \frac{A_j(S)}{A_j} = \sum_S \chi_S \, u_j(S, P, M) \frac{A_j(S)}{A_j},$$

[3] See the LIMITS database documentation for more details https://tntcat.iiasa.ac.at/LIMITSDB/static/download/LIMITS_overview_SOM_Study_Protocol_Final.pdf

In principle, in our approach, the elasticity coefficient could be estimated empirically for the specific sectors of the sovereign issuers in the portfolio. In this work, the data to carry out this estimation was not available. Being our goal to provide an estimation of the upper bounds of the magnitude of the shocks due to a given climate policy scenarios P (see section 5), where the shock is transmitted to the value of the sovereign bond via the change in sectors' market share, GDP and fiscal assets, we have assumed a value of χ constant and equal to 1 (typical empirical values range between 0.2 and 0.6).

3. Pricing climate risk in equity holdings

In this section, we focus on the risk-neutral valuation of equity holdings in sectors subject to potential forward-looking climate policy shocks. We first derive the valuation formula in the case where the timing and the characteristics of climate policy shock shock are known. Then, we discuss how to extend the valuation model in the case in which the timing and magnitude of the climate policy shock are subject to further uncertainty.

In the valuation model, $t_0 = 0$ denotes the time at which valuation is carried out and E denotes a generic equity contract. In absence of climate policy, we assume that all relevant information is captured by expected future flow of dividends $(\mathrm{div}(t))_{t \geq t_0}$ and, following Gordon's formulation (Gordon 1959), we further consider that dividends grow at a constant rate $g(B)$ so that for all $t \geq t_0$, $\mathrm{div}(t+1) = (1+g(B))\mathrm{div}(t)$. Denoting by r the cost of risky capital, the value of equity is then determined as the net present value of future dividends, that is:

$$V_E^{B,t_0} = \sum_{t=1}^{+\infty} \frac{(1+g(B))^t \mathrm{div}(t_0)}{(1+r)^t} = \frac{\mathrm{div}(B)(1+g(B))}{r-g(B)} \tag{1}$$

where $\mathrm{div}(B) = \mathrm{div}(t_0)$.

We then consider a situation where a climate policy shock is assumed to occur at time t^* following which the dividend is assumed to shift to $\mathrm{div}(P)$ and the growth rate of dividends to $g(P)$ where P identifies a specific climate policy scenario. The value of equity is then determined as

$$V_E^{P,t^*} = \sum_{t=1}^{t^*} \frac{(1+g_0)^t \mathrm{div}(B)}{(1+r)^t} + \sum_{t=t^*+1}^{+\infty} \frac{(1+g(P))^{t-t^*} \mathrm{div}(P)}{(1+r)^t} \tag{2}$$

or equivalently

$$V_E^{P,t^*} = (1 - \frac{1+g_0}{1+r})^{t^*-t_0} \frac{\mathrm{div}(B)(1+g(B))}{r-g(B)} + \frac{1}{(1+r)^{t^*}} \frac{\mathrm{div}(P)(1+g(P))}{r-g(P)} \tag{3}$$

In particular, if the climate policy shock occurs at valuation time, i.e. $t^* = t_0$, we obtain

$$V_E^{P,t_0} = \frac{\mathrm{div}(P)(1+g(P))}{r-g(P)} \tag{4}$$

In a climate policy scenario P, it is expected that $\mathrm{div}(P)$ and $g(P)$ decrease for carbon-intensive economic activities and increase for low-carbon economic activities. In sectors such as energy production, where climate policy shocks induce substitution from high-carbon to low-carbon sources, these impacts can be directly inferred from market shares under the assumption that (i) the growth rate of total revenues in the sector (high-carbon plus low-carbon) remain constant, (ii) the dividend to revenue ratio is similar across subsectors and (iii) dividends are proportional to market share. Indeed, one then has $g(P) = g(B)$, and using the notations of the preceding section, one has (up to a discount factor if $t^* > t_0$):

$$\mathrm{div}(P) = \frac{m_E(S,P,M)}{m_E(S,B,M)} \mathrm{div}(B). \tag{5}$$

We further highlight two basic applications of our equity valuation methodology:

- The discontinuous change of valuation in the case of a disorderly transition occurring at time t^* is given by $V_E^{B,t^*} - V_E^{P,t^*}$.
- Given a probability distribution $\mathbb{P}$ on the time of occurrence and/or the impact of the policy scenarios, one can compute the expected value and the value-at-risk or order α associated to an equity contract respectively as $\int V_E^{P,t_0} d\mathbb{P}(P,t_0)$ and X such that $\mathbb{P}(V_E^{P,t_0} \geq X) = 1-\alpha$.

4. Pricing climate transition risk in corporate bonds

We define here a model for counterparty valuation in the case of a corporate bonds issuer and we define the default conditions and default probability.

4.1. Model for corporate bonds valuation

We consider a risky (defaultable) bond of corporate issuer j, issued at t_0 with maturity T. The bond value at T, with R bond *Recovery Rate* (i.e. % of notional recovered upon default), and LGD *Loss-Given-Default* (i.e. % loss) can be defined as:

$$v_j(T) = \begin{cases} R_j = (1 - \mathrm{LGD}_j) & \text{if j defaults (with prob. } q_j) \\ 1 & \text{else (with prob. } 1 - q_j) \end{cases}$$

The expected value of bond's payoff can then be written as:

$$\mathbb{E}[v_j] = (1 - q_j) + q_j\, R_j = 1 - q_j\,(1 - R_j) = 1 - q_j\,\mathrm{LGD}_j$$

The bond price v_j^* is equal to the bond discounted expected value, with y_f risk-free rate. The price defines implicitly the yield y_j of bond j (under risk neutral measure) as follows:

$$v_j^* = e^{-y_f\,T}\,\mathbb{E}[v_j] = e^{-y_f\,T}\,(1 - q_j \mathrm{LGD}_j) = e^{-y_j\,T}$$

Finally, the bond spread can be defined as: $s_j = y_j - y_f$, with $e^{-s_j\,T} = 1 - q_j\,\mathrm{LGD}_j$

An useful fact about spread is that:

$$s_j \approx \frac{1}{T}\,q_j(1 - R_j) = \frac{1}{T}\,q_j\,\mathrm{LGD}_j (\text{for small } s_j)$$

4.2. Corporate bond default conditions

We consider the corporate bond issuer i balance sheet: $A_j(t_0)$, $A_j(T)$ **asset**, with t_0 issue time andT maturity; $L_j(T)$ liability.

The default condition (e.g. following Merton 1974) reads as

$$A_j(T) = A_j(t_0)(1 + \eta_j(T)) < L_j(T)$$

with $\eta_j(T) \in \mathbb{R}$: **idiosyncratic shock** (e.g. firm j productivity), $\phi(\eta_1, ..., \eta_j, \eta_n)$ **joint probability distribution** (possibly correlated)

We add the climate policy shock ξ_j on j's assets (as a "jump" up/down in the probability of default), assuming that the idiosyncratic shock η_j and the policy shock ξ_j are **independent**.

We can then define the new default condition as:

$$A_j(T) = A_j(t_0)(1 + \eta_j(T) + \xi_j(P)) < L_j(T)$$
$$\Longleftrightarrow \eta_j(T) \leq \theta_j(P) = L_j(T)/A_j(t_0) - 1 - \xi_j(T, P)$$

with $\theta_j(P)$ default threshold under scenario P and $\xi_j(P)$ the **climate policy shock** can be either positive or negative (given the composition of j: $\xi_j(P) > -1$), and possibly correlated across j.

4.3. Corporate default probability

We can define the **default probability (PD)** q_j of issuer j under Climate Policy Scenario P, with $\phi_P(\eta_j)$ being the probability distribution of the idiosyncratic shock η_j, η_{inf} lower bound of distribution support:

$q_j(P) = \mathcal{P}(\eta_j < \theta_j(P)) = \int_{\eta_{\text{inf}}}^{\theta_j(P)} \phi_P(\eta_j)\, d\eta_j$, We introduce now a proposition of the PD adjustment Δ under the climate policy shock following the intuition that frequent small productivity shocks across time and firms occur in a similar way with/without climate policy shock. Then, the policy shock shifts the probability distribution of the small productivity shocks and thus the default probability of j.

We introduce the following assumption: the idiosyncratic shocks are **independent** from policy shock, i.e. conditional to occurrence of ξ_j.

We obtain that the PD **adjustment** under policy shock scenario is:
$\Delta q_j(P) = q_j(P) - q_j(B) = \int_{\theta_j(B)}^{\theta_j(P)} \phi(\eta_j)\, d\eta_j$, with $\theta_j(P) = \theta_j(B) - \xi_j(P)$

Then, assuming that the idiosynchratic shocks are **independent** from the policy shock, and that the policy shock on assets is proportional to shock on GVA via elasticity $\xi_j = \chi_j\, u_j^{\mathrm{GVA}}(P)$, we obtain that the **adjustment** $\Delta q_j(P)$ in default probability of j under Climate Policy <u>Shock</u> Scenario:

- Increases with GVA shock magnitude $|u_j^{\mathrm{GVA}}(P)|$ if $u_j^{\mathrm{GVA}}(P) < 0$, and decreases viceversa (under mild condition on ϕ);
- Is proportional to the GVA shocks on climate relevant sectors (in the limit of small Climate Policy Shock):

$$\Delta q_j(P) \approx -\chi_j\, (u_{j,\mathrm{PrFos}}^{\mathrm{GVA}}\, w_{j,\mathrm{PrFos}}^{\mathrm{GVA}} + u_{j,\mathrm{ElFos}}^{\mathrm{GVA}}\, w_{j,\mathrm{ElFos}}^{\mathrm{GVA}} + u_{j,\mathrm{ElRen}}^{\mathrm{GVA}}\, w_{j,\mathrm{ElRen}}^{\mathrm{GVA}}).$$

Climate policy shock corporate bond value adjustment

Being Δv_j^* defined as the change in the discounted expected value of the corporate bond, v_j^*, conditional to a Climate Policy Shock Scenario $B \to P$

$$\Delta v_j^* = v_j^*(q_j(P) - v_j^*(q_j(B)) = -e^{-y_f\, T}\, \Delta q_j(P)\mathrm{LGD}_j$$

Proposition: conditional to policy shock scenario $B \to P$, and assuming everything else the same regarding the issuer's balance sheet, then the corporate bond value adjustment $\Delta v_j^*(P)$:

- Is negative and increases with magnitude of policy shock $|\xi_j(P)|$ if $\xi_j(P) < 0$;
- Is positive and increases with magnitude of policy shock if $\xi_j(P) > 0$, with the constraint $v_j^* \leq 1$;

5. Pricing climate transition risk in sovereign bonds

We define here a model for counterparty valuation in the case of a sovereign bond issuer and we define the default conditions and default probability.

5.1. *Model for sovereign bonds valuation*

We consider a risky (defaultable) bond of sovereign j, issued at t_0 with maturity T. The sovereign bond value at T, with R bond *Recovery Rate* (i.e. % of notional recovered upon default), and LGD *Loss-Given-Default* (i.e. % loss) can be defined as:

$$v_j(T) = \begin{cases} R_j = (1 - \mathrm{LGD}_j) & \text{if j defaults (with prob. } q_j) \\ 1 & \text{else (with prob. } 1 - q_j) \end{cases}$$

The expected value of bond's payoff can be defined then as:

$$\mathbb{E}[v_j] = (1 - q_j) + q_j\, R_j = 1 - q_j\,(1 - R_j) = 1 - q_j\,\mathrm{LGD}_j$$

The sovereign bond price v_j^* can be defined as the bond discounted expected value, with y_f risk-free rate.

The price defines implicitly the yield y_j of sovereing bond j (under risk neutral measure) as follows:

$$v_j^* = e^{-y_f\,T}\,\mathbb{E}[v_j] = e^{-y_f\,T}\,(1 - q_j\mathrm{LGD}_j) = e^{-y_j\,T}$$

Finally, the bond spread can be defined as: $s_j = y_j - y_f$, with $e^{-s_j\,T} = 1 - q_j\,\mathrm{LGD}_j$

An useful fact about spread is that:

$$s_j \approx \frac{1}{T}\,q_j(1 - R_j) = \frac{1}{T}\,q_j\,\mathrm{LGD}_j(\text{for small } s_j)$$

5.2. *Sovereign default conditions*

Following a stream of literature (Gray et al. 2007), we model the payoff of the defaultable sovereign bond as dependent on the ability of the sovereign to repay the debt out of its fiscal revenues accrued until the maturity. More in detail, the balance sheet of the sovereign entity is modelled as follows:

- Assets: net fiscal assets, i.e. the accrued value over time of tax revenues minus expenditures such as investments and subsides;
- Liabilities: debt securities issued as sovereign bonds with the same maturity.

We have a sovereign i balance sheet defined as: $A_j(t_0)$, $A_j(T)$ **net fiscal asset** at t_0 and maturity; $L_j(T)$ liability.

The default condition (e.g. Gray-Merton-Bodie 2007) reads as:

$$A_j(T) = A_j(t_0)(1 + \eta_j(T)) < L_j(T)$$

[

We add then a climate policy shock ξ_j on j's net fiscal assets ("jump" up/down), assuming idiosyncratic shock η_j and policy shock ξ_j are **independent**.

The new sovereign default condition reads as:

$$A_j(T) = A_j(t_0)(1 + \eta_j(T) + \xi_j(P)) < L_j(T)$$
$$\iff \eta_j(T) \leq \theta_j(P) = L_j(T)/A_j(t_0) - 1 - \xi_j(T, P)$$

where $\theta_j(P)$ is the default threshold under scenario P, $\xi_j(P)$ is the **climate policy shock** from B to P (can be positive or negative), $\xi_j(P) > -1$, possibly correlated across j.

Differently from Gray et al. 2007, we do not consider whether debt is issued in local or foreign currency, and we do not consider exchange rate risk.

In the context of climate change, there is a consensus among scholars and practitioners on the fact that markets and investors are not yet pricing in all the information available about climate-related financial risks. Therefore, we relax the classic assumptions of efficient and frictionless markets that is needed in the Merton model (Merton 1974) to solve the pricing in closed form. Our goal here is to model the mechanism of the shock transmission channel from fiscal revenue to the value of the sovereign bond, in a market that is non necessarily efficient.

5.3. Sovereign default probability

We can define the **Default probability PD** q_j of issuer j under Climate Policy Scenario P, with $\phi_P(\eta_j)$ probability distribution of idiosyncratic shock η_j, $\eta_{\inf}$ lower bound of distribution support:
$q_j(P) = \mathcal{P}(\eta_j < \theta_j(P)) = \int_{\eta_{\inf}}^{\theta_j(P)} \phi_P(\eta_j)\, d\eta_j,$

We introduce now a proposition of the PD adjustment Δ under the climate policy shock following the intuition that frequent small productivity shocks across time and firms occur in a similar way with/without climate policy shock. Then, the policy shock shifts the probability distribution of the small productivity shocks and thus the default probability of issuer j.

We introduce the assumption that the idiosyncratic shocks are **independent** from policy shock, i.e. conditional to occurrence of ξ_j.

And we obtain that the PD **adjustment** under policy shock scenario is:
$\Delta q_j(P) = q_j(P) - q_j(B) = \int_{\theta_j(B)}^{\theta_j(P)} \phi(\eta_j)\, d\eta_j$, with $\theta_j(P) = \theta_j(B) - \xi_j(P)$

Then, assuming that:

- The idiosynchratic shocks are **independent** from the policy shock;
- The policy shock on fiscal asset is proportional to shock on GVA via elasticity $\xi_j = \chi_j\, u_j^{\mathrm{GVA}}(P)$

The **adjustment** $\Delta q_j(P)$ in default probability of sovereign j under Climate Policy Shock Scenario:

- Increases with GVA shock magnitude $|u_j^{\mathrm{GVA}}(P)|$ if $u_j^{\mathrm{GVA}}(P) < 0$, and decreases viceversa (under mild condition on ϕ);
- Is proportional to the GVA shocks on climate relevant sectors (in the limit of small Climate Policy Shock):

$$\Delta q_j(P) \approx -\chi_j\, (u_{j,\mathrm{PrFos}}^{\mathrm{GVA}}\, w_{j,\mathrm{PrFos}}^{\mathrm{GVA}} + u_{j,\mathrm{ElFos}}^{\mathrm{GVA}}\, w_{j,\mathrm{ElFos}}^{\mathrm{GVA}} + u_{j,\mathrm{ElRen}}^{\mathrm{GVA}}\, w_{j,\mathrm{ElRen}}^{\mathrm{GVA}}).$$

Climate policy shock sovereign bond value adjustment

Being Δv_j^* defined as the change in the discounted expected value of the bond, v_j^*, conditional to a Climate Policy Shock Scenario $B \to P$

$$\Delta v_j^* = v_j^*(q_j(P) - v_j^*(q_j(B)) = -e^{-y_f T} \Delta q_j(P)\mathrm{LGD}_j$$

Proposition: conditional to policy shock scenario $B \to P$, and assuming everything else the same regarding the issuer's balance sheet, then the bond value adjustment $\Delta v_j^*(P)$:

- Is negative and increases with magnitude of policy shock $|\xi_j(P)|$ if $\xi_j(P) < 0$;
- Is positive and increases with magnitude of policy shock if $\xi_j(P) > 0$, with the constraint $v_j^* \leq 1$;

6. Climate Spread

The **Climate spread** Δs_j is defined as the change in the spread s_j, conditional to Climate Policy Shock Scenario

$$\Delta s_j = s_j(q_j(P) - s_j(q_j(B))$$

Conditional to the climate policy shock scenario, the climate spread $s_j(P)$:

- Increases with magnitude of policy shock $|\xi_j(P)|$ if $\xi_j(P) < 0$;
- Decreases with magnitude of policy shock if $\xi_j(P) > 0$;
- For small GVA shocks $u_j^{\mathrm{GVA}}(P)$ it holds:

$$\Delta s_j \approx -\frac{1}{T}\chi_j \times$$
$$\times\, (u_{j,\mathrm{PrFos}}^{\mathrm{GVA}}\, w_{j,\mathrm{PrFos}}^{\mathrm{GVA}} + u_{j,\mathrm{ElFos}}^{\mathrm{GVA}}\, w_{j,\mathrm{ElFos}}^{\mathrm{GVA}} + u_{j,\mathrm{ElRen}}^{\mathrm{GVA}}\, w_{j,\mathrm{ElRen}}^{\mathrm{GVA}})$$

7. Investor and Portfolio Value-at-Risk and Climate Value-at-Risk

We can define an investor i's *portfolio value* z_i and *portfolio rate of return* π_i at T, with W_{ij} amount (numeraire) of j's bond purchased by i as:

$$z_i(T) = \sum_j W_{ij} v_j(T), \qquad \pi_i = \frac{z_i(T) - z_i(t_0)}{z_i(t_0)}.$$

The **Value-at-Risk** (VaR) on investor's rate of return is the "worst case loss" at confidence level C^{VaR}. Given the probability distribution $\psi(\pi_i(T))$,

the **VaR** = value of return π_i (e.g. left tail) such that:

$$\mathcal{P}\{\pi_i < \text{VaR}\} = \int_{\inf(\pi_i)}^{\text{VaR}} \pi_i \, \psi_i(\pi_i) \, d\pi_i = C^{VaR}$$

The **Climate VaR** is defined as the Value-at-Risk of the portfolio of the investor, conditional to Climate Policy Shock Scenario with π portfolio return, $\psi_P(\pi)$ distribution of returns conditional to the climate policy shock:

$$\text{ClimateVaR}(P) = \int_{\inf(\pi)}^{\text{ClimateVaR}} \pi \, \psi_P(\pi) \, d\pi = C^{VaR}$$

.

Conditional to the policy shock scenario $B \to P$, the ClimateVaR(P):

- Increases with magnitude of policy shock $|\xi_j(P)|$ if $\xi_j(P) < 0$;
- Decreases with magnitude of policy shock if $\xi_j(P) > 0$;
- Increases with marginal default probability adjustment $\Delta q_j(P)$ of bond j.

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Does Climate VaR add financial value : Some empirical evidence

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* Competing Interests : The authors are currently employed at State Street Global Advisors, a leading asset management firm, and are responsible for building climate aware equity portfolios. The work herein was undertaken at State Street Global Advisors

Does Climate VaR add financial value : Some empirical evidence

Abstract

Increasing carbon-emissions and changes in the Earth's surface temperature have brought about a large incidence of climate-related disasters over the past decade, with even worse outcomes expected in the near future. In this study, we attempt to de-risk a Russell 1000 index portfolio by utilizing physical Climate VaR (CVaR) metrics and excluding securities most exposed to such events. The exclusions are carried out based on sectors to avoid any biases from sectoral deviations. We find that the so-created CVaR portfolio often outperforms the benchmark with the excluded stocks exhibiting much lower returns over the 2018 to 2022 period, a result which is further bolstered during climate disasters. Moreover, we observe that only 25% of the excess return over time can be explained by existing factors which ties in with the fact that we see only half of the active risk coming from factors.

JEL Classification Codes : G11, G12, G14, G32

Keywords: Climate VaR; transition risk; mitigation risk; low carbon investing; ESG

Key Takeaways:

- Climate VaR (CVaR) has a very limited history available
- Based on the available history, we find that CVaR portfolios outperform the benchmark, and the majority of their excess returns cannot be explained by factors
- We also find that the securities excluded by CVaR have performed poorly in the periods following extreme climate events

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Background

With the industrial revolution gaining headway in the United Kingdom in the 19th century, many economists were worried about the depleting coal resource and thereby argued for a more efficient use, increasing availability of the same. This, while true, did not provide a complete picture of the phenomena. William Jevon showed that an increased efficiency would often be followed by a lowering of cost which in turn would lead to an increase in demand (a rebound effect). This was referred to as 'Jevons Paradox'(York, 2006). While primarily meant for coal, the effect can be attributed as one of the largest pitfalls in environmental economics.

Fossil fuel energy demand alone rose by over 2000% from the 1860s (brink of the industrial revolution) to the 2000's (Malm, 2016). This use, while a boon for our civilization in many ways, like all other things, came with a hidden cost in the form of carbon emissions. These emissions trap the heat within the atmosphere and lead to an increase in the global temperature. The IPCC (Intergovernmental Panel on Climate Change) reports suggest that the average surface temperature had risen by approximately 1.1°C (as of 2017) with a further threshold of 420 billion Tonnes of CO_2 before the temperature would rise to 1.5°C (IPCC, 2015). Given an average yearly emission of 40 billion Tonnes, this number does not seem far off. Both Current Policy and Moderate Action Reference Pathways (as obtained from the IPCC AR6 database) indicate this point by 2030 (Figures 1 and 2) (Byers, Edward et al., 2022).

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Figure 1 – Baseline Reference Scenarios as per IPCC AR6 Database

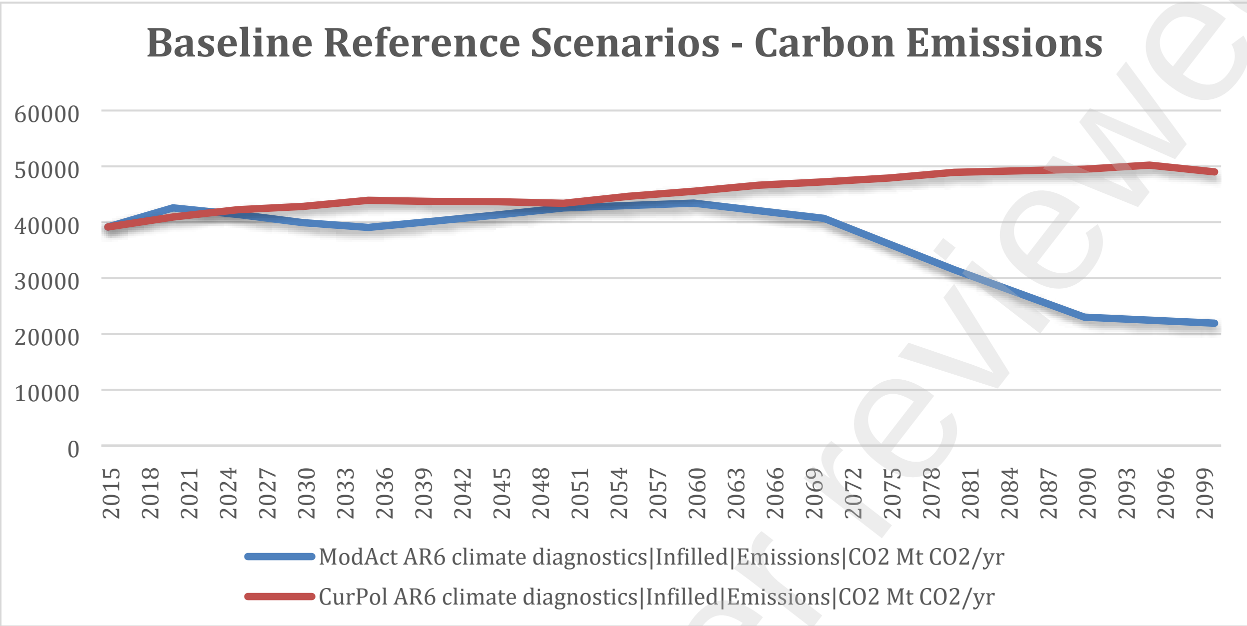
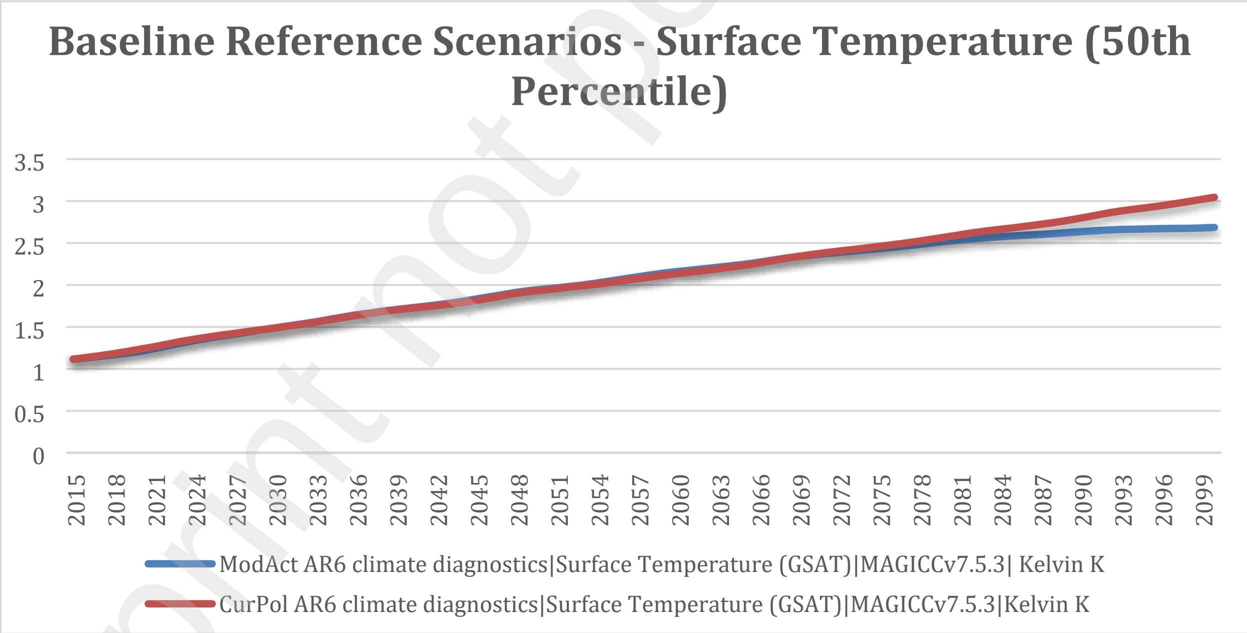


Figure 2- Predicted increase in surface temperature corresponding to reference scenarios as per IPCC AR6 Database



The IPCC Special Report lists 5 Reasons for Concern associated with increasing temperature, ranging from threats to various systems to large singular events – with most of them being

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demarcated as high-moderate risks at a 1.5°C mark (O'Neill et al, 2017) -This is further corroborated by NOAA climate.gov which sees a vast jump in climate related disasters over the past few years, associating a cost of $742.1 billion in the period 2017-2021 as opposed to a net cost of $872.9 and $556.8 billion over the decades of 2010's and 2000's respectively with these events.

These weather-related disasters have an adverse effect on the functioning of firms within the affected regions. For example, many transport, agriculture, oil, and gas etc. industries in Louisiana suffered large losses due to Hurricane Ida.

To counter/safeguard against these events in portfolios, we can use an iteration of the widely used Value-at-Risk metric dubbed as the Climate Value-at-Risk (CVaR). CVaR is a relatively new concept based incorporating the *"size of loss attributable to climate related financial risks by comparing the value of assets in a world with climate change relative to the same world without climate change"* (Task Force on Climate-related Financial Disclosures, 2020)

One of the earliest iterations of the metrics calculated the value at risk of global financial assets based on a business as usual (BAU) scenario (based on a 2.5°C pathway) and a 2°C carbon emission mitigation pathway (Dietz et al., 2016). It observed that nearly 1.77% of the financial assets (~$2.5 trillion) were at risk based on a mean value for climate change between 2015 - 2100 relative to a 1.18% at a 2°C pathway, with most of the risk lying in the tail with a 99% CVaR jumping to 16.86% (~$24.2 trillion) on a BAU scenario. The differences clearly exemplified the

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need to move towards a more environmentally friendly solution with mitigation strategies required to reduce tail risk. While foreboding, these numbers may be conservative given that latest evidence based on the IPCC WG III reference pathways link to a current policy temperature rise closer to 3-4^{o}C (Shukla et al., 2022).

Recent studies have tried to identify market responses to uncertainty faced by firms regarding both the potential incidence of extreme weather events and subsequent economic impact on the US market (with a focus on hurricanes). Comparing the ex-ante expected volatility with ex-post realized volatility shows a significant underestimation of weather uncertainty (though it does start diminishing post hurricane Sandy). They also observed that there was a large dispersion (underperformance) in cumulative abnormal stock returns for the affected firm up to 6 months after the event relative to the control group (Kruttli et al., 2021).

Studies have also attempted to find whether climate risks are priced in security prices. It was observed that only imminent climate policy news is accounted for in prices, that too, primarily post 2012 (Faccini et al., 2021). Their findings revealed that the risks generated by government intervention (and not direct risks from climate change) were priced into the stock market. These could be attributed to – investors only paying attention when climate risks became an issue for US politics; lack of information on exposure to climate risks; and the myopic view of financial investors on risks with immediate effects – thereby leading to a market failure in pricing the stocks.

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Data and Methodology

Climate VaR is estimated by several financial and ESG data vendors including MSCI, ISS, etc. Most of these vendors align with the Task Force on Climate-related Financial Disclosures (TCFD) recommendations for conducting scenario analysis.

For the exercise, we primarily use the MSCI Value-at-Risk Metrics provided by MSCI ESG Research. These metrics aim to provide a forward looking and returns based valuation assessments to measure climate related risks and opportunities associated with a security based on a 15-year horizon (MSCI, 2022).

The dataset can be fundamentally broken down into 3 components - physical risks, policy risks and technological opportunities. For this exercise, we primarily restrict ourselves to physical risks, given that these are readily observable today with many of the transition risks and technological opportunities (country-wide policies, carbon pricing, green-innovations, etc.) likely to come into play in the future with many countries still taking a soft stance on the issue.

The physical risk scenarios as defined as possible climatic consequences resulting from increased levels of GHG emissions and the ensuing financial burden (or opportunities) borne by businesses and their investors. The expected costs of physical risks are calculated as a function of vulnerability (cost function), hazard (type of weather event) and exposure (location and allocation of company facilities) (MSCI, 2021). Here, we restrict ourselves to the aggressive scenario (as provided by the

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dataset) based on an RCP 8.5 (Representative Concentration Pathway corresponding to about a 4.3°C increase in temperature by the year 2100).

The metric we use provides an equity's upside or downside potential (as a % of market value) assuming trends in extreme cold, extreme heat, extreme precipitation, heavy snowfall, extreme wind, coastal flooding, fluvial flooding, tropical cyclones, and river low flow. The values can theoretically range from -100% to +100% (positive CVaR numbers are however quite rare and represent a 'reduction in current costs' due to a given weather effect – e.g., easier transport due to a decline in snowfall; rather than a 'profit'). Here, we use the latest available CVaR dataset as of May 31, 2022. This represents the latest scores with model updates and provides us with an updated outlook with max coverage on securities.

While one should ideally use point-in-time CVaR for constructing these portfolios – the history available for these metrics is limited, and hence we use the security level CVaR as of May 31, 2022 historically. While this might be construed as a forward looking bias, we make this modelling choice due to multiple reasons – firstly, the underlying data that goes into the computation of CVaR is relatively slow moving. Additionally, as a relatively new metric, any historical data available would be backfilled and runs the risk of being overfitted. Thirdly, as a new metric with limited history at our disposal, a portfolio constructed with current data filled historically should give more information than a point in time analysis.

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We use these scores to calculate security CVaR scores which enables us to identify the securities most likely to be affected by extreme weather events and exclude them thereby de-risking our portfolio (to climate events) and compare its performance to the benchmark and a portfolio comprised of the excluded securities over) our four year testing period. The portfolio CVaR scores are calculated using the following equation:

$$VaR_p = \frac{\sum_q VaR_q * w_q}{\sum_q w_q}$$

which states that the CVaR of the portfolio can be calculated by using the weighted average of the security CVaR.

For the benchmark index, we used the Russell 1000 index constituents and their weights. Restricting the index to US only securities provides a 2-fold advantage. One, it helps us ensure a steady coverage of the index. (The coverage (in terms of market cap) at the beginning period (June 2018) is about 91.7% and sees a steady rise to ultimately covering about 98.4% of the same). Second, it can help restrict country-wise effects and with the US having a wide-ranging topography, provide a more accurate assessment of the relative effects of climate disasters as opposed to ones on the extreme end (e.g., Japan – very prone to flooding activities).

We evaluate the efficacy of this metric by constructing portfolios based on this – and then studying their risk return characteristics. Climate risks have a significant sectoral deviation, and a naïve portfolio construction would be susceptible to large sectoral deviations. If one were to exclude the

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bottom 10% of the securities in the entire universe, without controlling for sectors, as much as 38% of utilities would get excluded.

Table 1 – Weighted Average CVaR per Sector, and exclusions based on naïve approach (as of March 2022)

Sector	Total Names	Names in Bottom VaR Decile	% Names in Bottom VaR Decile	% Weight in Bottom VaR Decile	Weighted Average CVaR
Communication Services	61	7	11%	11%	-0.50
Consumer Discretionary	140	8	6%	2%	-0.22
Consumer Staples	58	18	31%	27%	-0.73
Energy	47	7	15%	5%	-0.26
Financials	151	8	5%	3%	-0.52
Health Care	134	6	4%	3%	-0.59
Industrials	164	11	7%	4%	-0.42
Information Technology	184	6	3%	0%	-0.38
Materials	59	4	7%	8%	-0.12
Real Estate	84	7	8%	4%	-0.12
Utilities	39	15	38%	38%	-0.36

Source : SSGA, MSCI

Thus, we adopt a worst in class screening approach within every sector, since CVaR is built as a risk measure. The detailed methodology is detailed below.

- Separate securities which do not have CVaR data into bucket B1. The remaining securities are in bucket B2
- For bucket B2, calculate the weight of every sector.
- Within every sector in B2, select the top 80% securities based on their CVaR. Distribute the weight of the excluded securities proportionally to the selected securities, so that the sector remains at benchmark weight. The resulting portfolio is B2`

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- Combine the buckets B2` with B1 – essentially adding the uncovered securities at benchmark weight and keeping the sector weights aligned with the benchmark – forming the final portfolio (referred to as *CVaR Aware Portfolio)*

To further study the effect of exclusions, we also build a worst in class portfolio, by following the same methodology, but selecting the worst 20% securities instead (referred to as *CVaR Exclusions Portfolio*).

Results and Discussion

Table 2 – Portfolio Analysis (Backtested Returns, June 2018 to March 2022)

Performance Metrics	CVaR Aware Portfolio	CVaR Exclusion Portfolio	Benchmark
Return (%)	17.97	5.88	16.44
Risk (%)	18.21	21.01	18.25
Sharpe Ratio	0.99	0.28	0.90
Excess Return (%)	1.53	-10.57	-
Tracking Error (%)	0.88	7.94	-
Information Ratio	1.73	-1.33	-
Max Drawdown (%)	-19.57	-30.20	-20.31
Beta	1.00	1.07	
Average Number of Names	903	358	-
Average Active Factor Risk (%)	51.38	54.93	-
Weighted CVaR (%)	-3.01	-17.02	-4.69

Source : SSGA, MSCI

It comes as no surprise that the CVaR aware portfolio has lower Climate VaR. We observe that the CVaR aware portfolio consistently performs better than the benchmark over the longer period. Conversely, the exclusions portfolio consistently performs worse than the benchmark. As evident from the methodology discussion – the sector weights do not differ between the benchmark and the portfolios – hence once can safely conclude that all the return differentials are being driven by

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selection effects, rather than mis-weighting of sectors, which underscores that incorporating Climate VaR does have a positive effect on returns.

To anecdotally ascertain the behavior of these portfolios, we examine their returns during periods of climate disasters. In the months of Jun – Oct 2021, the US suffered a heat wave (Western Draught) and Hurricane Ida. During this period (both months inclusive) – the CVaR aware portfolio returned 86 bps over the benchmark, whereas the CVaR exclusions returned a complete 850 bps lower than the benchmark – in fact, had an absolute return of -1.3% during the period.

Similarly, during the Mississippi and Missouri River flooding's in Mar – Jul 2019, the portfolios returned 8.4% and 2% respectively, as opposed to a benchmark return of 7.7%. This further indicates that Climate VaR does protect our portfolios from downside risks around climate events.

To also understand if this performance differential was motivated by any implicit exposure to any style factors, we also look at a factor return attribution for these portfolios. We observe that only 39 bps of the excess return over time can be explained by existing factors. This also ties in with the fact that we see only half of the active risk coming from factors

However, given that we use the available dataset as of March 2022, we would like to remind of the limitations of this exercise, and the potential for a forward looking bias

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Conclusions

Using Climate VaR data, we explored the impact of integrating Climate VaR into portfolio construction, and find that prima facie, it adds value and captures information not proxied by existing metrics.

That said, further analysis is required to ascertain how this behavior can be integrated into standard climate transition portfolios, and how they fit into the larger scheme of mitigation metrics.

Also, it would be interesting to repeat this exercise after a sufficient period of live Climate VaR data is available, and see whether the effectiveness of the metric still holds up. Additionally, it also needs to be explored whether the observed effects are regional in nature, or if they can be replicated in other regions, with different economic structures, and environmental regulations on industries. We leave this for future research.

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ORIGINAL ARTICLE

Climate-related risks in financial assets

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Abstract

The financial risks and potential systemic impacts induced by climate change and the transition to a low-carbon economy have become a central issue for both financial investors and their regulators. In this article, we develop a critical review of the empirical and theoretical literature concerning the impact of climate-related risks on the price of financial assets. We first present the theoretical links between asset pricing and climate-related risks and develop a theory of how climate risk drivers transmit costs to firms and lead to asset price changes. We then discuss studies looking at past climate-related events, which show that both climate physical impacts and transition dynamics can trigger a revaluation of financial assets through multiple direct and indirect channels. Finally, we review the emerging literature that uses forward-looking methodologies to estimate future climate-related asset price changes, which suggests that climate financial risks can indeed have significant implications on financial stability.

KEYWORDS
asset pricing, climate change, climate-related financial risks, financial stability, low-carbon transition

1 | INTRODUCTION

Recent years have seen an expansion of the debate on the links between climate change and the financial system. Both private actors (e.g., firms, banks, asset managers, financial service providers) and public institutions (e.g., central banks, financial supervisors) have been trying to understand how economic and financial stability might be affected by (i) physical climate change impacts and (ii) the transition to a carbon-free economy. The main concern is that a combination of climate-related drivers (e.g., an abrupt introduction of mitigation policies following an extreme physical event) could cause economic costs to firms, which could then be transmitted to financial institutions via defaults and drops in market capitalization. If the drop in financial asset prices is large enough, it could lead to a financial crisis with systemic economic and social ramifications; a concept referred to as a ‘Green Swan’ (Bolton et al., 2020) or a ‘Climate Minsky moment’ (Carney, 2015).

While this conceptualization provides important insights into the exploration of possible futures, it is still not clear how likely a Green Swan scenario would actually be. In particular, under which conditions should we really expect a significant drop in the price of financial assets as a consequence of climate-related drivers? The answer to this question depends not only on the realization (or not) of specific future events, but also on the degree to which the realization of climate-related risk is already accounted for in current asset prices.

The aim of this article is to develop a critical review of the existing literature investigating the links between climate change, the low-carbon transition and the price of financial assets. Previous reviews of related bodies of literature have focused on the state of environmental risk management at financial firms and supervisors (Breitenstein et al., 2021), the theory of including climate-related risks in macroeconomic models (Giglio et al., 2021), and specific asset classes such as equity (Venturini, 2022).

Our contribution covers equity, bonds, loans and real estate markets. We structure the literature further by distinguishing two main areas of analysis. First, we discuss the literature studying how real past physical and transition risk drivers have affected the prices in the stock, bond, loan and real estate markets, i.e. the backward-looking literature. Second, we examine the literature that uses possible scenarios of climate-related risk drivers to estimate future asset price revaluations, i.e. the forward-looking literature. Our review is preceded by an investigation into the conceptual links between climate-related risks, economic costs and asset pricing.

We find that investors do react to climate-related risks, leading to changes in asset prices, in the cost of capital for firms and in various assessments of financial risk. However, financial markets likely underprice these risks. Forward-looking methodologies, which include both stress tests and scenarios-led models, also find that climate-related risks can substantially impact financial asset prices. While this improves our understanding of the impact of climate-related risk drivers on financial assets, more research is needed to pinpoint the drivers of financial instability.

The remainder of the article is structured as follows. Section 2 introduces the conceptual foundations on which the literature builds. Section 3 reviews the backward-looking literature on climate-related risks and asset pricing. Section 4 explores the methodologies using forward-looking scenarios. Section 5 discusses current research gaps. Section 6 concludes.

2 | CLIMATE-RELATED RISKS AND ASSET PRICES

This section briefly presents the main asset pricing model categories currently used by financial market participants and discusses their accuracy in assessing climate-related risks. We introduce key concepts in the pricing of climate-related risks and distill four transmission channels through which climate-related risks could cause economic losses and changes in asset prices. We highlight how climate-related risks could be destabilizing for financial markets.

2.1 | The pricing of financial assets

2.1.1 | When does the price of a financial asset change?

According to standard asset pricing theory, the market price of a financial asset is equal to the expected net present value (NPV) of its expected future payoffs – that is, its future income flows (Cochrane, 2001). For equity instruments, payoffs are equivalent to the dividends paid by the firm issuing the equity. For debt instruments, they are the interests and the repayment of the principal by the borrower. Additionally, investors ask for a premium to compensate for the risk they take on (Pástor & Veronesi, 2013).

The price of a financial asset therefore largely depends on financial investors' expectations about payoffs and risk exposure. A revision of these expectations can lead to sharp price movements. We can distinguish (i) changes in expectations resulting from exogenous events; and (ii) endogenous expectations revisions. Exogenous changes are due to sudden unexpected events, either at the systemic level (e.g., the Covid-19 pandemic or an economic recession) or at a company level (e.g., the announcement of weak quarterly profits, a risky lawsuit or a sudden price increase of key production inputs), which are able to modify the near—or longer-term profit prospects. Endogenous reassessments are due to a change in the forecasting model or the parameters they are fed (e.g., new risk drivers are identified and their relationship to financial assets are better understood).

Additionally, the price of a financial asset can change with investors' risk perception. Changes in expected default probabilities, as well as in the expected values of liquidated assets or collateral, determine the amount of risk taken by investors. Higher financial risk would decrease financial asset prices or force the issuers of the asset to provide higher returns for investors as a compensation for the additional risk.

The nature of the financial instrument and the markets on which they are traded determine how their prices react to financial risks. Equity prices, which are valued in the very short term, will react almost immediately to emerging risks. Loans are not valued on such a short-term basis. Rather than revalued, their riskiness determines the future loan conditions for the same borrower. Bonds operate similarly if they are issued at fixed rates. They may also be issued at floating rates, with interest payments determined by underlying indices, altering their fundamental value in relation to the index. However, bonds are also traded on secondary markets and thus their yield can fluctuate more immediately based on new information.

2.1.2 | Asset pricing models

The asset pricing models, which have been mostly used in the context of climate risks, can be divided into two broad classes: models based on arbitrage mechanisms and models based on firms' fundamentals and risk exposures. They differ in their approaches to measuring mispricing. Arbitrage models identify mispricing by comparing the price of two assets generating similar expected financial return profiles (e.g., the Black-Scholes option pricing model; see Black & Scholes, 1973). Models based on firms' fundamentals and risk exposures assess mispricing by comparing the price of an asset with its theoretical fundamental value given its expected risk-return profile. This profile can be based on (i) macroeconomic factors (e.g., the Consumption-based Capital Asset Pricing Model (CAPM), see Breeden, 1979); (ii) firm-specific risk factors at the market level (e.g. the Fama-French model, see Fama & French, 1993; and the Carhart model, see Carhart, 1997) or (iii) firm-specific risk factors at the individual level (e.g., asset variance in the CAPM). Arbitrage and fundamental models both have their advantages and drawbacks: arbitrage models, based on comparing asset prices between themselves, cannot identify mispricing if markets are globally mispriced. Fundamental models, based on the estimation of a theoretical asset price, give imprecise assessments that are highly dependent on the assumptions underpinning the model.

Models based on fundamentals and risk exposures are however better suited to address climate-related risks for at least two reasons. First, since they are based on estimated future flows (income, cost) and risks, they can integrate projected values for these flows and risks in different climate scenarios. They therefore do not rely on past data. Previous research has stressed that the use of past data cannot capture the effects of climate change, a phenomenon for which economic consequences have not been fully observed yet (Dunz et al., 2021; Svartzman et al., 2021). Second, they provide an assessment of the alignment of overall financial prices with the value they could take under different climate scenarios. This is particularly useful to spot a general misalignment of financial prices – for example, when financial actors globally underestimate a risk factor, which could be the case for climate-related risks. Models based on arbitrage mechanisms, on the other hand, are less likely to identify such cases because they compare market prices relative to each other and thus would miss an overall misalignment of all prices. Models based on fundamentals and risk exposures have been mobilized in some of the studies that will be surveyed in Section 3 (Alessi et al., 2021; Monasterolo & de Angelis, 2020). Note, however, that asset pricing models are not applicable to some types of assets, such as loans (Ehlers et al., 2021) or real estate. Some papers may also deploy alternative identification strategies to understand the impact of a climate-related event on asset prices, like difference-in-differences approaches around a key event (e.g., Nguyen et al., 2020).

2.2 | Climate-related risks and asset prices

We now turn to the climate-specific aspects of asset pricing. Climate change and the low-carbon transition can modify financial asset prices via multiple channels. Figure 1 visually presents the main transmission channels (see Semieniuk et al., 2021 for more details on transition risk drivers and Clapp et al., 2017; Lepousez et al., 2017; TCFD, 2017 for details on physical risk drivers).

We can identify the types of climate-related risks. Since Carney (2015), the literature distinguishes between transition, physical and liability risks:

- *Transition risks* stem from the transition to a low-carbon economy. They include risks created by mitigation and adaptation policy, emerging clean technologies and behavioral changes of consumers and investors (TCFD, 2017).
- *Physical risks* emerge from a changing climate (i.e., a long-term shift in the mean and variance of temperatures and magnitude of weather events). Climate change redraws risk patterns for

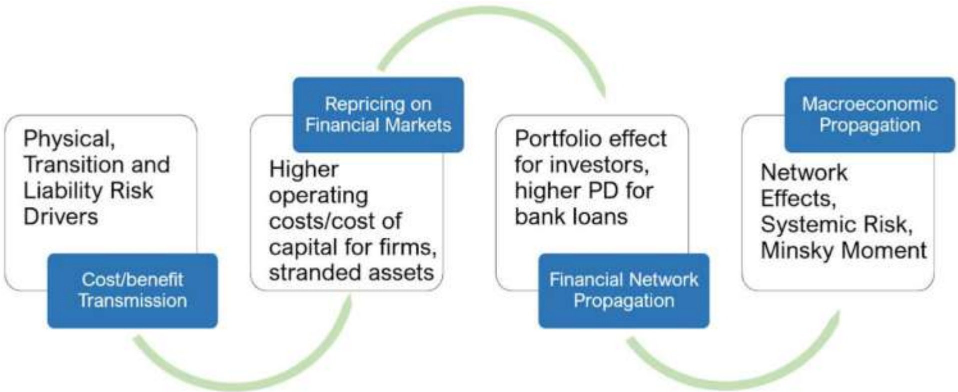


FIGURE 1 The journey from climate-related impacts to asset price changes [Colour figure can be viewed at wileyonlinelibrary.com]

assets, which can be either acute (e.g., from extreme weather events) or chronic (e.g., from sea-level rise). Physical changes do not only threaten built capital stocks and flows, such as output, but also labor productivity (Kjellstrom et al., 2009; Zander et al., 2015).

- *Liability risks* stem from the possibility of costly climate change litigation against polluting industries or inert governments and financial institutions (alternatively, they are referred to as litigation risks). While the importance of liability risks for asset prices remains under-researched, the Sabin Center for Climate Change Law (2022) documents that there have already been made a number of claims in the US, many against state and federal institutions, as well as the fossil fuel industry. Setzer and Higham (2021) find that climate change litigation is being brought before courts in an increasing number of countries.

Second, these drivers can affect the current or prospective profits of firms. We jointly consider physical, transition and liability risks to underline the conceptual similarity and complex interaction between them.[1]

While the three risk types have distinct drivers, their economic effects on the exposed firms share four main transmission channels:

- *Assets*: A climate-related event destroys capital assets, prohibits their use or makes them unprofitable to be used. For example, a carbon tax could trigger asset stranding or make previously productive capital uncompetitive (transition risk). Lower mean precipitation could, e.g., decrease the productivity of agricultural land (physical risk). The firm must prematurely write off its assets.
- *Investment*: A climate-related event forces a firm to update its infrastructure or production process. For example, a new clean technology standard (transition risk) or higher mean temperatures (physical risk) force upgrades to the infrastructure. The capital expenditure (CapEx) of the firm increases.
- *Production network*: A climate-related event creates costs by changing demand patterns, disrupting supply chains, or making it impossible to serve markets. A carbon border adjustment mechanism could reduce the demand for high-carbon imported inputs (transition risk). An extreme weather event could disrupt a trading route (physical risk). Climate-related litigation

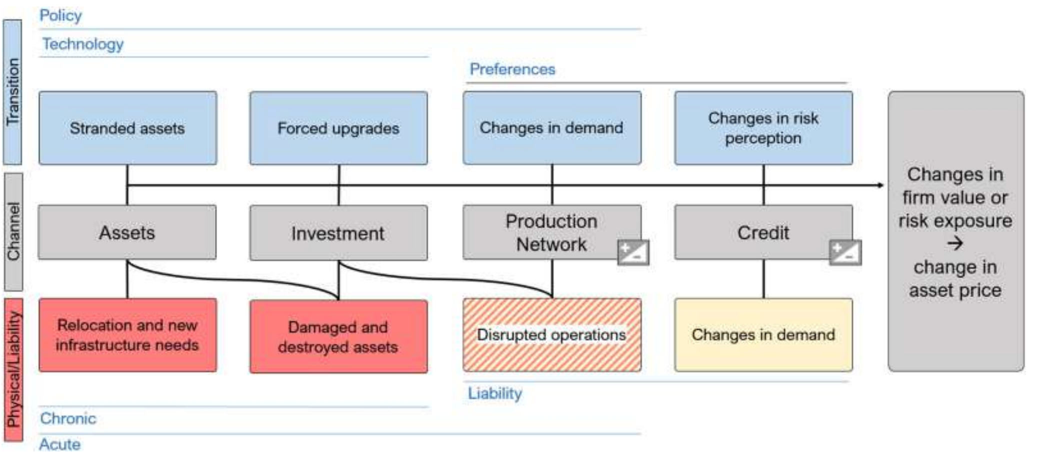


FIGURE 2 Four common transmission channels for impacts from physical (red), transition (blue) and liability (yellow) risks. Channels, which can transmit positive as well as negative changes, are marked (+/−) [Colour figure can be viewed at wileyonlinelibrary.com]

could reduce the willingness to do business with a firm (liability risks). Costs materialize as revenue losses or increased operating expenditure to keep up supply chains.

- *Credit*: A climate-related event leads to a reaction by capital markets, upon which a firm relies. A changed risk profile due to the exposure to transition, physical or liability risks could increase its interest rates for debt capital or insurance premia. If the firm's value decreases, so does its leverage for debt capital.

Figure 2 summarizes how transition, physical, and liability risk drivers can be jointly considered as impacting firms through four transmission channels. Some of these channels can act positively or or negatively on companies, as the low-carbon transition may also create value for some firms. While some regions may be affected by increased risk of drought, others may witness opposite trends (Hong et al., 2019).

From a methodological standpoint, climate factors are introduced both as macroeconomic factors that impact the market of a specific asset and as a source of risk to which specific firms are exposed. To assess whether climate-related risks are priced in, researchers are working around three lines. Some of them estimate the impact of climate events on firms' fundamentals (gains and losses, productivity, etc.) and then check whether market prices reflect these impacts (Hong et al., 2019). Others compare the risk premium[2] of assets exposed to climate-related risks with those that are not (or less) exposed to them, to see whether market participants price the difference in risk exposure (Alessi et al., 2021; Wen et al., 2020). Finally, researchers also check whether market prices react to news on climate risks, as should efficient markets do (Byrd & Cooperman, 2018; Faccini et al., 2021).

Third, the change in actual or expected company profit prospects will change the price of their financial assets. We can distinguish two types:

- *Exogenous shocks* from materializing climate-related risks affect a company's ability to service debt obligations or share profits with equity owners, leading to revaluations of their financial contracts. Additionally, new information on a firm's exposure to climate-related risks can lead to reassessments of the risk premium asked by investors. The fundamental uncertainty over the course of climate-related impacts, both over physical climate change (Deser et al., 2012; Shepherd, 2014) and the policy response (Fried et al., 2019), could manifest as a higher risk premium.

- *'Endogenous' reassessments* by investors can change their perception of a firm's exposure to climate-related risks. For example, a change in the model used for forecasting revenues could lead to a reassessment of the firm's value and thus of the value of its assets. Methodologies incorporating climate-related risks are increasingly used and developed by investors (Monnin, 2018).

Networks in financial markets can amplify initial direct losses incurred due to assets' vulnerability to climate-related risks (e.g., a value drop of fossil fuel companies' securities), resulting in financial instability. Indeed, financial markets are deeply interconnected, multi-layered webs of debt and credit relationships. As such, adverse network externalities have been found to play an important role in spreading financial risks that had originally affected only one counterparty, with possible systemic implications if many actors are concerned (Acemoglu et al., 2015; Gai & Kapadia, 2010). In the context of climate-related risks, studies have shown that initial, seemingly innocuous shocks can have far-reaching consequences if network externalities are accounted for, even for agents not concerned by the initial shock (Battiston et al., 2012; Krause & Giansante, 2012). These models have mostly focused on contagion within the interbank market, whereby balance sheet shocks due to climate-related risks increase counterparty risk and propagate losses amongst banks by diminishing the value of their claims (Battiston et al., 2017). Subsequent papers have added relationships between banks and investment funds, as well as fire-sale dynamics (Roncoroni et al., 2021). Of course, these papers do not exhaust the range of possible mechanisms,[3] which also encompass default cascades (Allen & Gale, 2000), liquidity crunches (Gai et al., 2011) or bearish herd behavior (Kiyotaki & Moore, 2002). On the latter, an emerging literature has emphasized the role of "climate sentiment" in shaping climate risk dynamics. On theoretical grounds, Dunz et al. (2021) and Battiston et al. (2021) have insisted on the importance of investors' non-rational expectations in driving transition outcomes and risk exposures. On the empirical side, an emerging literature has intended to measure "climate sentiments" through textual analysis from newspapers (Ardia et al., 2020; Engle et al., 2020) and Twitter (Baylis, 2020; Santi, 2021). It has notably shown that investors' perception of climate-related risks greatly hinged on the occurrence of physical risks events (Choi et al., 2020), with short-lived and small effects on asset prices (Pástor et al., 2021). Brière and Ramelli (2021) show that arbitrage activity in the form of inflows into green exchange-traded funds (ETFs) can be used to capture investor demand for green investments and that these sentiments do not reflect fundamental changes in the underlying securities. All these interlinks could play out in case of climate-related shock, calling for more work in exploring all possible ramifications (Battiston & Martinez-Jaramillo, 2018).

Increased attention to climate financial risk in the absence of information about climate-related impacts could trigger a system-wide reassessment of losses from climate change exacerbated by herd behavior (Jaffe, 2020; Palao & Pardo, 2017). Materializing climate-related risks could trigger a steep fall of prices across all asset classes and tighten financial conditions, a phenomenon referred to as 'climate Minsky moment' (Carney, 2018). Such moments, referring to theories on investor behavior developed by Hyman Minsky (1970), are defined as a time of reckoning among market participants after a period of stable growth and prosperity. Market confidence, the theory goes, encourages investors to shed their risk aversion (Bellofiore & Halevi, 2011) and enter increasingly speculative investments with borrowed money (Henningsson, 2019).

Nikolaidi (2017) describes a third scenario for a 'climate Minsky moment'. In the case that mitigation policy is effective, a "green bubble" could emerge as a result of investors' exaggerated confidence. Semieniuk et al. (2021) discuss the possibility of a credit bubble in sunrise industries (i.e., those that stand to gain from the structural change accompanying the low-carbon transition) in this context. They find that the current literature on financial risks from the low-carbon transition is largely silent on a green bubble and instead emphasizes the financial instability concerns from overinvestment in sunset industries (i.e., those that stand to lose). The authors observe that this is an inversion of the prevailing Schumpeterian view that sunrise sectors are (more) likely to cause overinvestment and financial losses. A possible explanation for this inversion may be that the cause of the low-carbon transition is not only driven by opportunity and a price advantage within the sunrise industries, but also by opportunity cost and political will.

The emergence of clean technologies could also fuel asset bubbles or 'manias.' Previous technological transitions, such as the emergence of the internet, have been associated with such asset bubbles. In the case of the low-carbon transition, financial markets have shown great appetite for products with a green label. Aramonte and Zabai (2021) describe the recent growth in investor interest in environmental finance as a potential source of finance instability. According to the data analyzed by the authors, magnitudes of the current growth of investments with ESG (i.e., considering environmental, social and governance criteria) labels (especially in mutual funds and ETFs) are comparable to the growth of mortgage-backed securities in the time before the Great Financial Crisis. The fundamental social change associated with this asset boom is akin to a transition risk driver in the sense we defined above. However, the current asset boom and the potential asset price deflation that could follow are endogenous processes to financial markets. This endogeneity makes a potential green asset bubble slightly different from the other kinds of climate-related risks we survey here. Given this and the small number of publications on "green bubble" risk, we do not focus on this literature in the review below.

3 | BACKWARD-LOOKING METHODOLOGIES

After having discussed the general conceptual framework of this literature, we now study the empirical evidence offered by backward-looking studies. We try to address two fundamental questions. (i) Do climate-related risks influence asset prices? And (ii) are climate-related risks *efficiently* priced-in on asset markets? We turn to each of these questions separately

3.1 | Do climate-related risks influence asset prices?

To approach this question, we review the literature focusing on the observable links between climate-related risk drivers and asset prices.[4] A significant and diversified body of work exists by now, studying different types of assets with different methodological approaches, and obtaining sometimes opposite results. We digest this heterogeneity by identifying key dimensions to categorize available studies.

A first differentiation can be drawn by distinguishing the contributions investigating the effects of climate-related risks on 'negatively exposed' assets, and those studying instead 'positively exposed' assets:

- *Negatively exposed assets* are those assets that are assumed to be the losers of a low-carbon transition (e.g., assets from fossil fuel corporations and firms with high carbon intensity) or affected by physical climate change (e.g. bonds from municipalities with inundated areas from sea-level rise or equity of firms with production facilities close to disaster zones).
- *Positively exposed assets* on the other hand are assumed to be beneficiaries of a low-carbon transition (e.g., assets from renewable energy producers and firms with low carbon intensity).

3.1.1 | Negatively exposed assets

We report the findings of the literature focusing on negatively exposed assets in Panel 1 and in Tables A1 (physical risk drivers) and A2 (transition risk drivers) in the appendix. Given the wealth of different approaches in the literature, we identify three key dimensions to categorize the contributions: (i) type of asset; (ii) measure of impact; and (iii) direction of the effects.

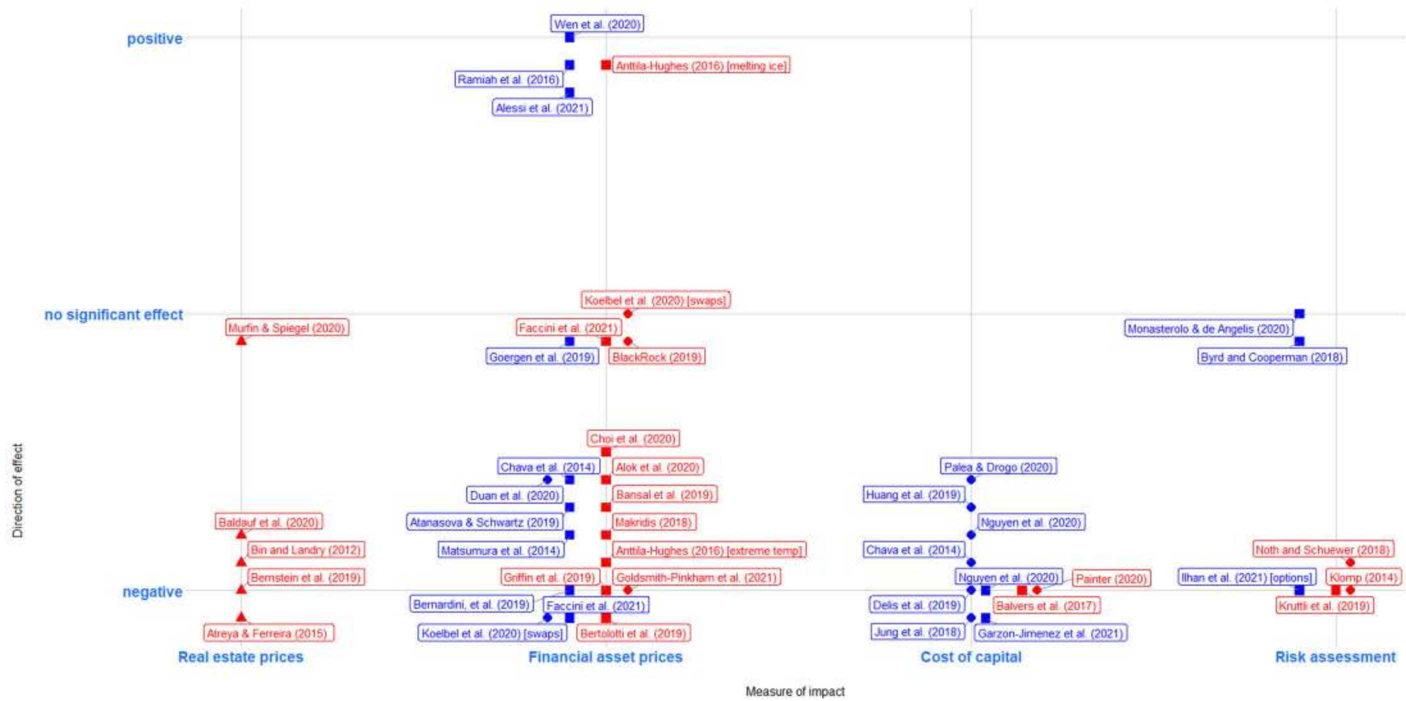
First, we distinguish between different types of assets being studied: equity, bonds, loans and real estate. We identify them in Panel 1 by using different symbols. Second, we distinguish four main types of impact measure, that is the indicator used to compute the extent to which asset prices are affected by the climate-related risk drivers (the columns of Panel 1):

- *Financial asset prices* refers to changes in the price of stocks and derivatives, as well as the valuation of bonds.
- *Real estate prices* refers to changes in real estate prices affected by climate impacts. While real estate is not a financial asset per se, it is frequently used as collateral for loans, which in turn appear on the balance sheet of listed financial institutions or are traded within mortgage-backed securities.
- *Cost of capital* refers to changes in the cost of equity or the cost of debt firms face. The category encompasses measures for the cost of equity, loan rates/spreads and issuance cost for debt instruments.
- *Risk assessment* refers to a change in financial risk as measured by financial risk metrics. This category encompasses papers that use the following measures of impact: tail risk, capital adequacy ratio (CAR), implied volatility, rate of non-performing loans and distance-to-default.

Third, where multiple contributions look at the same asset class using broadly similar impact measures, we differentiate them according to the results they obtain: negative effects (that is a drop in the asset price or an increase in the cost of capital), no effects or positive effects (lower, middle and upper row, respectively, in Panel 1). Finally, we also distinguish transition (blue) and physical (orange) risk drivers by color.

Based on our analysis of the literature, summarized in panel 1, we can establish some conclusions:

- The effects of physical and transition risk drivers across all four measures of impact are predominantly negative. Yet, some positive effects are detected in studies focusing on financial asset prices.
- Positive effects for negatively exposed assets are only documented as far as equity price changes are concerned. Three out of the four papers finding positive asset price reactions focus on transition risks. In particular, investors that learn about a firm's environmental impact from mandatory disclosures (Alessi et al., 2021) and their eligibility for carbon pricing schemes



PANEL 1 Backward-looking literature studying changes in the price of assets negatively exposed to physical (red) and transition (blue) risk drivers. Symbols denote impacts on stocks and options (■); bonds and loans (●); and real estate (▲). More details on the papers cited here can be found in Tables A1 and A2 in the Appendix [Colour figure can be viewed at wileyonlinelibrary.com]

(Wen et al., 2020) seem to ask a risk premium from issuers. This increment is now referred to as a "carbon premium" in the literature (Alessi et al., 2021; Bolton & Kacperczyk, 2021). Anttila-Hughes (2016) finds that extreme temperature events depress asset prices of fossil-fuel producing energy firms in the ten days period after the event. However, news of collapsing polar ice sheets have positive effects. He attributes this to the possibly reduced cost of energy firms' access to polar resources.

- Real estate prices are predominantly negatively affected by physical risk drivers. Exposure to sea-level rise (Bernstein et al., 2019), as well as a location in flood plains or the path of a hurricane is penalized with lower prices (Atreya & Ferreira, 2015; Bin & Landry, 2013). Murfin and Spiegel (2020), however, find no price effect for houses that have shorter inundation times in the event of a flood when controlling for other house specific factors.
- Lenders seem to price in possible climate-related risks when making lending decisions and setting interest rates, although the magnitude of effects overall is low. In the literature, firms exposed to physical and transition risks face higher cost of capital, evidenced in higher interest rates for loans (Chava, 2014; Huang et al., 2019) and fewer positive lending decisions (Nguyen et al., 2020). Cost of equity is also affected (Garzón-Jiménez & Zorio-Grima, 2021; Nguyen et al., 2020).

3.1.2 | Positively exposed assets

We also review the related literature studying assets that may benefit from a low-carbon transition, i.e. *positively exposed assets* (for an overview, see Table A3 in the Appendix). Such positive exposure may come in the form of compliance with the EU-ETS (the European Union's emission trading scheme) (Ravina, 2020; Ravina & Kaffel, 2020), relatively lower emissions (Bernardini et al., 2021; Cheema-Fox et al., 2019; Monasterolo & de Angelis, 2020; Soh et al., 2017) and renewable energy and cleantech firms (Kempa et al., 2021; Noailly et al., 2021). Almost all papers in this category focus on transition risks, with most contributions studying price effects on stocks (Bernardini et al., 2021; Cheema-Fox et al., 2019; Ramelli et al., 2019; Ravina & Kaffel, 2020; Soh et al., 2017) and bonds (Ravina, 2020). One paper investigates the effect of environmental policy stringency on the cost of debt for non-renewable energy firms (Kempa et al., 2021); another on the probability to receive venture capital funding when climate sentiments are high (Noailly et al., 2021). Two contributions study the effect of transition risk drivers on the value given by financial risk metrics, that is, the rate of non-performing loans at banks (Cui et al., 2018) and the systemic risk associated with equity (Monasterolo & de Angelis, 2020), respectively. Anttila-Hughes (2016) is the only paper investigating assets that may be positively exposed to physical climate risks: stocks of energy firms show positive abnormal returns in response to news of collapsing polar ice sheets.

All but one paper in this category (Bernardini et al., 2021) find that transition risk drivers have positive effects on asset prices and decrease riskiness or the cost of capital of positively exposed firms. This is a similar result to the predominantly negative effects we document for negatively exposed assets above. However, it follows a different logic. The fact that physical and transition risk drivers may create costs for negatively exposed firms does not imply that other, non-exposed firms would benefit economically. Thus, such positive price effects may be the result of capital shifting out of assets exposed to climate-related risks and into non-exposed assets.

Returning to the question asked at the outset of this section, we conclude that climate-related risks do influence asset prices. This influence is mostly negative for negatively exposed assets, that is, firms' (equity) value decreases, the perceived risks associated with their assets increase, or firms face higher cost of capital; and positive for positively exposed assets. The heterogeneity in the methodologies employed by authors to understand the differentiated impact of climate-related risk drivers on asset prices means that results (and especially their magnitude) are not easily comparable. In our review, we cannot do enough justice to this circumstance, which is why we have limited our visualization to the extent that it only reports the direction of the effect, not the magnitude. That being said, results are usually robust to a wide range of robustness checks (e.g., Delis et al., 2019), and to the precise specification of asset pricing models. Across papers, results are for instance broadly consistent across Fama-French five-factor models (Bolton & Kacperczyk, 2021) and a Fama-French three-factor model (Bernardini et al., 2021). Finally, within papers, authors tend to estimate carbon risks based on several asset pricing models, showing qualitatively similar results (Bernardini et al., 2021; Görgen et al., 2019).

3.2 | Are climate-related risks efficiently priced?

The discussion above has shown that financial markets tend to increasingly account for climate-related risks, although the magnitude of detected effects varies across asset classes, locations, and sectors. It remains to assess whether these estimates correspond to an "efficient" pricing of climate-related risks, that is, whether movements in asset prices signal an adequate hedge against physical and transition risks.

Most papers limit themselves to the display of effects, without discussing efficiency. Yet, some authors, based on theoretical discussions (Griffin et al., 2015) or the low magnitude of detected effects (Delis et al., 2019), provide informal appreciations of whether pricing is adequate, and often conclude that it is not the case.

Proving efficient pricing rigorously would require discussing whether the Efficient Market Hypothesis (EMH) holds in the context of climate-related risks. However, such an endeavor faces a "joint hypothesis" issue, a circularity implying that the measure of abnormal returns requires that the asset pricing model at hand operates at equilibrium, and therefore that measured prices are equilibrium prices. Whether pricing is efficient or not is therefore an impossible question to answer. For instance, whether the size of a risk premium is indeed the right one cannot be said with certainty. Qualitative insights, however, have been provided by some papers. They test whether the conditions for the EMH hold in presence of climate-related risks. These conditions can be summarized as follows:

- *Predictability of returns*: Information about climate-related impacts, including indicative data such as temperatures or policy proposals, from one period should not be able to forecast returns in the next period, because investors make use of forecasts in their decisions.
- *Forecast revisions*: Investors should revise expected payoffs once new climate-related information becomes first available, because they can interpret the economic and financial costs of such an event.
- *Climate risk premium*: Assets exposed to climate-related risks should trade with a premium.

Exercises of this type have so far mostly been carried out in the context of physical risks, with the exception of the work of Bolton and Kacperczyk (2021b). They show a mixed picture, with a greater number of papers pointing to an underreaction of markets to climate-related risks (see Table 1). Another strand of the literature, based on portfolio analysis, has consistently shown that there exists a significant green premium or "greenium", allowing portfolios long on low-carbon

TABLE 1 Summary of the literature review on efficient pricing of climate-related risks

Authors	Hypothesis	Conclusion
Predictability of returns		
Hong et al. (2019)	A higher incidence of droughts caused by climate change will reduce profits of food producers.	The authors find that a trend ranking can be used to forecast profit growth and stock returns of food companies. This return predictability is consistent with food stock prices underreacting to climate change risks.
Kumar et al. (2019)	A firms' sensitivity to abnormally high temperatures can be used to forecast stock returns.	Firms with lower sensitivity yield higher returns, but effects fade quickly. The authors conclude that stock markets underreact to climate sensitivity.
Forecast revisions		
Schlenker and Taylor (2019)	Prices of affected assets will not change after observable climate-related events. Or, if previously not priced in, investors will revise their expectations once risks materialize.	Investors' expectations are closely oriented along climate data. Hedging markets against temperature-related risks operate efficiently.
Addoum et al. (2020)	Analysts' forecasts for earnings change after the occurrence of 8′584 extreme temperature events in the U.S, which were identified as relevant for firms' earnings.	There is no evidence that analysts adjust their earnings forecasts after the firms they cover have experienced an extreme temperature event, which suggest that analysts do not fully integrate the impact of climate change in their expectations.
Griffin et al. (2019)	The equity price volatility firms complacent to Extreme High Surface Temperature (EHST) events is expected to increase. Further, investors recognize climate change as a driver of EHST events only after 2013, and assume they are random up until 2003.	Investors underprice physical risks because the authors observe negative excess equity returns to EHST events.
Climate risk premium		
Bolton and Kacperczyk (2021a)	Stock returns are not affected by corporate carbon emissions.	Higher carbon emissions at the firm level are associated with higher stock returns in all sectors and on all continents, despite the fact that they should face very different levels of transition risk in principle.

assets and short on high-carbon ones to quasi-systematically beat the market (e.g., Cheema-Fox et al., 2019; Ravina & Kaffel, 2020). Such results stand in sharp contrast with the EMH. Finally, it must be noted that the EMH has come under significant fire after the Great Financial Crisis, with a large literature rebutting it as theoretically flawed (Crotty, 2008). In the more precise context of climate-related risks, lengthy scholarship has also expressed doubts as to the validity of the EMH from behavioral and institutionalist standpoints (Ameli et al., 2020; Thomä & Chenet, 2017).

All in all, the literature tends to tilt towards the opinion that climate-related risks are inefficiently priced and financial markets underreact to them. As more climate-related risks materialize, financial markets may suffer, to a certain extent, from climate-related risks, as they seem so far not priced-in to their full extent. The question, in turn, is that of the magnitude of these potential financial disturbances, which cannot be answered based on backward-looking studies alone. Rather, this requires the use of forward-looking methodologies, to which we turn in the next section.

4 | FORWARD-LOOKING METHODOLOGIES

Forward-looking methodologies aim to include the impact of uncertain, but conceivable climate-related events in their foresight. We use the term 'methodology' here broadly to refer to models, analyses and estimation techniques.

Projecting how climate-related events may result in financial asset price changes requires models to make assumptions about future climate change; which climate mitigation policies will be implemented; the channels through which climate-related events impact firms and their business operations; and how these impacts translate into asset price changes and financial market dynamics.

While methodologies share important characteristics, they also differ considerably within each of these categories. In the following, we organize our discussion of the differences as follows. We first discuss two key choices that methodologies face: that of the forward-looking scenario and of the time horizon. We then turn to four other steps in the estimation, responsible for most of the heterogeneity in reported asset price changes: The exposure of an asset to climate-related risk drivers; the translation of economic costs to financial costs; the extent to which financial markets mitigate or amplify initial costs; and the measure of impact.

4.1 | Key choices for forward-looking methodologies

4.1.1 | Constructing forward-looking scenarios

A necessary step in the process of investigating the future financial impact of climate-related risks is to develop assumptions on what the future might look like. These visions of the future take the form of scenarios, which are usually not guided by probabilities (an exception is Battiston & Monasterolo, 2021). This is because there is uncertainty over feedback effects and tipping points in the climate system. Policy paths in democracies are also plagued with uncertainty (Chenet et al., 2019).

Scenarios are an established means to deal with this uncertainty. They "should have a clear, plausible, qualitative narrative but also be data-driven" (NGFS, 2019, p. 22). In the field we are reviewing and following the tradition of Integrated Assessment Modeling (IAM), a critical variable defining scenarios is the long-term increase in global temperatures with respect to pre-industrial averages. It makes sense to group scenarios[5] by the degree of expected warming, which co-determines the stringency of climate policy and thus of transition risks:

- **Policy action scenarios** that limit the warming over the next half-century or so to 1.5–2°C are associated with the strictest transition measures, while physical impacts appear more manageable. In these scenarios, the shape of the transition determines the shocks to economic activity: a target temperature rise of below 2°C could materialize either through a gradual transition of the economy or through an abrupt transformation leaving some key industries behind.
- **Extrapolating scenarios** are oriented along the temperature path associated with current emission levels. Taking the Paris Accord's nationally defined contributions (NDCs) as a baseline, temperatures in 2100 are likely to exceed the 2°C target by several decimal points (Robiou Du Pont & Meinshausen, 2018). Current emission pathways assessed in the UNEP Emissions Gap Report show that a warming of 3°C is most likely (Edo et al., 2019). These scenarios are thus associated with both transition risks, which in some scenarios are directly derived from NDCs, and physical risks.
- **No-policy action scenarios** take current emissions or even an increase in fossil fuel use as given and put global warming by the end of the century at anywhere from 4°C to more than 8°C. They are associated with virtually no transition risks. Physical climate risks are most pronounced in these scenarios.

In addition, considerations around the shape of the transition have become increasingly important, as a specific target could be obtained through both a gradual non-disruptive transformation and an abrupt transition with systemic disruptions. The Network for Greening the Financial System (NGFS), for example, recommends organizing scenarios along two dimensions: first according to whether climate targets are met or not, and second whether the transition happens in an orderly manner or not (NGFS, 2019). This classification generates four scenario categories. (i) An orderly transition that achieves climate goals (that is, stays below 1.5 or 2°C of warming); (ii) a disorderly transition that achieves climate goals, (iii) a disorderly transition that happens too late to meet the climate goals ("too little, too late") and (iv) a "hot-house-world" scenario without a disorderly transition but in which climate goals are not met. The NGFS has since developed six individual scenarios, two in each category with the exception of the "hot-house-world" category. They are partly based on current signals from governments to decarbonize and are supposed to provide financial institutions with a common starting point for an analysis of impacts to their measures of interest (NGFS, 2021). Some methodologies apply the NGFS suggestions (Allen et al., 2020) or congruent scenarios that follow the logic of "orderly", "disorderly" and "no transition" (Bongiorno et al., 2020). However, other institutions have simultaneously developed their own scenarios, e.g., focusing on the differences between technological and policy-induced transition risks (ESRB, 2021; Vermeulen et al., 2018).

The choice of which specific scenario to investigate also depends on the scope of the research. For instance, studies focusing on transition risks might only look at a 2°C-scenario. On the other hand, studies focusing on physical risk drivers might limit their analysis only to emission pathways creating an increase of temperatures of more than 2°C. Studies can also include both transition and physical risks, typically involving a trade-off between the two. Mercer (2019) and UNEP FI (2019) are examples of studies combining both physical and transition risks.

4.1.2 | Time horizons: long-term forecasts versus stress tests

The speed and modalities of implementation of mitigation policies are crucial, as they determine the magnitude of both transition and physical risks. The forward-looking literature offers two possibilities to project the speed of change: current portfolios are either stressed with events that are expected to materialize in the future; or the development of portfolios is extrapolated into a point in time in the future when climate-related risks are expected to fully materialize. We thus distinguish methodologies by their focus on either long-term scenarios or on short-term stress tests.

- *Stress tests* impose physical or transitional shocks on individual institutions and their portfolios or on the financial system as a whole. They are short-term and instantaneous in nature but are sometimes used to shock future projected developments of a portfolio. This approach resembles the stress test exercises routinely administered by financial market regulators (for an introduction into stress testing for banks see Dent et al., 2016). Shock scenarios aim at creating unusual stress and so focus on "tail risks", referring to the tails of probability distributions.
- *Long-term scenarios* incorporate transition and/or physical effects of probable emission pathways and analyze their effects on macro—or company-level variables over the next 30–100 years. Given the high uncertainty around the stringency of climate policy and the development of carbon-sequestering technologies, some of the scenarios also aim to comprise tail risks.

4.2 | Options within different estimation steps

Once the basic choices about the scenario and the time horizon of studies have been made, several specific methodological options are possible when estimating physical and transition costs. These include:

1. *Determining the exposure of an asset*. Methodologies must determine the degree to which a company and its assets are exposed to climate-related risks to be able to estimate the costs of the shock.
2. *Determining the financial costs of the economic shock*. The economic impacts, however calculated, need to be translated into financial impacts. Methodologies in this step strongly differ across studies.
3. *Including financial and non-financial market dynamics*. Methodologies can consider how financial networks amplify initial financial effects.
4. *Choosing the measure of impact*. Methodologies can present the financial impacts of the scenarios or stress tests using several measures.

We present these options below along the different steps that characterize most methodologies.

4.2.1 | Determine the exposure of an asset

Different companies and assets are treated unequally by climate change and climate policy. The pricing of climate-related risks must consider this heterogeneity by assessing the exposure of assets to climate-related risks and the firm's sensitivity, that is, the ability to respond and adapt to the exposure. Hubert et al. (2018) define exposure as "the presence of the system of interest in a place and setting that could be adversely affected by a hazard." This presupposes detailed knowledge of a company's assets and business model and how they might be exposed to climate-related risks.

Such knowledge includes spatial information on the exact geographic locations of a company's facilities, as well as expected climate impacts. These should be combined with the sectoral disaggregation of financial portfolios to account both for common traits of industries and the heterogeneous spatial exposure of companies of the same sector. In the case of transition risks, companies of the same sector may operate in different jurisdictions, subjecting them to different policies. Finally, additional analysis should include information on market power, which could affect the pricing of products. Such an approach would highlight that not all companies have the same scope of action when exposed to a shock.

In practice and among methodologies, approaches vary significantly in the granularity and breadth of exposure analysis. On transition risks, some use impacts on (sectoral) value-added, calculated for several mitigation scenarios, to determine the potential financial losses (Mercer, 2019). Others create a factor from empirical information that links the average CO2 intensity of an industry's production to asset returns in 56 industries (Vermeulen et al., 2019). HSBC (2019) uses an Integrated Assessment Model (TIAM-Grantham) to derive a set of trajectories for sectoral activity, emissions, energy use and carbon prices, which are then transformed into changes in company-level revenues and costs through additional bottom-up models. On physical risks, Four Twenty Seven and Deutsche Asset Management (2017) map facilities and their exposure to flood plains. Using this information, they find that firms with spatial diversity fare better against acute climate risks. Others use spatial data on asset locations and on climate change impacts (up until 2100) not only to determine exposure to direct physical risks but also relevant second-order financial effects (BlackRock, 2019). Where data is sparse, employing qualitative empirical research, such as interviews, can help determine the exposure of loan portfolios (Vermeulen et al., 2019). Another time-intensive way to determine loans' exposure is to identify corporate loans to fossil fuel producing firms, factoring in non-fossil fuel dependent business activities (Weyzig et al., 2014).

Such approaches are characterized by a 'top-down' approach, which involves using a macroeconomic model to translate physical impacts and transition costs into effects on GDP, inflation and interest rates, prices of intermediate and consumption goods (energy commodities, in particular), changes in trade patterns, and others. Where data availability allows, methodologies build exposure analyses 'bottom up', from the asset, firm or sectoral level.

This is the case, for instance, of UNEP FI (2019), which uses a number of models to evaluate both the physical and transition impacts on the costs and revenues of companies. Trucost (2019) uses different carbon price scenarios to calculate the company-level carbon costs and the resulting 'earnings at risk', before aggregating the impacts at the portfolio level. The underlying methodological approaches and modeling structures are likely to have a strong impact on the results. Most models assume some form of maximization, usually in the form of an intertemporal optimization of a welfare function, to determine carbon price trajectories and other macroeconomic variables, given certain emission scenarios. Others, most notably E3ME, are governed by macro-econometric functions and are demand- rather than supply-driven, meaning that transition-related investments are treated as a positive increase in expenditure (and hence GDP) rather than a utility-reducing costs.

Disaggregated information about exposure is important to show that some assets or loans of a company may be more at risk than others. In the past, it has been difficult to obtain project-specific data to estimate loan or bond exposure to climate-related risks and, to a lesser degree, that of equity. Disclosures of climate-related risks, as recommended by the Taskforce on Climate-related Financial Disclosures (TCFD, 2017) can help to fill this information gap. But they might be insufficient if they are not widely adopted by issuers and if investors do not use the information that they provide. The EU taxonomy for sustainable activities ("EU Green Taxonomy" for short; European Commission, 2020), which defines screening criteria for sustainable economic activities, will be used to make the contents of sustainable finance products more transparent. Financial institutions will have clear guidelines as to what they can label a "sustainable" product. This could further incentivize them to improve the screening of an asset's exposure to transition risks. However, it should be pointed out that an asset's degree of alignment with the EU Green Taxonomy does not correspond directly to its exposure to climate-related risks (Monasterolo, 2020).

4.2.2 | Determine the financial costs of the economic shock

The economic impacts, however calculated, need to be translated into financial impacts. Given the many assumptions necessary for this step, the methods strongly differ across studies. Dietz et al. (2016), for instance, after using the DICE model to calculate the GDP impacts of different mitigation scenarios, assume corporate earnings to be a constant share of GDP in the long-run, and the value of financial assets to be a function of discounted cash flows. In Mercer (2019), a heatmap of sensitivities of different industries and asset classes is developed, to transform sectoral GDP impacts into returns for different asset classes, disaggregated by industry. In UNEP FI (2019) the present value of the projected costs and opportunities from transition and physical impacts are compared to the current market valuation of the enterprise to calculate the Climate Value at Risk of the company. Ralite and Thomä (2019) use a sensitivity factor based on the correlation between GDP growth and share prices found in the stress tests of the European Systemic Risk Board (ESRB) to turn GDP impacts into stock price changes. Allen et al. (2020) use a dividend discount model (DDM), which translates their results at the level of sectoral value-added into dividends and thus stock value. Vermeulen et al. (2018, 2019) assign sector-specific transition vulnerability factors and prospected equity returns to assets and securities in 56 industries (using NACE categories). The vulnerability factors are based on the amount of carbon emissions used to generate value-added. In addition, they employ their own survey data to estimate the corporate loan exposures of the largest Dutch banks.

4.2.3 | Include financial network dynamics

Financial networks play an important role in spreading financial risks that had originally affected only one counterparty (Bateson & Saccardi, 2020; Battiston et al., 2017; Mandel et al., 2021; Roncoroni et al., 2021). The direct financial risks posed by climate change might seem manageable at first sight, but the asset price revaluations that they can trigger can be much larger than the initial shock. Some methodologies thus consider amplification mechanisms and propagation in financial markets. These amplifications are conceptualized as network effects, "contagion" (Roncoroni et al., 2021) or "second round effects" (Battiston et al., 2017).

Models of loss contagion among banks have been explored widely in the aftermath of the Great Financial Crisis of 2007. This literature, which focuses on the role of interbank markets (Georg, 2013; Krause & Giansante, 2012) has been a starting point to consider the role of networks in transmitting climate-related shocks (Bateson & Saccardi, 2020; Roncoroni et al., 2021). However, there are also multiple indirect network effects that can amplify initial shocks. First, rapid revaluations of certain assets can translate into a broad decline of asset prices through balance sheet readjustments and fire-sales (see, e.g., Krishnamurthy, 2010 or Shleifer & Vishny, 2011). In such a case, a decline in the price of some assets deteriorates the balance sheet of investors, causing them to liquidate other assets, which in turn lowers prices and deteriorates balance sheets even further. Recently, such fire-sale dynamics have been added as “third-round effects” to models of financial contagion in the case of climate-related risks (Roncoroni et al., 2021). Second, a related channel of contagion could be activated by the sudden revision of expectations. Herding behavior (Kiyotaki & Moore, 2002) and speculation may exacerbate climate-related risks due to a lack of information on the change in fundamentals (Jaffe, 2020; Palao & Pardo, 2017). Herding would be problematic, if there was evidence that investors base their expectations on similar observable events. An emerging literature has emphasized the role of “climate sentiments”, that is, investors’ expectations of future profitability and thus investment preferences under climate change, in shaping climate risk dynamics (Dunz et al., 2021). For example, “Climate sentiments” run high during times of attention-grabbing events such as UN Conferences of the Parties (COP) and have a larger effect on stock prices during those times (Santi, 2021). Finally, there are a range of possible mechanisms, which have not been explored in the climate risk case. These include default cascades (Allen & Gale, 2000) and liquidity crunches (Gai et al., 2011).

In the literature we review, most methodologies limit themselves to evaluating first-round effects, i.e. the asset price changes in direct response to a scenario-induced economic shock. Exceptions are Battiston et al. (2017), who introduce network effects in the form of a liquidity shock through a model of interbank lending markets and Roncoroni et al. (2021). The latter extend the interbank model with third-round effects from fire sales and fourth-round effects from losses that go beyond banks’ ability to absorb the shock and consequently affect external creditors. Such network effects are in some cases larger than the direct effects and might trigger wider systemic implications.

4.2.4 | Include non-financial market dynamics

Just as asset price changes can cascade through financial networks, climate-related costs to one firm can also spread to other firms through supply chains or to customers through selling markets. Cahen-Fourot et al. (2021) construct a model from Input-Output tables to show that a policy shock initially affecting few industries can have material consequences along their supply chain. A cap on fossil fuel production would strand assets in the extractive sector and lead to idle assets in electricity and gas, basic metals, coke and refined petroleum products, transportation, etc. A key finding from their analysis is that even if a sector is not directly affected by a risk, it may not be a sound alternative to move financial capital into. A similar approach is used by Godin and Hadji-Lazaro (2020) in the case of South Africa, with comparable qualitative results.

4.2.5 | Choose the measure of impact

To interpret the results from methodologies, the measure of impact must be considered, i.e., how asset price changes are reported. Sometimes, typical indicators of financial risk are reinterpreted for climate-related risks. UNEP FI (2019), as well as Dietz et al. (2016) and – for their distributed shocks model – Battiston et al. (2017) calculate a 'Climate Value at Risk' (VaR). However, its precise definition differs across methodologies. Mercer (2019) uses the annualized value of the impact of climate scenarios on the portfolio return. Barker et al. (2015) analyze the impact of carbon taxation on profit-before-tax of companies listed in the MSCI World index (a global weighted index of around 1500 companies) and assume it serves as a proxy for the potential loss of future market (and thus equity) value. Similarly, HSBC (2019) reports the change in the NPV of the profits within an MSCI World index. CISL (2015) reports the 5-year performance of the portfolios they have analyzed, for three different scenarios.

Another way of displaying the scenario performance of asset classes or portfolios is to report the earnings at risk (Trucost, 2019) or the change in stocks' share prices in comparison to those in a baseline scenario.

Battiston et al. (2017) specify equity losses of banks as a percentage of their total equity holdings. Vermeulen et al. (2019) state losses relative to the total assets of each sector (what they refer to as "total stressed assets"). Equity changes can have three sources: changes to the risk-free interest rate; exposure to carbon-reliant industries; and exposure to other industries. BlackRock (2019), looking at corporate mortgage backed securities, reports the increase in expected default rates on these instruments. Trucost (2019b) uses scenario-led methodologies to test the impact of climate-related risks on credit or corporate bond ratings. Finally, some methodologies opt for reporting risk scores or ratings for assets, portfolios or even sovereigns. The CRIS methodology, put forward by Lepousez et al. (2017), uses detailed information on physical hazards and asset exposure to derive scoreboards for individual assets. These include (for a corporate bond) information on the hazards that the business activity is most exposed to and the locations that are most at risk. They report an overall score on a scale from 0 to 99 instead of a monetary measure. We do not showcase them in Table 2.

4.3 | Reported asset price changes

In this section, we present the academic and industry contributions that have already tried to estimate the impact of climate-related risks on asset prices. We review the main estimates available in the literature for the *future* impact of physical and transition costs on financial assets as opposed to historical events, which we covered in Section 2.

Table 2 summarizes the results. We report (1) the types of risk under consideration, (2) the portfolio or index that is exposed to the risks, (3) the measure of impact, (4) the asset classes considered and (5) the time horizon of the scenario analysis or, if applicable, the assumed year of the stress test. To group scenarios, we refer to the relative temperature increase over pre-industrial levels by the end of the century that is assumed in the scenario. Where this information is not readily available, we refer to the names given by the authors.

Looking at the results, stress tests tend to expose more extreme asset price or earnings changes. Especially in harsher scenarios, stress tests give estimates at the upper end of the spectrum. Ralite and Thomä (2019) report a negative change in share prices of up to 60% under their "too late and too sudden" scenario. Similarly, Trucost (2019) estimate that earnings at risk in a hypothetical scenario can be as high as 140% in the case of utilities (although they show how heterogeneously this risk is distributed within the industry). Equally grim is the outlook on utilities under a stringent transition scenario by Barker et al. (2015), estimating a profit loss of up to 76.5%. Battiston et al. (2017) report high increases in equity loss if second-round losses via the interbank lending markets

TABLE 2 Estimates for asset price changes from selected literature (continues over 4 pages)

Study (Model)	Type of Risk (Type of Analysis)	Portfolio/Exposure	Measure	Asset class	Time horizon	Scenarios		
						3-4°C	**1.5°–2°C**	
Barker et al., 2015 (not specified)	Transition (Stress test)	MSCI World Index (Utilities)	Profit before tax	equity	2020	−15.3%	−76.5%	
		MSCI World Index (Basic materials)				−4.2%	−19.4%	
		MSCI World Index (Energy)				−2.8%	−11.8%	
		MSCI World Index (Industrials)				−1.5%	−7.2%	
						2°C	**2-2.5°C**	**No mitigation**
CISL, 2015 (GEM)	Transition (Stress test)	High fixed income	5-year portfolio performance	Equity, bonds, and other assets	5 years	−3%	4%	−4%
		Conservative				9%	12%	−26%
		Balanced				17%	16%	−30%
		Aggressive				25%	25%	−45%
						2°C	**2.5°C**	
Dietz et al., 2016 (DICE)	Physical and transition (Long term)	Stock of global financial asset	Climate VaR (impact of scenarios on present value of assets) –mean	Equity and bonds	2100	−1,18%	−1,77%	

(Continues)

TABLE 2 (Continued)

Study (Model)	Type of Risk (Type of Analysis)	Portfolio/Exposure	Measure	Asset class	Time horizon	Scenarios 3-4°C	1.5°–2°C		
						Fossil-Fuel	Fossil-Fuel + Utilities	F-F + Util. + Energy-intensive	F-F + Util. + E-intens. + Housing????+ Transp.
Battiston et al., 2017 (DebtRank)	Transition (Stress test: reported sectors 100% devalued)	Eurozone Banks	total relative equity loss	equity, bonds and loans, after first round	shock occurs in 2017	2.55%	3.79%	13.18%	15.09%
				after first and second round		6.08%*	9.75%*	27.91%*	30.24%*
	Transition (Stress test: with shock distributions)		VaR (5%)			**Fossil-Fuel Primary**	**F-F Primary + F-F Secondary**	**F-F P + Renew. Secondary**	**Renew. Secondary**
				first round		0.26%	0.41%	0.19%	0.06%
				first and second round		0.63%	0.96%	0.47%	0.13%
						Policy shock	**Tech. Shock**	**Double shock**	**Confidence shock**
Vermeulen et al., 2018 (NiGEM)	Transition (Stress test)	Dutch banks	Asset loss	Equity, bonds, loans	5 years	2,17%	1,14%	2,73%	1,67%

(Continues)

TABLE 2 (Continued)

Study (Model)	Type of Risk (Type of Analysis)	Portfolio/Exposure	Measure	Asset class	Time horizon	Scenarios 3-4°C	1.5°–2°C		
		Dutch insurers				8,12%	2,08%	10,83%	2,68%
		Dutch pension funds				6,73%	2,99%	10,16%	6,65%
						Disorderly			
Monasterolo et al., 2018	Transition (Stress-test)	Chinese Development Banks	Portfolio value	Syndicated Loans		4.2%–22% loss			
							*reported with standard deviations		
Mercer, 2019 (E3ME)	Physical & Transition (Long-term)	Representative growth portfolio	Impact of scenario on portfolio return (per year average)			2°C	3°C	4°C	
				Total portfolio	2030	0,11%	−0,02%	−0,07%	
					2050	−0,05%	−0,09%	−0,14%	
					2100	−0,07%	−0,12%	−0,18%	
				Equity (developed)	2100	−0,10%	0,10%	−0,20%	
				Equity (emerging)		−0,20%	−0,30%	−0,40%	
				Growth bonds		0,00%	0,00%	−0,10%	
						1.5°C	**2°C**	**3°C**	

(Continues)

TABLE 2 (Continued)

Study (Model)	Type of Risk (Type of Analysis)	Portfolio/Exposure	Measure	Asset class	Time horizon	Scenarios 3-4°C	1.5°–2°C	
UNEP FI, 2019 (REMIND)	Physical & Transition (Long-term)	Market Portfolio of 30,000 companies	Company Climate VaR (ratio between present-value climate-related costs/profits and current market value)	Equity	15 years	−4,56%	−3,36%	−1,84%
		1200 Top companies				0,05%	−0,46%	−0,80%
						2°C		
HSBC, 2019 (TIAM-Grantham)	Transition (Long term)	MSCI ACWI (All countries World Index)	Change in profits (NPV) relative to No Policy scenario	Equity	2050	−2%		
						Smooth Transition	**Too late, too sudden**	
Ralite & Thomä, 2019 (Discounted Cash Flow)	Transition (Stress test)		change in share prices compared to baseline	equity	shock occurs in 2025	−20–50%	−30–60%	
						4°C		
BlackRock, 2019 (RHG-NEMS)	Physical (Long term)	(Bloomberg Barclays Aggregate Index)	Default rate on CMBS	Commercial Mortgage Backed Securities	2060–2080	+ 0.6%		
						2°C		

(Continues)

TABLE 2 (Continued)

Study (Model)	Type of Risk (Type of Analysis)	Portfolio/Exposure	Measure	Asset class	Time horizon	Scenarios 3-4°C	1.5°–2°C		
Trucost, 2019 (not specified)	Transition (Stress test)	Utilities	Earnings at Risk	Equity	2030	~140%			
		Materials				~100%			
		Energy				~55%			
		Industrials				~12%			
						2°C (Ref-Pol450)	**2°C (Ref-Pol500)**		
Battiston & Monas-terolo, 2019 WITCH/GCA	Transition (Stress-test)	OeNB	Portfolio value	Sovereign bonds	Shock	−0.13% −+0.12%	−0.36% −+0.08%		
						2°C (Ref-Pol450, mild market condi-tion)	**2°C (Ref-Pol450, adverse market condi-tion)**	**2°C (RefPol500, mild market condition)**	**2°C (RefPol500, adverse market condition)**
Battiston et al., 2019 (CLI-MAFIN)	Transition (Stress-test)	EU/EEA Insurance companies	Portfolio value	Sovereign Bonds	Shock	up to 0.6% loss	up to 2.6% loss	up to 0.4% loss	~1.8% loss
						2°C, Orderly	**2°C, Disor-derly**	**Failed Transition**	

(Continues)

TABLE 2 (Continued)

Study (Model)	Type of Risk (Type of Analysis)	Portfolio/Exposure	Measure	Asset class	Time horizon	Scenarios 3-4°C	1.5°–2°C	
Bongiorno et al., 2020 (ClimateMAPS)	Physical & Transition (Long-run)	Global	Median equity market returns	Equity	around 2025	Small losses	−18%	no losses
					2060	−15%	−25%	−50%
						Delayed Transition	**Sudden Transition**	
Allen et al., 2020 (NiGEM)	Transition (Long-run)	France, Europe, ROW	Equity price	Equity	expectations change today about 2050	−2% to −8%	−5% to −20%	
						2°C (Fossil Fuel + Util.)	**2°C (+other sectors)**	
Bateson and Saccardi (2020)	Transition (Stress-test)	US Banks	Portfolio value	Syndicated loans	Initial shock	−3% loss	−18% loss	
					After 2nd round	−8% loss		
						Policy shock	**Techno shock**	
ESRB (2021)	Transition (Stress-test)	Banks, pension funds	Mark to-market losses	All assets	5 years	−0.8%	−0.5%	
						Disorderly		

(Continues)

TABLE 2 (Continued)

Study (Model)	Type of Risk (Type of Analysis)	Portfolio/Exposure	Measure	Asset class	Time horizon	Scenarios 3-4°C	Scenarios 1.5°–2°C
EIOPA (2020)	Transition (Stress-test)	EU Insurers	Portfolio value	Equity	Shock	−25%	
						Disorderly	
Grippa et al. (2020)	Transition (Stress-test)	All financial actors (Norway)	Mark to-market losses	Equity	2020-2040	−5% to −6%	
						Disorderly (RefPol-500)	
Roncoroni et al., 2021 (GCAM)	Transition (Stress-test)	Mexican Banks & Investment Funds	Relative equity loss	All	Shock	2.5-4% ot total asset value	

are considered. The stress test of the Dutch financial sector by Vermeulen et al. (2019) exemplifies that the co-occurrence of two shocks, i.e. technology and policy, can significantly exacerbate transition risks for financial actors. Long-term studies focusing on profitability of portfolios, such as HSBC (2019) and Mercer (2019), report relatively minor losses. Research using VaR as a measure of future impacts on asset prices report relatively high values, see the results by Dietz et al. (2016) and UNEP FI (2019). The latter also shows that a global, broadly invested portfolio will likely suffer more from both transition and physical risk scenarios than the top 1200 companies.

5 | RESEARCH GAPS

Despite a leap in the breadth and depth of the literature on climate-related risks in asset prices, some research challenges remain. First, more must be done to better understand how climate events can trigger abrupt price corrections on financial markets. Second, a recent push to improve the available climate-related data raises issues for financial market participants and supervisors. Third, there are implications for the forward-looking methodologies, which must adapt to the changing data landscape.

5.1 | Potential risks to financial stability

From extreme weather events to more stringent climate policies and litigation costs, climate-related risk drivers abound. Empirical evidence tends to indicate that such climate risks are not fully priced in by market participants, a fact which is often highlighted by policy-makers, including central bankers and financial supervisors. This opens the door to potential sharp price corrections as investors revise their expectations.

Our review of the backward-looking literature showed that additional climate-related information overwhelmingly leads to changes in asset prices, which are predominantly negative. As we have discussed at the outset of this paper, the sudden revision of expectations about the ability of assets to generate a return or about the financial risks they face, may have consequences for financial stability. A better understanding of what could trigger such expectations revisions is key to anticipate episodes of financial instability. However, there is currently no framework that offers an explanation to when such a 'Climate Minsky moment' (Carney, 2018) would occur. Future research will thus have to investigate what determines tipping points in the financial system.

Furthermore, little is known about how initial climate shocks on asset prices propagate and are amplified by financial markets. Some pioneering work has already been done with financial network models to assess such propagation and amplification mechanisms. They usually show that indirect exposures to climate-related risks are material. Some banks can be severely affected by them, even if they seem to have no exposure at first sight (see, e.g., Roncoroni et al., 2021). Similarly, both physical and transition-related shocks can propagate along the economic value chain, affecting economic actors well beyond those that are directly hit (see, e.g., Cahen-Fourot et al., 2021). Such network effects are usually absent from forward-looking methodologies.

Another potential source of financial instability could come from the creation of a green bubble, i.e. the overinvestment in low-carbon technologies and the heightened interest in financial assets labeled as "green" or "ESG", which has thus far seen very little empirical analysis (Semieniuk et al., 2021). Given that sources of renewable energy now undercut certain fossil fuels in the cost of power generation (IRENA, 2021), the risk of a green bubble may also rise, requiring more research to understand under which conditions it could emerge and burst.

5.2 | Climate-related disclosures and financial supervisors

There is currently a push to develop common frameworks under which to report climate-related disclosures. The guidelines set by the Task Force on Climate-Related Financial Disclosure (TCFD, 2017) are becoming the international standard for that. Such initiatives are supported by financial supervisors, who increasingly tend to support mandatory disclosure guidelines for firms. Parallel to that, policy-makers are also engaged in defining economic activities, which support the transition to a low-carbon economy and are thus eligible for green investment labels. The most notable examples of such taxonomies are China's *Green Bond Endorsed Project Catalogue* issued in 2015 and the EU's *Taxonomy for sustainable activities* issued in 2021.

Such initiatives are welcome: more data will improve the assessment of climate financial risks. However, further research should aim to understand which data best reflect firms' and households' exposure to climate-related risks. Transition risks are a case in point: exposure to transition risks greatly depends on a firm's current and future actions and investments to ensure its transition to low-carbon technologies. There is no consensus on what forward-looking indicators to use to capture such plans. Current emissions, one of the main indicators used to assess transition risks, are limited in this context.

Collecting the right information to assess climate-related risks is further complicated by the fact that financial supervisors need such data from a diverse range of economic actors. Small and medium enterprises (SMEs) represent a bottleneck in this respect. Knowledge about their activities is needed to assess a banks' exposure to climate-related risks, but SME's capacity to deliver the complex data required for climate risk assessments is limited. Future research should Identify appropriate indicators that balance complexity and robustness.

5.3 | Dealing with uncertainty in forward-looking methodologies

Financial firms are looking for better toolkits to assess their exposure to climate-related risk (see for instance the survey of Gibbs et al., 2020). We identify two areas for further developing forward-looking methodologies to meet this demand: dealing with uncertainty and reflecting financial market dynamics.

Despite ever-greater efforts by climate science to understand the complex interactions in the climate system, the unprecedented nature of climate change means that fundamental uncertainty about future impacts will remain. Using multiple plausible scenarios and employing inter-model comparison exercises (i.e. running a number of different models using the same set of scenarios) are established means to deal with this uncertainty. As new knowledge about climate impacts and their assigned probabilities constantly emerges, scenarios should be updated frequently to reflect this change in what is deemed plausible. Methodologies should be flexible enough to quickly adapt to updated scenarios.

Second, as highlighted above, the propagation of climate-related risks through financial and non-financial networks remains understudied. A distinction must be made between the effects of gradual changes to economic processes and shock scenarios. Treating the financial system as a force that shapes the macro-economy, through changing expectations about the realization of climate risk, could help understand better the drivers of systemic risks.

6 | CONCLUSIONS

In this paper, we review the literature studying the pricing of climate-related financial risks. We summarize the current theoretical perspective on climate-related risks (encompassing physical, transition and liability risks) and discuss how they enter asset pricing frameworks. We offer a novel perspective on how climate-related risks materialize as economic costs for firms through four distinct channels and how these economic costs translate into financial asset price changes.

We structure the backward-looking literature (i.e., literature using historical-empirical data), distinguishing two types of assets (*negatively* and *positively exposed assets*) and four different measures of impact (*financial asset prices, real estate prices, cost of capital* and *risk assessment*). We show that new information about climate-related risk drivers predominantly leads to negative effects across the four measures of impact. Only in the categories of risk assessment and financial asset prices, there seems to be some ambiguity in findings. When an asset is positively exposed to transition risks (as, for example, in the case of renewable energy firms), most papers in our review find that transition risk drivers have positive effects on the asset prices, or that they reduce the risk exposure or cost of capital of the firms. We conclude that climate-related risks do influence asset prices and that results are usually robust to a wide range of alternative specifications of asset pricing models. At the same time, the results suggest that climate-related risks are not fully priced. We find mixed evidence on whether risks are priced efficiently.

Given the current turn towards forward-looking methodologies, we also review the literature focusing on the asset price impact of long-term climate and transition scenarios and stress tests. This literature is mostly guided by considerations around tail risk and plausibility rather than probability. We highlight the heterogeneity of the methodological choices to make in this context, including scenarios, the relevant time horizon, the method to determine the exposure of an asset to climate-related risks, the translation of economic costs to financial costs, and others. Model components, which study the amplification or mitigation of initial effects through financial networks, are only sparingly applied.

This heterogeneity in approaches and scope of forward-looking methodologies makes it difficult to compare results. Most methodologies focusing on transition risks test at least one climate mitigation scenario (in which the anthropogenic mean temperature increase stays below two degrees). Some choose instead to juxtapose a "smooth" and a "sudden" transition path. Methodologies focusing on the impact of physical climate risks employ at least one scenario, where the two-degree-target is overshot. The losses estimated both by the stress test and the long-term approaches are economically significant, but stress tests with their focus on tail risks report starker estimates. Network effects and co-occurrence of risk are likely to substantially increase initial financial losses.

Stress tests seem to be the avenue that most financial regulators and private actors opt for today. Given the remaining uncertainty over the exact consequences financial actors need to expect from both climate change and climate policy, stress testing is a promising way to periodically receive information about financial reactions to plausible scenarios. Regulators and central banks should continue to build their expertise in climate stress testing. Their emphasis should be in detecting systemic risks and including the analysis of the potential of propagation of initial shocks through production and financial networks.

Finally, while regular stress tests can keep regulators and financial actors informed about worst-case scenarios, long-term scenario analysis can improve their understanding of alternative climate futures under fundamental uncertainty. Their use and scope should be increased and refined, rather than concentrated around a few scenarios that seem most likely at a particular point in time. The impact of physical climate risk drivers should be considered in combination with transition and liability risks, as the future will most likely hold a mix of the three.

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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ENDNOTES

[1] These interactions are non-trivial. To name but two examples, higher transition risks from stricter climate policies are likely to limit physical risks in the future. Higher physical risks from unmitigated climate change on the other hand will spur litigation against governments and firms responsible for inaction. For a thorough discussion about the possible interactions of risk drivers, see Basel Committee on Banking Supervision (2021).

[2] When explicit asset pricing models are used, climate-related risks are included as a risk factor after being estimated through common methodologies (e.g., Fama & MacBeth, 1973).

[3] See Battiston and Martinez-Jaramillo (2018) for a review of existing models.

[4] While scientists increasingly use attribution science to link 'natural' catastrophes to man-made climate change, epistemological difficulties persist (Eckstein et al., 2020, p. 10). Some weather phenomena have increased in frequency, intensity and duration concurrently with a warming atmosphere (Committee on Extreme Weather Events et al., 2016). This section reviews the financial impacts of all event types, which could be attributed to climate change in principle, regardless of whether the authors use attribution science to create a causal link between a physical event and climate change.

[5] Labeling the scenarios is a delicate matter, as it can involve value statements. Most contributions, like ours, use labels to make scenarios easily recognizable. Hausfather and Peters (2020) point out, however, that referring to the "no-policy-action scenarios" as "business-as-usual (BAU) scenarios" overestimates the likelihood of such a scenario.

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APPENDIX

TABLE A1 Backward-looking literature studying assets negatively exposed to physical climate risk drivers

Authors	Asset class	Climate risk driver	Measure of impact	Effect on measure	Results
Bin and Landry (2013)	Real Estate	Disaster	(real) asset price	Negative	−5.7 to −8.8% on prices for houses in an affected area after hurricanes materialize. Other houses trade with a risk premium of 6.0–20.2% if located in a potential flood zone
Bernstein et al. (2019)	Real Estate	Sea-level rise (SLR)	(real) asset price	Negative	−7% discount relative to similar but unaffected properties
Murfin and Spiegel (2020)	Real Estate	Sea-level rise	(real) asset price	No significant effect	No price effect
Atreya and Ferreira (2015)	Real Estate	Disaster	(real) asset price	Negative	Houses in inundated areas trade with a markdown of 36–48% after the flood
Baldauf et al. (2020)	Real Estate	Sea-level rise	(real) asset price	Negative (lower pricies in “believer” neighborhoods than “denier” neighborhoods)	Houses located in “denier” neighborhoods cost around 7% more than those in “believer” neighborhoods
BlackRock (2019)	Bonds (Municipal)	Hurricanes	asset price	No significant effect	No price effect of heightened exposure of municipal bonds to storm risk
Kölbel et al. (2020)	Credit-default swaps	Custom climate risk measure based on language algorithm	asset price	No significant effect	For physical risks, there is no statistically significant impact on CDS spreads
Makridis (2018)	Stocks (all sectors)	extreme temperatures	asset price	Negative	−0.1 percentage point decline in stock returns for one standard deviation increase in monthly degrees at extreme temperature (below 15 degrees or above 84°F)
Anttila-Hughes (2016)	Stocks (energy)	News (extreme temperatures)	asset price	Negative	−1% (temperature records) and + 3% (melted ice shelves) return over 10 days
Anttila-Hughes (2016)	Stocks (energy)	News (Melting polar ice)	asset price	Positive	+3% return over 10 days after the news
Bansal et al. (2019)	Stocks (all sectors)	extreme temperatures	asset price	Negative	A one standard deviation increase in the long-run temperature leads to a 3% decline in equity valuations

(Continues)

TABLE A1 (Continued)

Authors	Asset class	Climate risk driver	Measure of impact	Effect on measure	Results
Griffin et al. (2019)	Stocks (all sectors)	extreme temperatures	asset price	Negative	Cumulative excess returns of −0.42%, more negative for costlier (−1.38%) and longer (−0.68%) Extreme High Surface Temperature (EHST) events. No effects for extreme cold temperatures
Bertolotti et al. (2019)	Stocks (electric utilities)	Disaster	asset price	Negative	−1.5% stock prices and +6 percentage points implied volatility for firms affected by the hurricane
Choi et al. (2020)	Stocks (all sectors)	extreme temperatures	asset price	Negative	−48 bps in the long-short emission-minus-clean portfolio
Alok et al. (2020)	Stocks (all sectors)	Disaster	asset price	Negative	Post-disaster, portfolio weights of stocks linked to disaster zones decrease for all funds regardless of location, but far more for funds close to the disaster zone
Faccini et al. (2021)	Stocks (U.S. common stocks)	News	asset price	No significant effect	No price effects detected
Goldsmith-Pinkham et al. (2021)	Bonds (Munici-pal)	Sea-level rise	asset price	Negative	A one standard deviation increase in SLR exposure leads to a 2–5% reduction in the present value of a municipal bonds or an increase of 1% to 3% in the volatility of local government cash flows
Painter (2020)	Bonds (Munici-pal)	Sea-level rise	cost of capital	Negative	U.S. counties exposed to physical risk face higher costs of refinancing: A one percent increase in climate-related risk increases the annualized issuance costs by 23.4 basis points for long-term maturity bonds
Balvers et al. (2017)	Stocks (all sectors)	extreme temperatures	cost of capital	Negative	The cost of equity capital rises by 0.22% due to the additional burden of climate-related risks, corresponding to a present value loss of 7.92%
Klomp (2014)	Loans (Com-mercial banks global)	Disaster	risk	Negative	Banks' distance-to-default decreases when home country is hit by a large-scale disaster. Disasters also lead to a credit-crunch, especially in emerging economies
Noth and Schüwer (2018)	Loans (Com-mercial banks US)	Disaster	risk	Negative	More non-performing loans and higher foreclosure ratios in the years following an event
Kruttli et al. (2019)	Stocks (all sectors)	Disaster	risk	Negative (higher implied volatility)	+5–10 percentage points implied volatility for firms affected by the hurricane

TABLE A2 Backward-looking literature studying assets negatively exposed to transition risk drivers

Authors	Asset class	Climate risk driver	Measure of impact	Effect on measure	Results
Kölbel et al. (2020)	Credit-default swaps	Custom climate risk measure based on language algorithm	asset price	Negative	Transition risks increase CDS spreads especially after the Paris Agreement. Transition exposed CDS experiences reduction in the range of 71–119 bps after the paris agreement
Chava (2014)	Stocks (S&P 500 & Russell 2000)	Custom Environmental Concern Measures	asset price	Negative	7% carbon premium on stocks
Bernardini et al. (2021)	Profits [stocks, if listed] (Utility sector)	Policy shock	asset price	Negative	Falling profits of high carbon firms. Lower profits also resulted in falling stock prices
Ramiah et al. (2016)	Stocks (all sectors)	Policy shock	asset price	Positive	Environmental regulations increase volatility and can generate abnormal returns in the range of 30–40%. Even if most of the news items refer to stricter regulation, most abnormal returns are positive.
Görgen et al. (2019)	Stocks (all sectors)	Custom Brown-Green-Score (BGS)	asset price	No significant effect	The Brown-minus-Green portfolio has a statistically insignificant negative risk premium of −0.097% per month
Faccini et al. (2021)	Stocks (U.S. common stocks)	News	asset price	Negative	There is only evidence that news about US climate policy is priced, and more pronounced after 2012. The spread's alpha ranges between 0.46% and 0.96% for decile portfolios.
Alessi et al. (2021)	Stocks (all sectors)	Custom score	asset price	Positive	Markets attach a negative risk premium to greener portfolio (disclosing environmental performance and with lower emissions). This means dirty stocks trade with a premium. Markets attach a risk factor if quality of disclosure is accounted for alongside emission performances
Wen et al. (2020)	Stocks (included in Shenzhen Pilot ETS)	Policy shock	asset price	Positive	The stock returns of companies participating in the Shenzhen ETS pilot experience positive returns after the start of the pilot, indicating a carbon premium. The authors theorize that this is because of the higher carbon exposures of companies trading under the ETS

(Continues)

TABLE A2 (Continued)

Authors	Asset class	Climate risk driver	Measure of impact	Effect on measure	Results
Duan et al. (2020)	Bonds (all sectors US)	Carbon intensity	asset price	Negative	Presence of significant carbon alphas on bonds (average +16 basis points), attributed to investor's underreaction
Noailly et al. (2021)	Stocks	News index	asset price	Negative	Four basis points drop in excess stock returns for firms with one-SD above mean CO2 emissions, following a one-SD increase in EnvP news index
Matsumura et al. (2014)	Stocks (S&P 500)	Carbon emissions	asset price (firm value)	Negative	Median +$2.3bn of market capitalization for firms disclosing carbon emissions. For each additional thousand metric tons of carbon emissions, firm value decreases by $212,000
Atanasova and Schwartz (2019)	Stocks (Fossil fuel firms)	Growth of undeveloped oil reserves	asset price (Tobin's Q)	Negative	A 1%-increase in investment in undeveloped proven reserves decreases Tobin's Q by .00002
Chava (2014)	Loans (S&P 500 & Russell 2000)	Custom Environmental Concern Measures	cost of capital	Negative	20% higher loan rates for environmentally hazardous firms (25 bps)
Nguyen et al. (2020)	Stocks (all sectors Australia)	Policy shock	cost of capital	Negative	Higher cost of capital (+2.5–3 basis points cost of equity) for polluting firms after the ratification of the Kyoto Protocol. Emitters' implied cost of equity increases by 2.5% post-ratification
Nguyen et al. (2020)	Loans (all sectors Australia)	Policy shock	cost of capital	Negative	Higher cost of capital (+5–6 basis points cost of debt) for polluting firms after the ratification of the Kyoto Protocol. Relative to non-emitters, this is an increase in the interest rate spread of 5.4% post-ratification
Jung et al. (2018)	Loans & Bonds (all sectors Australia)	Carbon emissions	cost of capital	Negative	+38–62 basis points in cost of debt for one standard deviation in scope 1 emissions
Huang et al. (2019)	Loans	Policy shock	cost of capital	Negative	Loan spread to high-polluting firms increases by 5.5% (i.e., a higher risk premium after the policy shock); default rates of these firms rose by around 50%
Delis et al. (2019)	Loans	Policy shock	cost of capital	Negative	Fossil fuel firms experience rising credit cost by 16 basis points

(Continues)

TABLE A2 (Continued)

Authors	Asset class	Climate risk driver	Measure of impact	Effect on measure	Results
Palea and Drogo (2020)	Loans and bonds (Non-financial sectors Eurozone)	Carbon-intensity/Policy shock	cost of capital	Negative	A 1-point increase in carbon itensity (Scope 1 & 2) increases cost of debt by 5%. After the Paris Agreement, while high emitters' cost of debt was not affected (because it was already priced), low emitting industries saw their cost of debt increase
Garzón-Jiménez and Zorio-Grima (2021)	Stocks (all sectors Emerging Markets)	Carbon emissions	cost of capital	Negative	A 1%-increase in scope 1 and 2 emissions increases cost of equity by 0.03 units
Ilhan et al. (2021)	Options (S&P 500)	Carbon intensity	risk	Negative	Downward tail risk increase (very) sligtly with industry's carbon intensity
Byrd and Cooper-man (2018)	Stocks (Coal)	News	risk	No signifi-cant effect	0.05%–3.24% (mean 1.2%) CAR upon positive news; no significant reaction to negative news
Monasterolo and de Angelis (2020)	Stocks	Policy shock	risk	No signifi-cant effect	Carbon-intensive assets are not yet penalized

TABLE A3 Backward-looking literature studying assets **positively** exposed to transition risk drivers

Authors	Asset class	Climate risk driver	Measure of impact	Effect on measure	Results
Ravina and Kaffel (2020)	Stocks (all sectors Europe)	Policy shock	Positive	asset price	Higher returns (0.2%-—0.34%) on EU-ETS compliant portfolios (i.e not paying a carbon price)
Bernardini et al. (2021)	Profits [stocks, if listed] (Utility sector)	Policy shock	No significant effect	asset price	No effects for low carbon firms.
Ramelli et al. (2019)	Stocks	News	Positive	asset price	Transition-proof companies experienced positive abnormal returns of 62 basis points ten days after the election of Donald Trump and 101 basis points after the nomination of Scott Pruitt as head of EPA.
Ravina (2020)	Bonds (all sectors Europe)	Policy shock	Positive	asset price	Higher returns (0.03-—0.13%) on EU-ETS compliant portfolios (i.e not paying a carbon price)
Soh et al. (2017)	Stocks (all sectors US)	Carbon intensity	Positive	asset price	Low-carbon portfolios outperform high-carbon one (Abnormal returns of 3.5%–5.4%)

(Continues)

TABLE A3 (Continued)

Authors	Asset class	Climate risk driver	Measure of impact	Effect on measure	Results
Cheema-Fox et al. (2019)	Stocks (all sectors US and Europe)	Carbon emissions	Positive	asset price	+2% annual alpha on decarbonised porfolios
Noailly et al. (2021)	Equity of cleantech firms	News index	Positive	cost of capital	A higher EnvP news index is associated with cleantech startups receiving venture capital funding at a greater probability
Kempa et al. (2021)	Loans (renewable energy firms)	Policy shock	Positive	cost of capital	A one standard deviation increase in the OECD Environmental Policy stringency Index decreases the costs of debt of renewable energy firms by 19% relative to those of non-renewable energy firms. Environmental policies are likely to have an risk-reducing effect. This results in a lower risk premium on renewables of .15–.4 basis points
Cui et al. (2018)	Loans (Banks China)	Policy shock	Positive	risk	Banks with a higher green credit ratio experience a lower rate of non-performing loans
Monasterolo and de Angelis (2020)	Stocks	Policy shock	Positive	risk	The systemic risk associated with low-carbon indices drops after the announcement of the Paris Agreement. The relative weight of low-carbon indices in an optimal portfolio increases after the announcement

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'Climate value at risk' of global financial assets

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Investors and financial regulators are increasingly aware of climate-change risks. So far, most of the attention has fallen on whether controls on carbon emissions will strand the assets of fossil-fuel companies[1,2]. However, it is no less important to ask, what might be the impact of climate change itself on asset values? Here we show how a leading integrated assessment model can be used to estimate the impact of twenty-first-century climate change on the present market value of global financial assets. We find that the expected 'climate value at risk' (climate VaR) of global financial assets today is 1.8% along a business-as-usual emissions path. Taking a representative estimate of global financial assets, this amounts to US$2.5 trillion. However, much of the risk is in the tail. For example, the 99th percentile climate VaR is 16.9%, or US$24.2 trillion. These estimates would constitute a substantial write-down in the fundamental value of financial assets. Cutting emissions to limit warming to no more than 2 °C reduces the climate VaR by an expected 0.6 percentage points, and the 99th percentile reduction is 7.7 percentage points. Including mitigation costs, the present value of global financial assets is an expected 0.2% higher when warming is limited to no more than 2 °C, compared with business as usual. The 99th percentile is 9.1% higher. Limiting warming to no more than 2 °C makes financial sense to risk-neutral investors—and even more so to the risk averse.

The impact of climate change on the financial sector has been little researched so far, with the exception of some kinds of insurance[3]. Yet, if the economic impacts of climate change are as large as some studies have suggested[4–6], then, because financial assets are ultimately backed by economic activities, it follows that the impact of climate change on financial assets could also be significant.

The value of a financial asset derives from its owner's contractual claim on income such as a bond or share/stock. It is created by an economic agent raising a liability that will ultimately be paid off from a flow of output of goods and services. For example, a firm pays its shareholders' dividends out of its production earnings, and a household usually pays its mortgage from its wages. Output is the result of a production process, which combines knowledge, labour, intermediate inputs and non-financial or capital assets. Therefore, there are two principal ways in which climate change can affect the value of financial assets. First, it can directly destroy or accelerate the depreciation of capital assets, for example through its connection with extreme weather events[7]. Second, it can change (usually reduce) the outputs achievable with given inputs, which amounts to a change in the return on capital assets, in the productivity of knowledge[8], and/or in labour productivity and hence wages[9].

Why is it important to know the impact of climate change on asset values? Institutional investors, notably pension funds, have been in the vanguard of work in this area[10]: for them, the possibility that climate change will reduce the long-term returns on investments makes it a matter of fiduciary duty towards fund beneficiaries, which is why it is not unusual to see pension funds advocating significant emissions reductions[11]. Despite this, levels of awareness about climate change remain low in the financial sector as a whole[3], so one purpose of this exercise is to raise them. For their part, financial regulators need to ensure that financial institutions such as banks are resilient to shocks, hence their growing interest in the possibility of a climate-generated shock[12,13]. Value at risk (VaR) quantifies the size of loss on a portfolio of assets over a given time horizon, at given probability. Thus, our estimates of VaR from climate change can be seen as a measure of the potential for asset-price corrections due to climate change.

The difficult question in practice is how to construct a global estimate of the impact of climate change on financial assets, given the paucity of existing research. How can we get a handle on the magnitude of the effect? Typical approaches in the finance industry involve directly estimating the returns to different asset classes in different regions, as well as the co-variances between them[14]. In principle, these could be modelled as being dependent on climate change, yet at present there is a lack of knowledge of the economic/financial impacts of climate change at this granularity.

In contrast, it is possible to show how existing, aggregated integrated assessment models (IAMs) can be used to obtain a first estimate of the climate VaR, that is, the probability distribution of the present market value (PV) of losses on global financial assets due to climate change. The argument is in three stages.

First, in the benchmark valuation model of corporate finance, an asset is valued at its discounted cash flow. For a stock, this is the PV of future dividends. Of course, many stocks do not pay dividends (so-called 'growth stocks'), and their value in the short run lies in expected increases in the stock price. However, in the long run a dividend must be paid, else the stock is worthless. For a bond, the discounted cash flow is the PV of future interest payments.

Second, corporate earnings account for a roughly constant share of GDP (gross domestic product) in the long run[15], so those earnings should grow at roughly the same rate as the economy. This is related to Kaldor's famous 'stylized fact' that the shares of national income received by labour and capital are roughly constant over long periods of time[16,17]. As corporate earnings ultimately accrue to the owners of the financial liabilities of the corporate sector in one form or another, the (undiscounted) cash flow from a globally diversified portfolio of stocks should also grow at roughly the same rate as the economy[15].

Third, assuming debt and equity are perfect substitutes as stores of value, which is consistent with the neoclassical model of economic growth underpinning those aggregated IAMs that represent it explicitly, the same relationship will govern the cash flow from bonds, the other principal type of financial asset. According to

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Table 1 | The present value at risk of global financial assets from climate change between 2015 and 2100—the climate VaR.

Emissions scenario	1st pctl.	5th	Mean	95th	99th
BAU (expected warming of 2.5 °C in 2100)	0.46%	0.54%	1.77%	4.76%	16.86%
Mitigation to limit warming to 2 °C with 2/3 probability	0.35%	0.41%	1.18%	2.92%	9.17%

the Modigliani–Miller theorem of corporate finance, under certain assumptions, any future changes in capital structure will not change the expected value of today's aggregate portfolio[18,19]. Therefore, we can use forecasts of global GDP growth with and without climate change to make a first approximation of the climate VaR of financial assets.

In particular, the ingredients for the calculation are IAM-based estimates of the rate of GDP growth along various scenarios (the basic climate VaR is a comparison, for given emissions, of GDP growth after climate change with counterfactual GDP growth without climate change), a schedule of discount rates, and an estimate of today's stock of global financial assets (see Methods). It is important to note that the discount rate applied in valuing a portfolio of privately held financial assets is that of a private investor, and is given by the opportunity cost of capital appropriate for the riskiness of the portfolio. Thus, the extensive literature on social discount rates for appraisal of climate-change policies[20] is not relevant. We also highlight that the climate VaR, by definition, includes only the effect on asset values of climate impacts (that is, adaptation costs and residual damages). It does not include mitigation costs, which for a low-emissions path could be considerable. However, at the end of this paper we do tackle the wider issue of the PV of assets when mitigation costs are also included.

We use an extended version of Nordhaus's DICE model[21] to estimate the impact of climate change on GDP growth. Our version allows for a portion of the damages from climate change to fall directly on the capital stock[22,23], rather than simply reducing the output that can be obtained from given capital and labour inputs (see Methods). Thus, it is capable of representing the two broad ways in which climate change affects financial asset values that we identified above, and it has been argued more generally that such a representation of climate impacts is important in understanding the full potential for climate change to compromise growth in the long run[8].

We conduct a Monte Carlo simulation of DICE to estimate the VaR at different probabilities. We focus on four key uncertainties in the model, identified by previous studies (see Methods)[21,24,25]. The first is the rate of productivity growth, which in the neoclassical model is the sole determinant of long-run growth of GDP per capita, absent climate damages. Productivity growth influences the stock of assets in the future, but, because unmitigated industrial carbon dioxide emissions are proportional to GDP, it also influences warming and the magnitude of climate damages. The second is the climate sensitivity parameter, that is, the increase in the equilibrium global mean temperature in response to a doubling of atmospheric carbon. The third is an element of the damage function linking warming with losses in GDP. In particular, we parameterize uncertainty about a higher-order term in the damage function[5]. The uncertainty is best regarded as capturing the range of subjective views about the potential for catastrophic climate impacts in the region of at least 4 °C warming. The fourth controls the costs of emissions abatement.

Table 1 provides estimates of the impact of climate change over the course of this century on the PV of global financial assets. Along the DICE baseline or business-as-usual (BAU) emissions scenario, in which the expected increase in the global mean temperature in 2100, relative to pre-industrial, is about 2.5 °C (see Supplementary Information), the expected climate VaR of global financial assets today is 1.8%. As Table 1 indicates, there is particularly significant tail risk attending to the climate VaR. The 95th percentile is 4.8% and the 99th percentile is 16.9%. This is important, because distribution percentage points deep in the tail have particular relevance in some financial risk management regimes, such as insurance (for example, the EU Solvency II Directive).

Analysis with Spearman's rank correlation coefficients (a linear regression model is a poor overall fit of the data) indicates that the most important of the three uncertain parameters in determining the expected climate VaR on BAU is the climate sensitivity, followed by the initial rate of productivity growth, with the curvature of the damage function least important (see Supplementary Information). Recall that abatement costs do not affect the climate VaR by definition. Nonetheless, whereas there is an evidential basis on which to calibrate uncertainty about productivity growth and climate sensitivity, the same cannot be said of the curvature of the damage function (see Methods), so in the Supplementary Information we carry out sensitivity analysis on an alternative calibration that concentrates probability mass in the middle of the range of estimates in the literature, rather than spreading it uniformly. We find that the expected climate VaR is a little lower

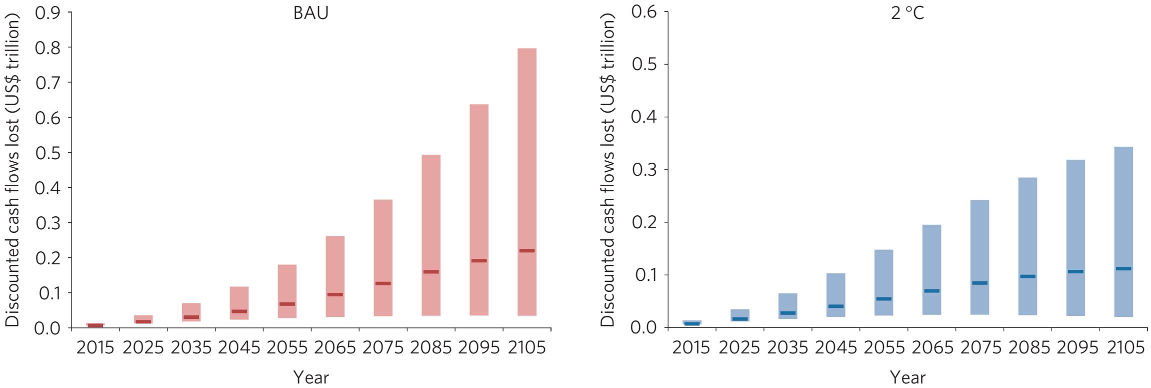

Figure 1 | The impact of climate change on discounted cash flows from the stock of global financial assets. The initial stock of assets is US$143 trillion for these calculations. The left panel shows discounted cash flows under business as usual (BAU), the right panel those under the mitigation scenario. Dashes are mean/expected values; the column corresponds with the 5–95% range.

Table 2 | The difference in the present value of global financial assets between mitigation to 2 °C and business as usual.

	1st pctl.	5th	Mean	95th	99th
2 °C–BAU	−0.61%	−0.48%	0.22%	1.77%	9.11%

(at 1.5%), but that the tail risk is considerably lower (at for example, 9.6% at the 99th percentile).

Table 1 also shows the equivalent climate VaR under a representative path of emissions reductions to limit the increase in the global mean temperature to no more than 2 °C, with a probability of 2/3 (see Methods). In this scenario the expected climate VaR is 1.2%, the 95th percentile is 2.9% and the 99th percentile is 9.2%. The expected reduction in the climate VaR due to mitigation is 0.6 percentage points, the 95th percentile reduction is 1.8 percentage points and the 99th percentile is 7.7 percentage points. Mitigation is hence particularly effective in reducing the tail risk.

How large is the climate VaR in absolute terms? Answering this question requires an appropriate estimate of the current stock of global financial assets. There is more uncertainty about this than one might perhaps imagine. The Financial Stability Board nonetheless puts the value of global non-bank financial assets at US$143.3 trillion in 2013[26]. This implies that the expected climate VaR under BAU is US$2.5 trillion, rising to US$24.2 trillion at the 99th percentile. Under the 2 °C mitigation scenario it is US$1.7 trillion, rising to US$13.2 trillion at the 99th percentile.

These estimates are not inconsiderable, particularly in the tail. To put them into perspective, the total stock market capitalization today of fossil-fuel companies has been estimated at US$5 trillion[27]. And whereas intra-day stock market movements are frequently considerably higher than our mean estimates, it can be argued that stock markets suffer from excess volatility, so increases in climate risk could trigger larger stock price movements than our estimates would suggest[28]. The risk is likely to be difficult to hedge fully, given the global incidence of climate impacts and the potentially long holding periods that would be required[29]. The nature of climate risk is such that, if it crystallizes, there would be no subsequent reversion to the previous trend growth path. Also, our approach assumes that debt will be affected as well as equities, and it smoothes the full effect of extreme weather on short-run volatility in economic performance.

Figure 1 analyses the contribution to the climate VaR of global financial assets today from impacts at different stages of the century. It makes clear that most of the climate VaR arises in the second half of the century. This suggests that the climate VaR ought to depend sensitively on the discount rate chosen. In the Supplementary Information, we apply an alternative, high discount rate of 7% initially (compared with 4.07%; see Methods) and find that the expected climate VaR along BAU is 1%, the 95th percentile is 2.4% and the 99th percentile is 7.7%. However, such a high discount rate is difficult to justify in relation to historical equity and bond returns at the global scale[30].

Table 2 and Fig. 2 compare the PV of global financial assets along the 2 °C mitigation scenario with its counterpart along BAU, when mitigation costs are included. The expected value of global financial assets is 0.2% higher along the mitigation scenario, although, as Fig. 2 shows, in fact roughly 65% of the distribution lies below zero, meaning that the PV of global financial assets is larger under BAU. This reflects the reduction in asset values brought about by paying abatement costs in the economy—including, for instance, the stranded assets of fossil-fuel companies—especially in the coming decades. It is consistent with cost–benefit analyses of climate change that show a horizon stretching beyond the end of this century may be necessary for emissions reductions to increase social welfare, as

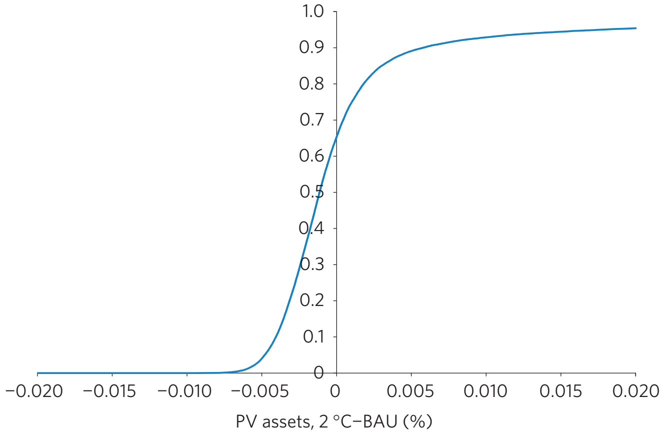

Figure 2 | The cumulative distribution function of the difference, in per cent, between the present value of global financial assets between mitigation to 2 °C and business as usual. Note the range of the *x* axis is truncated and should be read as ranging from −0.01% to 0.01%.

measured by net present value[4]. Similarly, if the non-market impacts of climate change (for example, on human health and ecosystems) would be greater than the damages represented in our version of the DICE model, then this would mean that the overall net present economic value of emissions reductions is greater than their net present financial value. Even so, because the PV of global financial assets is higher in expectations along the 2 °C path, mitigation is still preferred from the narrower perspective of financial assets, and more so the higher is risk aversion.

Methods

Methods and any associated references are available in the online version of the paper.

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Author contributions
S.D. led the project, from research design through modelling to writing the manuscript. A.B. helped design the research and draft the manuscript. P.G. helped design the research and run the model. C.D. also helped run the model.

Additional information
Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to S.D.

Competing financial interests
No competing financial interests have affected the conduct or results of this research. However, for the sake of transparency, the authors would like to make clear that they were employed by Vivid Economics Ltd during the production of this research. Vivid Economics Ltd is a London-based economics consultancy. Neither the authors nor the company stands to profit directly from this research.

Methods

The present value of global financial assets and value at risk. The PV of global financial assets is the discounted cash flow arising from holding these assets. For a globally diversified portfolio of stocks that is assumed to grow at the same rate as the economy,

$$\mathrm{PV} = D\sum_{t=0}^{T}\left[\prod_{s=1}^{t}\frac{(1+g_t)}{(1+r_t)}\right]$$

where D is the initial aggregate dividend payment, and g_t and r_t are the GDP growth rate and the discount rate at time t respectively. The climate VaR, in absolute terms, is the difference in PV with and without climate change, which reduces to

$$\mathrm{VaR} = D\sum_{t=0}^{T}\left[\prod_{s=1}^{t}\frac{(1+\bar{g}_t)}{(1+r_t)} - \prod_{s=1}^{t}\frac{(1+g_t^c)}{(1+r_t)}\right]$$

where $\bar{g}$ is the counterfactual growth rate in the absence of climate damages and g^c is the growth rate net of climate damages. Computed in this way, we assume that future climate damages are not already priced into D, which is consistent with low levels of overall awareness of climate risks in financial markets[3].

Relative to the PV of assets without climate change, the climate VaR is

$$\%\mathrm{VaR} = \sum_{t=0}^{T}\left[\prod_{s=1}^{t}\frac{(1+\bar{g}_t)}{(1+r_t)} - \prod_{s=1}^{t}\frac{(1+g_t^c)}{(1+r_t)}\right] \Bigg/ \sum_{t=0}^{T}\left[\prod_{s=1}^{t}\frac{(1+\bar{g}_t)}{(1+r_t)}\right] \qquad (1)$$

which is independent of the initial stock of assets. Therefore, equation (1) may also apply to the stock of bonds, assuming debt and equity are perfect substitutes as stores of value. As bonds typically pay fixed income, bond issuers are assumed to factor in the growth effect of climate change through the interest promised when entering into an agreement with the bondholder.

The discount rate r_t for a globally diversified portfolio of assets is calculated by making an initial estimate r_0 from economic/market data, and subsequently pegging $\{r_t\}_{t=1}^{T}$ to the GDP growth rate estimated by DICE. The initial estimate r_0 is 4.07% (in real terms). This is based on the long-term historical relationships between returns to world equities and bonds[30], and global GDP growth[31], weighted by an estimate of their current share in global financial assets[32]. According to this approach, a representative investor today holds bonds and equities in proportion circa 1.3:1, and if the relationship that held between world bonds and world GDP on average in the twentieth century, and world equities and world GDP in the same period, holds today and in the future, then the discount rate is 0.36 percentage points above the GDP growth rate, which DICE puts initially at 3.71%. For sensitivity analysis (see Supplementary Information), we set $r_0 = 7\%$.

We peg $\{r_t\}_{t=1}^{T}$ to $\{\bar{g}_t\}_{t=1}^{T}$, which again implies that investors do not incorporate climate-change forecasts in their asset valuations at present, nonetheless leading to a conservative estimate of the climate VaR as $g_t^c < \bar{g}_t$, for all t. In this sense, the assumption is behavioural rather than being based on rational expectations. Note that the initial year in the version of DICE that we use is 2005 (see below); we however treat 2015 as year 0 for the purposes of estimating PV and VaR.

Exceptionally, the analysis behind Fig. 1 requires an assumption about the initial cash flow D. We assume that the initial dividend yield is 2.76%, based on data on long-term mean dividend yields and bond interest payments for a world index comprising 19 countries[30], weighted like r_t in accordance with the proportion of stocks and bonds in global financial assets[32].

DICE model structure. We use an extended version of DICE2010 (ref. 33). Here we confine ourselves to reporting changes to the basic model, which is comprehensively described elsewhere[21].

We extend the model to partition climate damages between direct damages to the capital stock and damages to output, for given capital and labour inputs[22,23]:

$$D_t^K = f^K \cdot D_t$$

$$D_t^Y = 1 - \frac{(1-D_t)}{(1-D_t^K)}$$

where f^K is the share of damages D_t falling on capital, estimated at 0.3 (ref. 34).

As is well known, damages in DICE are a function of global mean temperature above the pre-industrial level T,

$$D_t = \frac{1}{1+g(T_t)}$$

and our specification of $g(T_t)$ is

$$g(T_t) = \alpha_1 T_t + \alpha_2 T_t^2 + (\tilde{\alpha}_3 T_t)^7$$

where α_i are coefficients used to calibrate the function on impacts studies and $\tilde{\alpha}_3$ is a random parameter (see below). We set $\alpha_1 = 0$ and $\alpha_2 = 0.0028$ as per the standard model. The element $(\tilde{\alpha}_3 T_t)^7$ roughly speaking introduces the possibility of catastrophic climate change[5,25]. It is worth noting that although the overall convexity of $g(T_t)$ is widely assumed, some of the most recent evidence suggests it might be approximately linear, if not indeed slightly concave[6].

Random parameters and Monte Carlo simulation. We incorporate uncertainty about TFP growth by parameterizing a probability distribution over the initial growth rate of global TFP. Long-run data suggest that this uncertainty can be represented by a normal distribution with a mean of 0.84% per year and a standard deviation of 0.59% per year[35].

We parameterize a probability distribution for the climate sensitivity S, which is a key parameter driving transient climate response in DICE, based on the consensus statements in the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report[36]. As IPCC AR5 gives ranges, here we report our specific assumptions: $p(S<1) = 0.025$, $p(S<1.5) = 0.085$, $p(S<4.5) = 0.915$ and $p(S<6) = 0.95$. Owing to the behaviour of DICE's physical climate model, we must place the additional restriction that $S \geq 0.75$. The best fit of these data is a Pearson type-V distribution with a shape parameter value of approximately 1.54 and a scale parameter value of approximately 0.9, giving $\bar{S} = 2.9$.

The random parameter on damages $\tilde{\alpha}_3$ is intended to span the spectrum of subjective beliefs of economists working on climate change about the level of aggregate damage at $T \geq 4\,^\circ\mathrm{C}$ (this spectrum is roughly Nordhaus–Weitzman–Stern). We follow the principle of insufficient reason in specifying a uniform distribution with a minimum of $\alpha_3 = 0$ (Nordhaus) and a maximum of $\alpha_3 \approx 0.248$ (which replicates the 'high' scenario in Stern's recent work[22]). However, alternative approaches to calibrating subjective uncertainty about this parameter are arguably no less valid, so in sensitivity analysis we investigate an alternative, normal distribution with a mean of 0.12 and a standard deviation of 0.04. This means that at -3σ the damage function reduces to Nordhaus's standard version, whereas at $+3\sigma$ it corresponds with Stern's high scenario.

We follow Nordhaus[21] and others in using uncertainty about the backstop price of abatement in DICE to create uncertainty about marginal abatement costs. Updating Nordhaus[21], we assume the initial cost of the backstop abatement technology (note: not the cheapest abatement technology) is normally distributed with a mean of approximately US\$343 per tCO_2 and a standard deviation of approximately US\$137.

For the Monte Carlo simulation, we take a Latin hypercube sample of the probability space with 50,000 draws. Each input distribution is assumed independent.

2 °C mitigation scenario. This is derived from a cost-effective path to keep the 'likely' increase in the global mean temperature to not more than 2 °C at all times. Likely is defined as per IPCC as 2/3 probability. Cost-effectiveness implies choosing the vector of emissions control rates in DICE so as to minimize the discounted sum of abatement costs, using the DICE standard social discount rate. The resulting schedule of emissions control rates for the twenty-first century, starting in 2015 and proceeding in increments of ten years, is 14.25%, 20%, 25.75%, 35.25%, 43.75%, 53.5%, 66.75%, 75%, 74.5% and 74.5%.

To compare the PV of global financial assets along this scenario with that along BAU, we apply equation (1), but where, instead of comparing GDP growth with and without climate damages, both along BAU, we have growth inclusive of climate damages and abatement costs along the 2 °C mitigation scenario and BAU.

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Climate Risks in Financial Assets

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Abstract

This note reviews the empirical evidence available in the academic literature about the impact of climate-related risks on financial assets. It addresses three main questions: does climate change already affect financial asset returns? What is the potential impact of future climate-related costs on financial asset prices? Do financial markets adequately price in these costs? We find compelling evidence that climate-related events such as hurricanes and droughts – i.e. physical risks – already have a negative impact on both equity and debt instruments through lower payoffs and higher non-performing loans. We also find early evidence that transition costs impact on some financial assets more than others. Evidence on the effects of future climate costs on financial assets indicates that the financial risks associated with them are financially significant, even with conservative estimation methodologies. The magnitude of these risks critically depends on the extent to which investors currently price them in and on potential second-round effects. Several empirical studies point to a lack of awareness about future climate costs by investors, which support the concerns that financial markets currently do not adequately price in climate financial risks.

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CONTENTS

1 Introduction

"Climate-related risks are a source of financial risk": the opening sentence of the first comprehensive report by the Central Banks and Supervisors Network for Greening the Financial System (NGFS 2019a) sounds like a wake-up call for the financial community. This warning, supported by more than 40 central banks and supervisors from all around the globe, must be taken seriously by financial investors. At the same time, central banks and financial supervisors frequently point to uncertainties around the magnitude and timing of climate change's impacts on financial assets as a reason for inaction. As a result, changes to their practice has been largely incremental.

Against this background, we review the empirical evidence on the link between climate risks and financial asset prices available to date in the academic literature. We address three main questions: is there empirical evidence that climate change already affects financial asset prices? What is the potential impact of future climate-related costs on financial assets? Do financial markets adequately price in these costs? We focus our survey on the impact of physical and transition costs on equity and debt instruments – i.e. on stocks, bonds, and loans, respectively. We also provide recommendations to bridge the knowledge gaps that we identify in our findings.

We find compelling evidence that the physical costs associated with climate-related events such as hurricanes and droughts have already a negative impact on both equity and debt instruments. They significantly decrease the payoffs of equities and increase the proportion of non-performing loans. As the occurrence of such events is projected to rise substantially with climate change, their impact on financial assets will also grow. Since the transition to a low-carbon economy is yet to happen, empirical evidence of the impact of transition costs on financial assets are scarcer, but the examples available indicate that transition costs have already reduced equity returns and increased default probabilities for some firms.

Turning to the effect of future physical and transition costs on financial assets, conservative stress tests for transition risks – i.e. without second round effects and without sudden revisions of investors' expectations – estimate that portfolios constituted of both equity and debt instruments could lose up to 10% of their value within 5 years. This loss could materialize within one year if investors suddenly revise their expectations to reflect future transition costs. For scenarios in which no transition happens – i.e. scenarios with maximum physical costs – a sudden revision of investors' expectations to account for future physical costs could generate losses up to 40% of the value of a diversified portfolio. In addition, second-round effects through investors' cross-exposure to each other are likely to significantly amplify losses.

Our review of the literature highlights that the impact of climate change on future financial asset performance crucially depends on whether physical and transition costs are already reflected in current asset prices. Empirical evidence on this issue is limited, but we find compelling evidence that points to a lack of awareness about future climate costs by investors. This strongly suggests that financial prices do not currently adequately reflect future climate costs. This concurs with the conclusion by the NGFS that “there is a strong risk that climate-related financial risks are not fully reflected in asset valuations.” (NGFS 2019a, p. 4)

Against this background, we urge both investors and financial regulators to systematically assess the climate risk exposure of their portfolio and of financial institutions that they supervise, respectively. For that, we believe that stress tests are the best way to evaluate shorter-term financial risks associated with climate change. The evidence presented in this study highlights that two key ingredients should be included in the design of such stress tests: first, the impact of swift revisions in investors’ expectations regarding future physical and transition costs, and second, the consequences of second-round effects on financial markets. Both features have a significant influence on the size of potential losses due to climate change, and both are likely to happen. Further research on the extent to which future climate costs are already priced in by financial markets, as well as a better understanding of second-round effects on financial markets, is also critical in this context.

This note is structured as follow: the next section describes the channels through which climate-related costs become financial costs and thus impact financial asset valuations. Section 3 reviews the evidence on the impact of climate-related costs on assets that have already been observed empirically. Section 4 collects the results from the available studies on the assessment of the impact of future physical and transitions costs on financial asset valuations. Section 5 presents the evidence on whether current financial markets adequately reflect future climate-related costs. Section 6 concludes and summarizes our recommendations.

2 From climate-related costs to a change in asset prices

This section describes the channels by which climate-related costs impact on equity and debt instruments’ market value. In short, the market price of a financial asset is equal to the present value of its expected future payoffs plus a risk premium. Any change in expected payoffs due to climate change will then result in an adjustment of asset prices on financial markets. To better understand how climate change can impact market prices, we thus first outline how climate-related physical and transition costs influence equity and debt instruments’ payoffs. We then focus on how climate change can lead to a revision of market participants' expectations about these payoffs. Finally, we emphasize that the market price revaluations triggered by climate change are likely to be amplified by financial markets.

2.1 CLIMATE-RELATED COSTS AND ASSET PAYOFFS

The market price of a financial asset is largely determined by its future payoffs – i.e. its future income flows. For equity instruments, payoffs are equivalent to the cash flows generated by the firm issuing the equity. For debt instruments, they are the interests paid by the borrower, as well as the final repayment of the principal. If the issuer of equity falls into bankruptcy or a debt instrument defaults, the payoffs are, for equity instruments, the liquidation value of the assets owned by the issuer, and, for debt instruments, the value of the assets posted as collateral by the issuer.

Climate-related costs are not different from any other financial costs: they decrease the income flow of the issuer of a financial instrument. This has two consequences: first, they impact the payoffs of equity instruments, by reducing the cash flows generated by the issuer. Second, they can impair the financial soundness of an issuer, which can trigger its default. Moreover, climate-related costs also impact payoffs by reducing the liquidation value of the assets owned by the issuer, in the case of equity instruments, and by decreasing the value of the assets posted as collateral by the issuer, in the case of debt instruments.

In this section, we describe in more detail the concrete channels by which climate-related costs affect the income flow of equity and debt instrument's issuers, as well as the value of the assets that they own.

Physical costs

Physical costs correspond to the economic and financial losses caused by climate-related hazards. Such hazards are divided into two categories: acute hazards and chronic hazards. Climate-related hazards are considered acute when they arise from extreme climate events such as droughts, floods and storms; they are chronic when they arise from progressive shifts in climate patterns such as increasing temperatures, sea-level rise and changes in precipitation. Costs from acute and chronic hazards comprise both their direct impacts (like e.g. damages to property or disruptions of firms' operations) and their indirect impacts (like e.g. disruptions in the supply chain or lower aggregate demand from affected markets).

Physical costs can negatively impact on asset payoffs through several channels such as reduced revenue from decreased production capacity (e.g. due to supply chain interruptions and worker absenteeism) and lower sales (e.g. due to demand shocks and transport difficulties), as well as increased operating costs (e.g. due to the need to source inputs from alternative more expensive supplies) and increased capital costs (e.g. due to damage to facilities). Physical costs can also reduce the value of issuers' assets both through direct damages e.g. to houses and factories during extreme weather events, but also through write-offs of assets situated in high-risk locations.

Transition costs

Transition costs can be defined as the costs of economic dislocation and financial losses associated with the process of adjusting toward a low-carbon economy. Three sources of transition costs are usually considered as relevant for the financial sector: changes in policy (e.g. higher carbon prices or limits on carbon emissions), changes in technology (e.g. low-carbon technologies becoming more competitive than carbon-intensive ones) and changes in market preferences (e.g. households switching toward greener consumption due to environmental concerns). All three types of change will require financial efforts for firms to adapt their business models to new economic conditions.

At the same time, not all firms will be equally impacted; winners and losers will emerge both at the sectoral and at the firm level. The availability of low-carbon alternatives to a sector and the preparedness of individual firms within a sector are key factors to consider in that context.

Transition costs can affect payoffs in several ways, including, for example, research and development expenditures in new and alternative technologies, costs to adopt and deploy new practices and processes, reduced demand for carbon-intensive products and services, as well as increased production costs due to changing input prices (e.g. for energy and water) and output requirements (e.g. for carbon emissions and waste treatment).

The transition to a low-carbon economy can also significantly affect the value of equity and debt issuers' assets: potential re-pricing of stranded fossil fuel assets is a case in point. Changes in real estate valuation due e.g. to stricter energy efficiency standards provide further illustration.

2.2 EXPECTATIONS ABOUT CLIMATE-RELATED COSTS

When the payoffs of an asset are not known in advance, the investors must rely on their forecasts to assess them and value financial assets. Expectations about future payoffs thus play a pivotal role in determining the market price of financial assets. Expected cash-flows, expected probabilities of default and expected values of liquidated assets and of collateral underpin all financial asset prices. On financial markets, asset price movements are thus highly dependent on the evolution of investors' expectations. A revision of these expectations can lead to sharp price movements. The asset price drop that happens in these cases constitutes a financial risk for investors.

We can distinguish two types of expectations revisions: a change in expectations that result from exogeneous events or an endogenous change in expectations. We describe these two different types in the case of climate change in the subsections below.

Climate-related shocks

In efficient financial markets, asset prices reflect market participants' forecasts of future cash-flows. Climate-related costs are part of that. The occurrence of an unexpected climate event might lead investors to update and revise their expectations about future climate costs and consequently about future payoffs. This translates into a change in asset price.

Acute climate hazards, like for example a flood, a storm or a drought, are very likely to trigger such asset price movements. A firm using agricultural products in its production might, for example, see the costs of its inputs significantly increase after a drought. If this firm is not able to pass these higher costs to its customers through higher prices, such an event will lower its profits over several quarters. If the drought is unexpected, then financial analysts will revise down their cash flow forecasts of this firm, and the price of its equity will fall accordingly.

The realization of transition risks can have similar effects. The introduction of policy measures such as a carbon tax by a country, for example, will impact the cash flows of local firms using carbon-intensive inputs. Financial analysts will integrate this fact in their payoffs forecasts when it becomes clear that the government will introduce such a policy and revalue assets accordingly. A technological breakthrough is another case of transition risk realization. New technologies to produce renewable energy, for example, can substantially modify the cost that firms within a sector are facing. As renewable energy becomes less costly, the firms using it as input will see their production costs decrease and their profits relatively increase compared to other firms. This will translate into a change in the relative asset prices between these firms.

Physical and transition risks may also lead investors to revise their assessment of uncertainty around future payoffs. If this uncertainty increases, investors will ask for a larger risk premium. This also translates into a fall in asset prices.

Note that a climate-related shock can potentially trigger a significant and rapid change in asset prices. Indeed, when such a shock happens, investors revise their expectation for the entire stream of future payoffs, incorporating all the costs that this firm will face in the future. Changes in costs that occur over relatively long periods of time are immediately integrated and cumulated in investors' expectations. A sharp drop in asset prices triggered by physical or policy events could amount to a 'climate Minsky moment' a scenario in which markets may be destabilized by the magnitude of losses. (Carney 2018).

Endogenous expectation revisions

Investors might also revise down their expectations about future payoffs endogenously. This is the case, e.g., when they switch to new forecasting models, revise the parameters of their current models or rely on newly available data to calibrate them. The introduction of new sources of costs into a forecasting model is a case in point for such endogenous expectation revision. This case is particularly relevant for climate-related costs. Indeed, for long these costs have been ignored or understated by financial analysts. Standard financial forecasting models were simply not integrating them. The situation is changing as the awareness of climate-related costs grows in the society. Models that integrate climate-related costs in asset valuation are now available (see, e.g., Monnin 2018) and an increasing number of investors are starting to use them.

A key question for financial risk is whether climate-related risks are sufficiently reflected in current financial markets. If they are not, then there is a risk that investors would significantly revise down their payoffs expectations once they start integrating them in their forecast. This could trigger a large downward revaluation of asset prices and thus constitute are risk for the financial sector.

2.3 AMPLIFICATION MECHANISMS ON FINANCIAL MARKETS

As described in the previous section, a revision of investors' expectation about climate-related costs can potentially lead to a downfall in asset prices. Such downward movements can then be exacerbated by the structure of financial markets itself and the way they are currently functioning. There are several channels by which an asset price downfall can be amplified (herding behavior, speculation, financial frictions, etc.). In this section, we highlight two of these mechanisms that we consider as particularly relevant in the case of climate risks.

Considering amplification mechanisms on financial markets is important because even if the direct financial risks posed by climate change might seem manageable at first sight, the asset price revaluations that they can trigger can be much larger than the initial shock. The last financial crisis illustrates this well: apparently small initial losses on the U.S. subprime mortgage market generated effects that threatened the stability of the global financial system.

Network effects

In the case of climate-related costs, an important distinction must be made between direct and indirect effects, both at the economic and the financial level. At the economic level, initial losses due to climate-related events in one sector percolate in the entire economy. Firms are not only affected by the consequences of climate change on their own activities but also by its effects on their supply chains or on their customers. Cahen-Fourot et al. (2019), for example, show that a cap on fossil fuel production would strand assets in the mining sector, but also trigger waves of asset stranding in other sectors – like, e.g., electricity and gas, coke and refined petroleum products, basic metals and transportation – through the input-output structure of the economy.

At the financial level, financial institutions that are exposed to climate risky assets will directly be impacted by a decrease in the price of these assets. But financial institutions that are not directly exposed to them might also suffer losses though their exposure to other financial institutions. Battiston et al. (2017), for example, show that the indirect exposure of European banks to climate-policy-relevant sectors is as large as their direct exposure.

Balance sheet effects

Losses in asset value can also translate into a larger decline in asset prices through balance sheet readjustments and fire-sales (see, e.g., Krishnamurthy 2010 or Shleifer and Vishny 2011). In such a case, a decline in the price of some assets deteriorates the balance sheet of investors. This might cause them to liquidate other assets, which lowers their prices and deteriorates balance sheets further. Although we are not aware the phenomenon has been considered in the literature with regards to climate related risks, such a vicious cycle induced by sell-offs may amplify the losses due to a climate event and affect assets and institutions that were not initially exposed to the shock, as well as trigger financial losses that are, overall, far larger than the direct losses due to climate risks.

3 Climate-related costs and asset prices: the evidence so far

While climate change is already influencing the economy, most of its financial effects are still ahead of us. Nonetheless, initial empirical evidence on its impact on asset prices is already starting to emerge. In this chapter, we point to economic effects, which are already empirically perceptible and relevant for asset prices: the impact of physical and transition costs on firms' profits and stock returns; and on borrowers' financial soundness. We focus our review on economy-wide studies.

3.1 Impact on firms' cash flows and stock returns

There is empirical evidence that physical and transition costs already impact on firms' cash flows, which is a key determinant of their stock performance. The next subsections present the empirical evidence of these impact on both cash flows and stock returns.

Physical costs

Droughts are a case in point for the impact of climate-related physical costs that have already reduced firms' cash flows. Hong et al. (2019) use a sample of weather data from 31 countries in the period 1985 to 2014 to show that dryer weather conditions are associated with lower profitability in the food industry. Higher temperatures are a further case in point. Addoum et al. (2019) and Hugon and Law (2019) show that, in the U.S., extremely hot summer temperatures negatively impact firms' earnings in some specific sectors. Addoum et al. (2019) find that profits are affected mainly through the consumer demand and labor productivity channels, while the crop yield channel is not an important determinant. Both studies also highlight that certain sectors or individual firms are benefiting from extreme temperature conditions, like warm autumns.

Kruttli et al. (2019) show that hurricanes, which are becoming more intense due to changes in the climate, impact stock prices in the US. They study the evolution of stock returns after hurricanes in the U.S. from 2002 to 2017 and find that within the 120 trading days after the landfall of hurricanes, the stock returns for firms operating in disaster regions are significantly lower than the returns of other firms.

Bansal et al. (2016) and Balvers et al. (2017) finds that stock returns are impacted by temperature shocks. Both studies analyze the U.S. stock market over a very long sample – 62 years for the former and 80 years for the latter. Bansal et al. (2016) also find similar evidence in a sample covering 39 countries over 42 years.

Transition costs

Evidence on transition costs are scarce as the transition to a low-carbon economy is yet to happen. Bernardini, et al. (2019) however provide some insights on how such a transition can impact firms' profits within a specific sector. For that they study the case of European electric utilities and show that, following the progressive introduction of economic incentives by the European Union to stimulate investment in renewable energy – i.e. a policy shock – the profit of electric utilities companies using non-renewable energy as input fell sharply whereas it stayed constant for companies using renewable energy as input. The negative impact on profits is transmitted to shareholders via lower stock prices.

3.2 IMPACT ON BORROWERS' FINANCIAL SOUNDNESS

Climate-related costs impose a burden on borrowers, which can lower their ability to service their debt. Some early evidence of this impact is already available for both physical and transition costs.

Physical costs

Physical damages from extreme weather events associated with climate change already affect the ability of debtors to service their loans. Noth and Schüwer (2018) study the impact of weather-related events on the performance of about 6’000 banks in the U.S. over a period from 1994 to 2012. They find that banks operating in regions hit by weather-related disasters observe higher non-performing loans and higher foreclosure ratios than other banks during the two years following an event. This significantly increases the failure probabilities of these banks. This effect holds when controlling for bank characteristics that are typically associated with bank failures, such as bank equity ratios or non-performing assets ratios. Klomp (2014) finds similar results for a sample off banks in 160 countries over the period from 1997 to 2010 that weather-related events impair the financial soundness of debtors.

Transition costs

Transition costs also impacts borrowers’ financial soundness. The measures taken by Chinese authorities to foster the transition to a low-carbon economy provide a useful case-study to highlight the impact of policy-triggered transition risks on debt instruments. Huang et al. (2019), for example, show that after the implementation of the Clean Air Action launched by the Chinese government in 2013, default rates of high-polluting firms rose by around 50%. In the same context, Cui et al. (2018) highlight that Chinese banks with a higher green credit ratio – i.e. banks that are less exposed to loans to polluting firms – experience lower non-performing loans.

4 Future Climate-related costs and asset prices: what lies in front of us?

In this chapter, we review the main estimates available in the literature for the *future* impact of physical and transition costs on financial assets. We first discuss the key initial choices that must be made in choosing the estimation methodology, we then look at the different methodological options available in each steps of the empirical estimations, and finally proceed to present and discuss the available estimates.

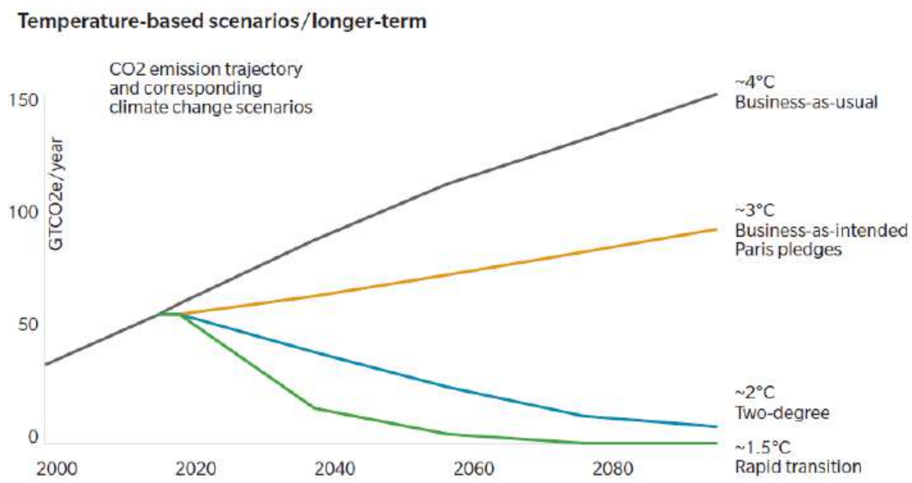
4.1 Key choices for an estimation methodology

Before estimating the future impact of physical and transition costs on financial asset prices, two important choices must be made: 1) which climate change scenarios will be used and 2) which type of scenarios do we want to analyze – long-term scenarios or stress-test scenarios?

Climate change scenarios

A necessary step in the process of investigating the future financial impact of climate-related factors is to develop assumptions on what the future might look like. These visions of the future take the form of scenarios considered both possible and relevant. In the field we are reviewing, and following the tradition of Integrated Assessment Modelling, a critical variable defining scenarios is the long-term increase in global temperatures with respect to pre-industrial averages. Common scenarios, especially in the studies focusing on transition risks, are the ones imposing a limit of 1.5°C and 2°C to temperature increase, as stated in the Paris Agreement (UNFCCC 2016). Other commonly used scenarios are those defined by policy commitments, such as the Nationally Defined Contributions (NDCs), and those which assume no transition. Figure 1 illustrates the four most common types of scenarios.

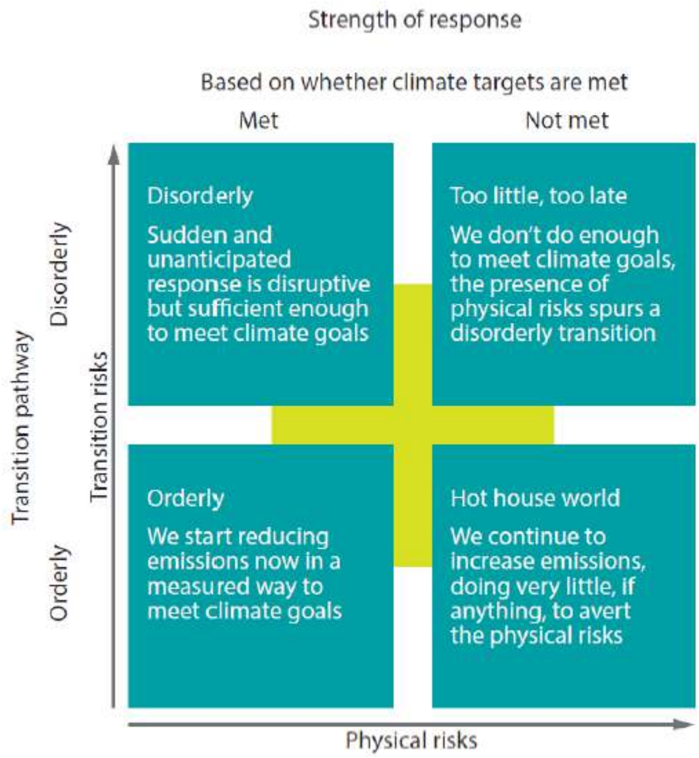
FIGURE 1: COMMON CLIMATE TRANSITION SCENARIOS



Source: Colas et al. (2019)

In addition, considerations around the shape of the transition have become increasingly important, as a specific target (e.g. 2°C) could be obtained through both a gradual non-disruptive transformation and an abrupt transition with systemic disruptions. The NGFS, for example, recommends using four different scenarios organized along two dimensions: first according to whether climate targets are met or not, and second whether the transition happens in an orderly manner or not (NGFS 2019b, p. 30). This classification generates four types of scenarios (see Figure 2): 1) an orderly transition that achieves climate goals, 2) a disorderly transition that achieves climate goals, 3) a disorderly transition that happens too late to meet the climate goals (“too little, too late”) and 4) a business-as-usual scenario with no disorderly transition but in which climate goals are not met (“hot house world”).

FIGURE 2: NGFS HIGH-LEVEL FRAMEWORK FOR SCENARIO ANALYSIS

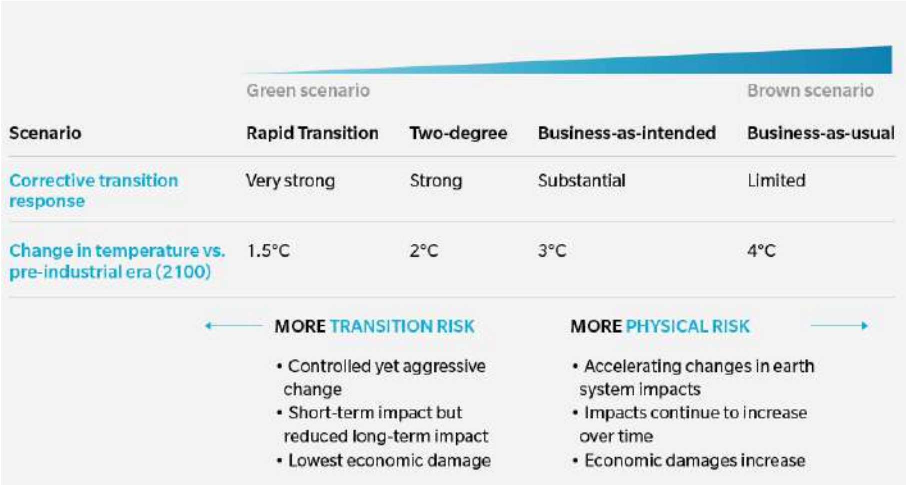


Source: NGFS (2019b)

The UK Prudential Regulatory Authority (PRA) has defined three stress test scenarios for its insurance sector (PRA 2019): i) a rapid policy action set to hit in 2022, achieving the 2°C goal through a disorderly process (a 'climate Minsky moment'); ii) an orderly transition, putting the global economy on a path to reach carbon neutrality by 2050 and keeping temperature increases well below 2°C and iii) the absence of all transition efforts. Some other studies also distinguish between an immediate and a delayed transition policy action, with the latter being more likely to create socioeconomic disruptions, as well as stronger climate impacts. HSBC (2019), for instance, distinguishes between a 2020 and a 2030 Policy Action scenario.

The choice of the specific scenarios to investigate depends on the scope of the research. For instance, studies focusing on transition risks might only look at 2°C, possibly distinguishing between different policy implementation timing or different technological development trajectories. On the other hand, studies focusing on physical impacts might limit their analysis only to emission pathways creating an increase of temperatures of 4°C or beyond. Studies can also include both transition and physical risks, typically involving a trade-off between the two (see Figure 3). Mercer (2019) and UNEP FI (2019) are examples of studies combining both physical and transition risks.

FIGURE 3: CLIMATE SCENARIOS AND RISK IMPLICATIONS



Scenario	Rapid Transition	Two-degree	Business-as-intended	Business-as-usual
	Green scenario			Brown scenario
Corrective transition response	Very strong	Strong	Substantial	Limited
Change in temperature vs. pre-industrial era (2100)	1.5°C	2°C	3°C	4°C

MORE TRANSITION RISK

- Controlled yet aggressive change
- Short-term impact but reduced long-term impact
- Lowest economic damage

MORE PHYSICAL RISK

- Accelerating changes in earth system impacts
- Impacts continue to increase over time
- Economic damages increase

Source: Colas et al. (2019)

Long-term studies vs. stress tests

Studies looking at the financial impacts of climate-related risks can be distinguished depending on whether they focus on long-term scenarios or on shock scenarios. Studies adopting a long-term perspective typically analyze the effects of different emission pathways and related temperature targets on macro- or company-level variables, with the aim of understanding whether certain portfolios would offer higher or lower average returns over the next 15, 30 or 100 years. The development of carbon-reducing technologies and the introduction of carbon prices is typically gradual and the results of the imposed emission/temperature targets, as determined by some macroeconomic and climate models. This is the case, among others, in Mercer (2019), UNEP FI (2019), HSBC (2019) and Dietz et al. (2016).

A different approach consists in imposing certain climate- or transition-related shocks to the system to see how financial variables would react in the short-term (usually one year, or slightly more). This approach is like the stress testing exercises routinely adopted to evaluate the solidity of financial institutions to tail risk (i.e. in the case of unlikely but plausible events), and consistent with the methodology typical of DSGE macroeconomic models. For instance, Vermeulen et al. (2018, 2019) look at four distinct transition scenarios characterized by a policy shock (the introduction of a global carbon price of USD 100 per ton of CO_2 emissions) or a technology shock (a doubling of the share of renewable energy in the energy mix in the coming five years), as well as both or none of the measures. CISL (2015) studies instead how different forward-looking ‘market sentiments’, i.e. expectations of financial markets about future transition patterns, affect current macroeconomic and financial variables. In other cases, stress test exercises directly impose specific financial impacts. Battiston et al. (2017) propose two different approaches to their stress test: First, they assume a 100% devaluation of the financial assets in the fossil industry (and successively in other sectors, namely utilities, energy-intensive industry, housing and transport) to estimate upper-bound losses to financial institutions. In a second test, they calculate shock distributions to the market share of three sub-sectors (fossil-fuels in the primary energy market, fossil-fuels in the secondary energy market, and renewables in the secondary energy market) and assume the changes in market shares to correspond to changes in equity before estimating banks' losses. PRA (2019) details specific impacts on the financial assets of different industries, building on the available evidence in the literature.

4.2 OPTIONS WITHIN THE DIFFERENT ESTIMATION STEPS

Once the basic choices about the scenario to study and the type of studies – long-term vs. stress tests – have been made, several specific methodological options are possible to estimate physical and transition costs. We present these options below along the different steps that characterize most methodologies (see Monnin 2018).

Economic impacts

To evaluate the impact of different scenarios on financial assets, one first needs to understand what the impact of these scenarios would be on economic variables. Broadly speaking, two main approaches are possible at this stage.

First, a 'top-down' approach can be adopted, which involves using a macroeconomic model to translate physical impacts and transition costs into effects on GDP, inflation and interest rates, prices of intermediate and consumption goods (energy commodities, in particular), changes in trade patterns, and others. These economic estimates are then translated into financial variables using additional modelling and valuation techniques (see next section). Mercer (2019), for instance, uses a macroeconometric model (E3ME) to obtain the sectoral GDP impacts of their scenarios of interest. HSBC (2019) uses an Integrated Assessment Model (TIAM-Grantham) to derive a set of trajectories for sectoral activity, emissions, energy use and carbon prices, which are then transformed into changes in company-level revenues and costs through additional bottom-up models. Vermeulen et al. (2018, 2019) use a macroeconometric model (NiGEM) to derive the impacts of their scenarios on both macroeconomic variables (GDP, inflation, etc.) and global stock prices. It then diversifies the impacts across industries by calculating their 'transition vulnerability factors' according to their level of embodied carbon emissions.

Second, one can use instead a 'bottom-up' approach, focusing directly on the company or asset level. This is the case, for instance, of UNEP-FI (2019), which uses a number of models to evaluate both the physical and transition impacts on the costs and revenues of companies.

Trucost (2019) uses different carbon price scenarios to calculate the company-level carbon costs and the resulting 'earnings at risk', before aggregating the impacts at the portfolio level.

The underlying methodological approaches and modelling structures are likely to have a strong impact on the results. Most models used assume some form of maximization, usually in the form of an intertemporal optimization of a welfare function, to determine carbon price trajectories and other macroeconomic variables, given certain emission scenarios. Others, most notably E3ME, are governed by macroeconometric functions and demand- rather than supply-driven, meaning that transition-related investments are treated as a positive increase in expenditure (and hence GDP) rather than a utility-reducing cost.

As discussed in UNEP FI (2019), the scope of the analysis, can differ quite dramatically, including a combination of some or all of the following elements: i) direct impacts on firms/sectors (in the form of direct climate-induced disruption of operations or policies imposing additional carbon costs); ii) impacts on the supply chain (in the form of climate-induced disruptions to suppliers or trade routes, or higher costs due to carbon prices being passed down the value chain from suppliers); iii) impacts on downstream markets (in the form of changes in the demand for specific goods and services); impacts on the macroeconomic environment (in the form of changes of aggregate economic activity, inflation or exchange rate).

In addition to the potential transition costs, some studies include the positive benefits of technological opportunities arising from the development of new industries (HSBC, 2019; UNEP FI, 2019). It should be noted that all studies using companies' portfolios take very specific circumstances as their base and so can only deliver partial analysis, unlikely to be representative of the reaction of the whole financial sector.

Financial impacts

The economic impacts, however calculated, need to be translated into financial impacts. Methodologies in this step strongly differ across studies.

Dietz et al. (2016), for instance, after using the DICE model to calculate the GDP impacts of different mitigation scenarios, assume corporate earnings to be a constant share of GDP in the long-run, and the value of financial assets to be a function of discounted cash flows. In Mercer (2019), a heatmap of sensitivities of different industries and asset classes is developed, to transform sectoral GDP impacts into returns for different asset classes, disaggregated by industry. In UNEP FI (2019) the present value of the projected costs and opportunities from transition and physical impacts are compared to the current market valuation of the enterprise to calculate the Climate Value at Risk of the company. Vermeulen et al. (2018, 2019) assign sector-specific transition vulnerability factors and prospected equity returns to assets and securities in 56 industries (using NACE categories). The vulnerability factors are based on the amount of carbon emissions used to generate value-added. In addition, they employ their own survey data to estimate the corporate loan exposures of the largest Dutch banks.

The approaches to evaluating the financial impact typically involve only first-round effects, i.e. they evaluate the sensitivity of firms/assets to certain scenario-induced economic trends, without considering further dynamic interactions. Battiston et al. (2017), on the other hand, introduce in their analysis a second-round effect, determined by exposure of financial institutions among themselves. These second-round effects are in some cases larger than the direct effects and might trigger wider systemic implications.

Exposure

Once the impact of future scenarios on different sectors/firms/assets has been evaluated, one can proceed to aggregate these impacts at a wider level, namely into portfolio holdings. In the literature, these can take the form of actual portfolios or just representative ones. UNEP FI (2019) considers two representative asset holdings: a 'market portfolio' composed of 30,000 companies equally weighted and a 'top 1,200 companies portfolio' closely mimicking the MSCI World Index. HSBC (2019) uses the MSCI ACWI (All Countries World Index). Mercer (2019) uses a representative growth portfolio made of a large variety of asset classes. In a similar fashion, CISL (2015) analyses four distinct portfolios representing the typical investment strategies of insurance companies ('High Fixed Income') and pension funds ('Aggressive', 'Balanced' and 'Conservative'). These include sovereign bonds, corporate bonds, and equities from both developed and emerging economies, as well as other types of asset classes.

Battiston et al. (2017) take instead the actual financial exposures of specific financial institutions. They analyze the exposure of about 80'000 disclosed equity holdings in the US and the EU to transition risk, using data from the Bureau van Dijk Orbis database. They also analyze bank loan portfolios, although a large part of their sectoral composition – and thus of the risk they are exposed to – must be inferred for a lack of data. Vermeulen et al. (2018, 2019) construct a database of the majority of the equity and bond exposures of Dutch financial institutions (that includes banks, pension funds and insurance companies), making use of the national bank's Securities Holdings Statistics. The method of looking at the financial exposure of investors to sectors/companies/assets likely to be affected by physical or transition risks has been adopted by several other works (see for instance: ESRB, 2016 and Giuzio et al., 2019), although without an explicit modulization of how the price or returns of financial assets would be affected.

Measure of impact

The results of the procedures discussed above can be presented in several forms, using several measures. Mercer (2019) uses the annualized value of the impact of climate scenarios on the portfolio return. UNEP FI (2019), as well as Dietz et al. (2016), Spedding et al. (2013), and – for their distributed shocks model – Battiston et al. (2017) calculate a 'Climate Value at Risk' (VaR), which is the present value of the costs or profits caused by each considered scenario, divided by the current market value of the company. Climate-related costs and profits reflect physical risks, transition risks and technological opportunities. CISL (2015) report the 5-year performance of the portfolios they have analyzed, for three different scenarios.

Another way of showcasing the scenario performance of asset classes or portfolios is to report the change in the net present value (NPV) of their profits (HSBC, 2019) or the change in stocks' share prices (Ralite and Thomä, 2019) in comparison to those in a baseline scenario. Vermeulen et al. (2018, 2019) and Battiston et al. (2017), in the case of their upper-bound estimates, report the asset loss feared in the respective scenarios. The latter show banks' equity losses as a percentage of total equity holdings. Vermeulen et al. (2018, 2019) report losses relative to the total assets of each sector ("total stressed assets"). In their study, they disaggregate reported equity changes into three sources of losses: changes in the risk-free interest rate; exposure to carbon intensive industries; and exposure to other industries.

4.3 AVAILABLE ESTIMATES

Table 1 summarizes the results of the main studies looking at the financial impact of climate-related risks. The next subsections present our analysis of these results.

Long-term studies

The long-term studies currently available give a homogeneous picture of the impact of physical and transition risks on financial assets: the impact is marginal in the long-term and it does not differ substantially between transition scenarios. These results must however be interpreted with a pinch of salt: the models underlying them are usually long-term macro-models in which financial markets play a smoothing role – i.e. investors do integrate climate change into their expectations and they constantly and progressively reallocate their asset portfolios. Such models do not give a good picture of what can happen on financial markets between now and the forecast horizon. For example, they are not conceived to simulate disorderly and abrupt transition paths, or to estimate the impact of the drastic changes in expectations, which could happen if investors currently do not integrate future climate costs, but suddenly revise their forecasts about them.

TABLE 1: ESTIMATIONS OF CLIMATE COSTS ON ASSET PRICES

Authors (Model used)	Type of Risk (Type of analysis)	Portfolio/ Exposure	Measure	Asset class	Time horizon	Scenarios		
						2°C	**3°C**	**4°C**
Mercer, 2019 (E3ME)	**Physical & Transition** (Long-term)	Represen-tative growth portfolio	Impact of scenario on portfolio return (year average)	Total portfolio	2030	0,11%	-0,02%	-0,07%
					2050	-0,05%	-0,09%	-0,14%
					2100	-0,07%	-0,12%	-0,18%
				Equity (developed)	2100	-0,10%	0,10%	-0,20%
				Equity (emerging)		-0,20%	-0,30%	-0,40%
				Growth bonds		0,00%	0,00%	-0,10%
						1.5°C	**2°C**	**3°C**
UNEP FI, 2019 (REMIND)	**Physical & Transition** (Long-term)	Market Portfolio of 30,000 firms	Company Climate VaR*	Equity	15 years	-4,56%	-3,36%	-1,84%
		1200 Top companies				0,05%	-0,46%	-0,80%
						2°C		
HSBC, 2019 (TIAM-Grantham)	**Transition** (Long-term)	MSCI ACWI (All countries World Index)	Change in profits relative to BAU	Equity	2050	-2%		
						2°C	**2.5°C**	
Dietz et al., 2016 (DICE)	**Physical & Transition** (Long-term)	Global stock of financial assets	Climate VaR (mean)	Equity and bonds	2100	-1,18%	-1,77%	
						2°C	**No action**	
CISL. 2015 (GEM)	**Transition** (Stress test)	High fixed income	Portfolio performance	Equity, bonds, and other assets	5 years	-3%	-4%	
		Conservative				9%	-26%	
		Balanced				17%	-30%	
		Aggressive				25%	-45%	

*refers to the ratio between present-value climate-related costs/profits and current market value.

Table 1 continued: Estimations of climate costs on asset prices

Authors (Model used)	Type of Risk (Type of analysis)	Portfolio/ Exposure	Measure	Asset class	Time horizon	Scenarios			
						Policy shock	**Tech. Shock**	**Double shock**	**Confidence shock**
Vermeulen et al., 2018 (NiGEM)	**Transition** (Stress test)	Dutch Banks	Asset loss	Equity, bonds, loans	5 years	-2,17%	-1,14%	-2,73%	-1,67%
		…Insurers				-8,12%	-2,08%	-10,83%	-2,68%
		…pension funds				-6,73%	-2,99%	-10,16%	-6,65%
						Fossil-Fuel	**Fossil-Fuel + Utilities**	**F-F + Util. + Energy-intensive**	**F-F + Util. + E-intens. + Housing + Transp.**
Battiston et al., 2017 (DebtRank)	**Transition** (Stress test: reported sectors 100% devalued)	Eurozone Banks	Total relative equity loss	equity, bonds, loans (first round)	shock occurs in 2017	2.55%	3.79%	13.18%	15.09%
				Ditto (first and second round)		6.08%*	9.75%*	27.91%*	30.24%*
	Transition (Stress test: with shock distributions)		VaR (5%)			**Fossil-Fuel Primary**	**F-F Primary + F-F Secondary**	**F-F P + Renew. Secondary**	**Renew. Secondary**
				Ditto (first round)		0.26%	0.41%	0.19%	0.06%
				Ditto (first and second round)		0.63%	0.96%	0.47%	0.13%

*reported with standard deviations

Stress test studies

Stress tests give a better picture of the risks that financial asset could be facing due to climate change in the short to medium term. Stress test scenarios are relatively severe but still plausible. Vermeulen et al. (2018, 2019) provide, in our view, the most sophisticated estimation of transition risks currently available. They show that, in the case of a transition triggered by both a policy and a technological shock, the portfolios held by Dutch insurers and pension funds, which include equities, bonds and loan instruments, could lose up to 10% of their value within 5 years. Note that his estimation does not consider neither possible second-round effects on financial markets, nor sharp expectations revisions by investors. The Value-at-Risk methodologies used by Dietz et al. (2016) also allows us to get an idea of stress test scenarios. They estimate that, with one percent probability, equity and bond market together could lose 17% of their value within 80 years if no transition happens and about 9% if the transition materializes.

The results presented above, together with others, can then be used to inform the definition of 'climate stress tests' that financial regulators can ask financial institutions to run in order to test their solidity to climate-related financial risks. One example is the new climate stress that the UK Prudential Regulatory Authority has asked insurance companies to run. The details of the stress test are shown in Table 2, where the first scenario describes a rapid and disorderly policy action with shock parameters set to hit in 2022; the second scenario describes an orderly transition, putting the global economy on a path to reach carbon neutrality in 2050; and the third scenario assumes no transition and a temperature increase of 4°C by 2100. Although these scenarios include different timeframes, the stress tests considered by the PRA simulate an instantaneous shock on the investment and liabilities. Note that the assumptions that the PRA uses in these scenarios have been put together for exploratory purposes and to ensure that firms complete the return on the same basis. The PRA underlines that "*this set of assumptions are developed for illustrative purposes only.*" (PRA 2019, p. 32). The Bank of England will run a more comprehensive stress test of the UK financial system's resilience to physical and transition risks in 2021 (see Bank of England 2019). This stress test aims at developing scenarios that are consistent with a range of possible climate pathways and integrate these pathways with macroeconomics and financial models. This exercise should provide parameters that are both more analytically grounded and coherent.

TABLE 2: PRA ILLUSTRATIVE STRESS TEST SCENARIOS

		Transition risks			Physical risks		
		Rapid and disorderly transition	Orderly transition	No Transition	Rapid and disorderly transition	Orderly transition	No Transition
Fuel extraction	Coal	-45%	-40%				
	Oil	-42%	-38%			-5%	-20%
	Gas	-25%	-15%				
Power generation	Coal	-65%	-55%				
	Oil	-35%	-30%			-5%	-20%
	Gas	-20%	-15%				
	Renewables (inc. nuclear)	10%	20%				
Transport	Automotive non EV	-30%	-10%				
	Automotive EV	15%	50%			-5%	-10%
	Marine (inc. ports)	-15%	-10%				
	Aviation (inc. airports)	-21%	-18%				
Energy intensive industries	Manufacturing heaviliy reliant on fossil fuels	-35%	-25%		-5%	-10%	-20%
	Other manufacturing	-15%	-10%		-5%	-10%	-20%
Agriculture and Food Security	Agriculture and food security sector	-65%	-50%		-5%	-10%	-20%
	Transporting/trading/supplying food	-15%	-10%			-5%	-10%
Real Estate Assets	Global Average	-10%				-15%	-30%
	North America	-10%				-15%	-30%
	Europe	-5%				-8%	-15%
	Asia and Pacific	-20%				-30%	-60%
Water utilities					-5%	-10%	-20%
Other sectors						-2%	-5%

Expectation revision and second round effects

The estimations mentioned above rely on the hypotheses that investors fully integrate climate change costs in their expectation for asset payoffs and that financial market will operate smoothly without amplifying asset price movements, through e.g. second round-effects (see Section 2.4). However, some studies do try to estimate the impact of sharp expectation revisions and of second-round effects. Their results show a significant impact on financial asset prices.

CISL (2015) estimate the impact of a sudden revision of investors' expectations about the impact of climate change on asset payoffs. Such a situation could happen when investors do not fully integrate climate costs in their forecasts, which seems to be currently the case (see Section 5) and then suddenly correct this omission. CISL estimate that such a change in investors' expectations could lead to a 40% correction within one year in the value of a balanced portfolio if investors integrate the consequences of a no transition scenario. This figure decreases to 10% in the case of a transition to a 2°C world.

Second-round effects seem also to be an important amplifying factor of climate change impact on financial markets. Battiston et al. (2017) assess how an initial transition shock would propagate in the banking sector through the cross-exposures of banks with each other. They find that such second-round effects could more than double the impact of the initial shock.

5 Do financial markets adequately price-in climate risks?

Climate-related physical and transition costs do already have an impact on financial asset prices – as documented in Chapter 3. To what extent future climate-related costs – – as outlined in Chapter 4 will result in corrections on financial markets depends on the degree to which they are already reflected in current asset prices. This chapter reviews the available empirical evidence that allows to answer this question.

Empirically, there are several ways to shed light on the question of whether climate-related financial risks are already priced-in in current markets. First, in efficient markets, if investors already integrate future climate costs in their valuations, then current information about such costs cannot be used to forecast future asset returns. Second, if analysts correctly understand the impact of climate events on asset payoffs, they should revise their payoff forecasts once such an event materializes. Third, if investors price in climate risks, then assets exposed to these risks should trade with a higher risk premium. In the next subsections, we review the empirical evidence corroborating or contradicting these tests.

5.1 PREDICTABILITY OF ASSET RETURNS

In efficient markets, investors use all available information to best forecast future payoffs and then price assets accordingly. In such a case, no information can be used to forecast asset returns. In other terms, if some piece of information is found to *ex ante* forecast the return of an asset, then it can be concluded that investors do not use this piece of information to forecast future asset payoffs – i.e. investors overlook this piece of information. In the context of climate-related costs, if information related to climate change is found to forecast future asset returns, that means that the impact of climate change on future payoffs is not adequately used by financial market participants – i.e. the impact of climate change is not priced-in.

There is some evidence that climate-related information can be used to forecast future asset returns. Hong et al. (2019), for example, find that, for a sample of 31 countries from 1985 to 2014, the trend in droughts in a country forecasts the stock returns for companies in the food industry. They conclude that "this return predictability is consistent with food stock prices underreacting to climate change risks." Kumar et al. (2019) find that firms' sensitivity to temperature anomalies forecast their stock returns. They measure firm's sensitivity by the impact of temperature anomalies in one period on its stock return in the same period and show that this measure is then able to predict firm's future stock returns. They conclude that "these findings are consistent with stock markets underreacting to firms' climate sensitivity."

5.2 FORECAST REVISIONS

Some climate-related events influence firms' profits (see Section 3.1). For example, extreme temperatures negatively impact firms' earnings in some specific sectors (Addoum et al., 2019, and Hugon and Law, 2019). If this impact is well understood by analysts, then the occurrence of such an event will lead them to revise down their earnings expectations for the firms that have been affected.

Addoum et al. (2019) test this hypothesis by looking at changes in analysts' forecasts for earnings before and after the occurrence of 8'584 extreme temperature events in the U.S. These events have been previously identified as relevant for firms' earnings. They find no evidence that analysts adjust their earnings forecasts after the firms they cover have experienced an extreme temperature event, which suggest that analysts do not fully integrate the impact of climate change in their expectations.

Griffin et al. (2015) provide a counterexample of analysts' forecasts revision after receiving news on transition risks. For that, they analyse the stock market reaction after the publication of a 2009 paper in *Nature*, which concluded that only a fraction of the world's existing oil, gas, and coal reserves could be emitted if global warming by 2050 were not to exceed 2 °C above pre-industrial levels. Griffin et al. find that this article prompted an average and permanent stock price drop of 1.5% to 2% for the largest U.S. oil and gas firms within three trading days. This result hints that investors revised their payoff forecast downward after becoming aware of possible stranded assets in the oil and gas sector. The small magnitude of the reaction contrasts however with the predictions of some analysts and commentators of a substantial decline in the shareholder value of fossil fuel companies from a carbon bubble.

5.3 CLIMATE RISK PREMIUM

Basic financial theory states that if an asset is riskier than another, then investors must be compensated with a premium to hold it. This also applies to climate risks: if an asset is exposed to higher physical and transition risks than others, then it should deliver higher returns to investors to compensate for their risk-taking. We survey evidence of such a risk premium in equities and bank loans.

Equities

Görgen et al. (2019) and Bernardini et al. (2019) find that stocks that are more exposed to transition risk deliver lower returns than others, which is inconsistent with a risk premium. Görgen et al. (2019) use a sample of about 1’600 globally listed firms over a period ranging from 2010 to 2017 and find that firms, which are more exposed to their measure of transition risk, underperform relative to other firms. Bernardini et al. (2019) focus on European electricity utilities. Their data show that firms, which were hit by a transition shock in the second part of their sample period (2013-2017), did not display higher returns on equity before the shock (2008-2012), which is a sign that the transition shock was not priced in.

Bank loans

If a firm is exposed to higher climate risks than others, then banks should also reflect this fact by charging a higher spread on loans to it. Delis et al. (2019) test this hypothesis in the context of stranded asset risk. For that, they compare the loan rate charged by banks to fossil fuel firms – along their climate policy exposure – to non-fossil fuel firms. They find that before 2015 banks did not price climate policy exposure of fossil fuel firms. After 2015, however, the risk starts to be priced, especially for firms holding more fossil fuel reserves. However, the economic significance of this risk premium is rather small and is very unlikely to match the potential losses from stranded assets.

Huang et al. (2019) find similar results: they show that after the implementation of the Clean Air Action by the Chinese authorities – i.e. after the materialization of a policy shock – Chinese banks increased the loan spread by 5.5% to high-polluting firms. Even if this increase corresponds to a higher risk premium, its size does not match the large increase in default rate observed for polluting firms after the policy shock. In short, both studies indicate that banks have started pricing climate-related risks, but not sufficiently.

6 Conclusions and recommendations

Our review of the literature highlights evidence that climate-related events do already have an impact on the performance of financial assets. Hurricanes and droughts, for example, have a negative impact on both equity and debt instruments – leading in some cases to a significant decrease in the payoffs of equities and increase in the proportion of non-performing loans. As the occurrence of such events is projected to rise substantially with climate change, their impacts on financial assets will also grow.

Forecasting the impact of future physical and transition costs comprises very long-term projections as well as shorter-term assessments. We believe that shorter-term stress tests are the best way to capture the current risks to which investors are exposed. The losses estimated with the stress tests that are available in the literature are economically significant, even with conservative methodologies. We found that expectation revisions and second round effects are likely to substantially increase initial financial losses due to climate-related events.

Whether investors currently adequately price in future physical and transition costs is crucial. The answer to this question conditions the size of potential financial losses. Empirical evidence is limited but we find convincing evidence that points to a lack of awareness about future climate costs by investors and that financial prices do not currently adequately reflect them. This concurs with the conclusion by the NGFS that "there is a strong risk that climate-related financial risks are not fully reflected in asset valuations." (NGFS 2019a, p. 4)

Against this background, we recommend investors to systematically assess the climate risks in their portfolios with a particular emphasis on the use of stress tests. In the conception of the stress test scenarios, two key dimensions should be included: first, the impact of a swift revision of market participants' expectations about future physical and transition risks should be assessed, as there are strong signals that financial markets currently do not adequately price in these costs. Furthermore, second-round financial effects should be considered in the models, as they have the potential to significantly amplify initial losses. Financial investors should also be supported by regulatory steps, such as obligatory disclosure by issuers of financial instruments of the climate financial risks, to which their underlying business is exposed. Disclosure initiatives such as the TCFD go in the right direction for that but they might fall short if they are not very widely adopted by issuers and if investors do not use the information that they provide.

Climate financial risk is also a challenge for central banks and financial regulators in charge of micro- and macro-supervisions (Campiglio et al. 2018). Here again, we urge financial authorities to use climate stress tests to assess the exposure of single financial institutions and of the financial system as a whole. When defining standard methodologies for stress tests to be performed by supervised institutions, special attention should be given to the development of relevant scenarios, such as those recently proposed by the NGFS (2019a). As for investors, we again emphasize the importance to integrate potential swift revisions of market expectations and second-round effects in the design of stress tests. When the exposure of financial institutions and of the financial system to climate risks is found to be significant, options are available to regulators to reduce it, like, e.g., systemic capital buffers (see, e.g., D'Orazio et al. 2019).

As emphasized several times in this note, whether climate risks are adequately reflected in current financial asset prices is a fundamental question. The size of future potential losses crucially depends on the answer to this question. Current academic literature offers anecdotal evidence on this matter and outlines pathways for further research on this this issue.

Finally, available empirical evidence on second round effects points to a substantial amplification of initial losses due to climate-related events, highlighting the need to include them into the design of stress tests. The methodologies to do so are in their infancy. Developing them further is critical.

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Climate Risk and Financial Stability: Evidence from Bank Lending

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Abstract

We study the impact of climate risk on banks' tail risks and systemic risk contribution. Employing climate risk measures developed using the Billion-Dollar Weather and Climate Disasters data from National Oceanic and Atmospheric Administration (NOAA) and Dealscan syndicated lending data, we find that banks' climate risk exposure acquired through the lending channel increases their tail risks and systemic risk contribution. Our results are robust to an instrumental variables approach, several alternative climate risk and systemic risk measures, and a variety of model specifications. We contribute to a growing literature on the impact climate risk on financial stability and the development towards robust measures of climate risk for banks.

Keywords: bank lending, climate change, climate risk, financial stability, systemic risk

JEL Classification: G20, G21, G30, G32, N20

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1. Introduction

What we have known simply as "climate change" for the past thirty five years is now a global crisis. According to World Economic Forum (2021), climate action failure, extreme weather conditions, and environmental damage arising from human activities are among the most likely risks that the world will be exposed to over the next decade. Regulators have paid close attention to climate change and its implications for financial stability.[1] Central banks and financial regulators have started to design scenarios for climate stress tests to gauge how vulnerable the financial system is to climate change. Despite the sense of urgency and policy significance of this topic, considerable gaps remain in the academic research. A major challenge facing both climate finance researchers and practitioners is the shortage of methodologies that facilitate robust measurement of climate risk and promote a successful assessment of the impact of climate change on financial stability (Bank for International Settlements, 2021; Battiston *et al.*, 2021). The aim of this paper is to make progress in this matter through developing a method to calibrate climate risk and to examine its impact on financial stability.

Prior studies document the effects of climate risks on both financial and nonfinancial firms. Firms that are more exposed to extremely high temperatures suffer lower revenues and operating income (Pankratz *et al.*, 2019). Climate risk is negatively associated with earnings of publicly listed firms and positively associated with their earnings and cash flows volatility, which further influences firm capital structure: firms in countries with higher climate risk tend to hold more long-term debt and cash while paying lower cash

[1]For example, the Financial Stability Board's (FSB) Task Force on Climate-related Financial Disclosures (TCFD) released its recommendations on climate risk management and disclosure for financial institutions in June 2017 with the objective of developing voluntary disclosure on climate risk. In November 2017, the Economic and Monetary Affairs Committee (EMAC) of the European Parliament issued a proposal that would amend the European Union's Capital Requirements Regulation to make climate risk management and disclosures mandatory. In July 2021, the FSB drew up a roadmap for addressing climate-related financial risks, which highlights four key interconnected blocks namely disclosures, data, vulnerabilities analysis, and regulatory practices and tools.

dividends (Huang *et al.*, 2017). Battiston *et al.* (2017) examine how climate policies affect revenues and costs for different sectors in the real economy with indirect effects on financial sectors. They find that the combined exposure to climate policy-relevant sectors is large and heterogeneous, and financial sectors are directly exposed to climate policy-relevant sectors. A further strand of literature focuses on banks' reaction to climate change, primarily reflected in the price discrimination embedded in loan pricing. Delis *et al.* (2019) show that banks started pricing climate policy risk by charging marginally higher loan rates to fossil fuel firms after 2015. Javadi and Masum (2021) document that firms in locations with higher exposure to climate risk pay significantly higher spreads on their bank loans. Similarly, Jiang *et al.* (2020) find that lender banks impose a higher cost of credit for fossil fuel firms that are subject to stricter climate policies and for firms exposed to greater sea level rise (SLR) risk. The awareness of the SLR risk is also reflected in prices in residential mortgage markets (Nguyen *et al.*, 2022).

Climate risk would appear to meet the minimal definition of a systemic risk proposed by Benoit *et al.* (2017), as the risk that many market participants are simultaneously affected by severe losses, which then spread through the system. Significant variation in levels of systemic risk has been determined conditional on the institution's noninterest income (Brunnermeier *et al.*, 2020), corporate governance (Anginer *et al.*, 2018), jurisdication (Bostandzic and Weiss, 2018), size (Laeven *et al.*, 2016; Pais and Stork, 2013), competition (Anginer *et al.*, 2014), network interdependence (Hautsch *et al.*, 2015), capital (Gauthier *et al.*, 2012) and the provision of government aid (Berger *et al.*, 2020). Despite the previously described catalyst for climate risk to contribute to bank systemic risk; however, only limited empirical support has been furnished.

Two main channels of risk transmission from climate change to financial stability have been identified: physical risks and transition risks. Physical climate risks arise when climate change causes damage to physical assets and disruption to operations of firms, generating increased credit risk for lender banks, increasing claims for insurance companies, and impairing the financial position of governments. Transition climate risks relate to unanticipated and sudden adjustments of asset prices (both positive and negative) and changes in default rates for entire asset classes due to shifts in policies, technology, and sentiment in the process of adjustment towards a low-carbon economy (Financial Stability Board, 2020). In this paper, we focus on physical climate risks.

Physical climate risks adversely affect banks in two primary ways. First, physical climate risks can directly cause damage to physical assets and accelerate depreciation of capital assets, for example, through its connection with extreme weather events such as flood, storm, or wildfire. Such impact can be offset as insurance generally covers losses due to unexpected catastrophic events. Second, a more relevant impact comes from the fact that physical climate risks can change (usually reduce) the outputs achievable with a given level of inputs, which amounts to a change in the return on capital assets. Banks' credit risk increases and loan quality declines when borrower firms' ability to repay loans is weakened by climate risk events. Dietz *et al.* (2016) document that the estimate of the impact of climate change on asset value (i.e., climate value at risk or climate VaR) is economically significant and mostly distributed in the tail. More importantly, it is difficult to model and to hedge climate risks given the unexpected nature and the long horizon over which such risks may materialize (Financial Stability Board, 2020).

We first create a bank-level climate risk measure using the Billion-Dollar Weather and Climate Disasters data from National Oceanic and Atmospheric Administration (NOAA) and Dealscan syndicated lending data. We then employ this measure to examine the effect of banks' climate risk exposure on their tail risks and systemic risk contribution based on a sample of 7,830 lender-borrower-year observations comprised of 31 lender banks and 1,778 borrower firms for the period of 1999–2017. Our identification strategy consists of three key elements: (1) lender bank and borrower firm fixed effects to control for latent constant characteristics of banks and borrowers as well as loan demand around loan origination, allowing variation in the bank-level climate risk measure to explain the remaining variation; (2) controlling of book value of loans (i.e., loan ratios) to filter out the incremental effect from syndicated lending; and (3) an instrumental variables approach that avails an exogenous source of variation in the bank-level climate risk. We find that banks' climate risk exposure acquired through the lending channel increases their tail risks and systemic risk contribution. This effect is both statistically and economically significant: An increase by one standard deviation in the bank-level climate risk measure leads to an increase of 3.1% in tail risk at 5%, 8.0% in tail risk at 1%, 8.7% in the marginal expected shortfall, 2.5% in the long-run marginal expected shortfall, 0.4% in systemic risk contribution at 5%, and 0.9% in systemic risk contribution at 1%. We perform additional tests and find that the results are robust to several alternative climate risk measures including an adjusted climate risk measure accounting for borrowers' vulnerability to climate change, a residual climate risk measure that is orthogonal to common bank risk factors, and an alternative climate risk measure computed following the Germanwatch method. Our results also hold with interaction tests that decompose the climate risk measure, with an alternative method to estimate systemic risk, with weighted least squares estimators, and with alternative methods to compute standard errors.

This paper makes several contributions. First, we contribute to the literature on systemic risk by documenting borrower firms' exposure to climate risk as a source for lender banks' systemic risk contribution. Second, we contribute to the literature on climate risk by proposing a climate risk measure that quantifies the extent to which banks have suffered direct losses due to extreme weather events such as storms, floods, heat waves, and wildfire. In contrast to the other climate risk measures that focus on, for example, heat exposure (Pankratz *et al.*, 2019), or the sea level rise (Nguyen *et al.*, 2022; Jiang *et al.*, 2020; Bernstein *et al.*, 2019), our measure captures the direct impact of economic losses due to climate change. We believe that this set of measures can create an avenue for future research that seeks to examine the impact of climate change on different aspects of social and economic life. Lastly, this paper is relevant to regulators' ongoing efforts in measuring climate risks and understanding their implications for financial stability, which also provide validation on central banks' involvement in safeguarding monetary and financial stability against climate change.

The remainder of the paper is organized as follows. Section 2 describes the data and approach employed to measure climate risk. Section 3 presents the empirical design. Section 4 presents baseline results. Section 5 reports robustness results. Section 6 concludes.

2. Measuring Climate Risk

2.1. Data

We use the Billion-Dollar Weather and Climate Disasters Data from the National Centers for Environmental Information (NCEI) database maintained by NOAA to measure the state-level climate risk. We employ extreme weather event data as physical climate risk is mostly driven by severe weather events (Li *et al.*, 2020). The NCEI database reports weather and climate disasters where overall losses equaled or exceeded $1 billion. Climate risk events are classified into seven disaster categories: drought, flooding, freeze, severe storm, tropical cyclone, wild fire, and winter storm. For the 1980–2020 reporting cycle, it reports 290 events with total human deaths of 14,492 and total losses exceeding $1.98 trillion[2], corresponding to an average of seven events and 353 deaths per year and a loss of $6.8 billion per event (NOAA, 2020).

We map the raw climate risk loss data to provide an overview of the variation in climate risk across the states. Figure 1 displays the cumulative losses due to climate risk

[2]CPI-adjusted to 2020.

events during the period of 1980–2020. Figure 2 maps the total number of climate risk events for the same period. Georgia, Mississippi, North Carolina, and Texas are among the high-risk states in terms of both loss severity and frequency over the years.

[Figure 1 and 2 about here.]

We collect data on syndicated loans from the Dealscan database maintained by the Loan Pricing Corporation (LPC). Dealscan provides comprehensive information on syndicated loans at origination, including loan amount, maturity, pricing, and identity of lenders and borrowers. A syndicated loan is facilitated by a syndicate of lenders jointly providing funding to a single borrower. The unit of observation in the Dealscan database is a facility (or tranche). A typical syndicated loan deal (or package) consists of multiple facilities initiated at the same time. A deal is arranged by sole or a few lead lenders who solicit the syndicated members and define the lending arrangement. We use the largest facility to represent the deal[3] and retain lead arrangers for each deal. Lead arrangers hold a larger loan share for signaling purposes (Sufi, 2007), make the loan pricing decisions, and are liable to reputational costs if they misprice loans. Following Bharath *et al.* (2011), we designate a bank as a lead arranger if the bank is the sole lender or the lender role is reported as *admin agent*, *agent*, *arranger*, or *lead bank* in Dealscan.

We restrict our analysis to credit lines and term loans made by US banks to domestic nonfinancial firms. We focus on credit lines and term loans because they are the dominant types of loans made by banks to nonfinancial firms (Colla *et al.*, 2013; Jiang *et al.*, 2010; Sufi, 2009). Following Chu *et al.* (2019), we define a lending observation as a credit line or term loan if it falls within one of the following categories: 364–day facility, revolver/line < 1 year, revolver/line $\geqslant 1$ year, revolver/term loan, term loan, and term loan A.

[3] Carey *et al.* (1998) and Ivashina (2009) demonstrate that this selection choice does not significantly affect the distribution of loans.

2.2. Measurement

Our approach to climate risk measurement is largely informed by the methodological framework developed by the Bank for International Settlements (2021), which involves scoring climate risk on the basis of accounting for portfolio and sectoral exposures. The measurement of climate risk comprises two major steps: We first create a state-level climate risk index (CRI_State), and then compute bank-level climate risk exposure (CRI_Bank) by weighting bank lending to a state by the climate risk index of the borrower's state (CRI_State).

The state-level climate risk index (CRI_State) quantifies the extent to which states have suffered direct loss associated with extreme weather events such as storms, floods, and heat waves. CRI_State is indicative of the severity of losses that a state suffers due to climate change, and is defined as the natural logarithm of the first principal component of six key climate risk indicators: (a) number of deaths, (b) number of deaths per 100,000 inhabitants, (c) sum of losses in USD at purchasing power parity (PPP), (d) losses per unit of Gross Domestic Product (GDP), (e) number of events, and (f) loss per event. A higher score for CRI_State corresponds to greater climate risk for state j in year t:

$$CRI\_State_{j,t} = pca(a_{j,t}, b_{j,t}, c_{j,t}, d_{j,t}, e_{j,t}, f_{j,t}). \tag{1}$$

The bank-level climate risk is the sum of a bank's lending share to an individual state weighted by the climate risk of the borrower's state, which can be expressed as follows:

$$CRI\_Bank_{i,t} = \sum \frac{L_{i,j,t}}{TL_{i,t}} CRI\_State_{j,t}, \tag{2}$$

where $L_{i,j,t}$ is the total outstanding loans made by bank i to borrowers in state j in year t. $TL_{i,t}$ is the total outstanding loans of bank i in year t. $\frac{L_{i,j,t}}{TL_{i,t}}$ measures a bank's lending share to a given state in a specific year. $CRI\_State_{j,t}$ is the climate risk index for state

j in year t as defined in Equation (1). For example, JP Morgan's lending share to Texas and Florida is 17% and 6% out of its total syndicated lending in 2016, respectively.

3. Empirical Design

3.1. Methodology

To examine the impact of bank-level climate risk on financial stability, we exploit the economic link between a lender bank and its borrower firms, and analyze how the exposure of a bank's borrowers to climate risk affects the bank's tail and systemic risk contribution. We specify our baseline model as follows:

$$Risk_{i,t} = \beta_0 + \beta_1 CRI\_Bank_{i,t-1} + \sum_{j=2}^{26} \beta_j Control_{i,t-1} + \text{FE} + \epsilon_{i,t}, \tag{3}$$

where $Risk_{i,t}$ is a set of variables of bank i at time t that is one of the following risk measures: TAIL5, TAIL1, Marginal Expected Shortfall (MES), Long-run Marginal Expected Shortfall (LRMES), ΔCoVaR5 and ΔCoVaR1. In detail, TAIL5 (TAIL1) is computed as expected shortfall (ES) at the 5% (1%) level:

$$ES_t^i = E[R_t^i | R_t^i \leqslant R_t^i(\alpha)], \tag{4}$$

where R_t^i denotes the daily stock return of bank i at time t. $R_t^i(\alpha)$ is the α quantile of bank returns. Setting α at 5% or 1%, ES measures the average return for a bank's stock during the 5% (1%) worst return days for the bank in a year.

Following Acharya *et al.* (2012), we compute MES as follows:

$$MES_t^i = E[R_t^i | R_t^m \leqslant q_\alpha], \tag{5}$$

where R_t^i is the same as previously defined; R_t^m represents the daily financial sector market return at time t; and q_α is the α quantile of market returns. Setting α=5%, MES measures the average bank equity return during the 5% worst return days for the banking industry in a year. MES quantifies the extent to which an individual bank's stock returns are low when market returns are low.

$LRMES$ is the long-run marginal expected shortfall (Acharya *et al.*, 2012) when the financial industry returns are below –2%, calculated as follows:

$$LRMES_t^i = 1 - exp(-18 \times (E[R_t^i | R_t^m < -2\%])). \tag{6}$$

We follow Adrian and Brunnermeier (2016) to estimate the time-varying $\Delta CoVaR$ for each bank at the 5% and 1% levels. Our estimation is based on quantile regressions using weekly data calculated using CRSP daily stock files for all financial institutions with two-digit Standard Industrial Classification (SIC) code between 60 and 67 inclusive.[4] We remove daily observations with missing or negative prices and retain banks with nonmissing stock return data on their ordinary common shares for a minimum of 260 weeks. We then merge the weekly stock data with quarterly balance sheet data from the CRSP/Compustat Merged dataset[5] and remove banks with book-to-market and leverage ratios that are less than zero or greater than 100.

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \epsilon_t^i, \tag{7}$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \epsilon_t^{system|i}, \tag{8}$$

where X_t^i is the daily return on the market-valued total assets of bank i at time t; X_t^{system} is the daily return of the financial system, calculated as the market-value weighted average

[4]We adjust the changes in SIC code due to conversions of several large institutions into bank holding companies.

[5]Both equity return and balance sheet data are adjusted for mergers and acquisitions.

change in asset values for financial institutions. M_{t-1} is a set of state variables that include the change in the three-month Treasury bill rate, the change in the slope of the yield curve (i.e., the spread between the composite long-term bond yield and three-month Treasury bill rate), a short-term TED spread (i.e., the difference between the three-month LIBOR rate and the three-month Treasury bill rate), the change in credit spread between Moody's seasoned BAA corporate bond yield and the ten-year Treasury rate, the weekly market return computed from the S&P 500 index, the weekly real estate sector return in excess of the financial sector return, and equity volatility calculated as the 22–day rolling standard deviation of the daily CRSP stock market return.

From the estimation of equations (5) and (6) we obtain:

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}, \tag{9}$$

$$CoVaR_t^i(q) = \hat{\alpha}_q^{system|i} + \hat{\beta}_q^{system|i} VaR_t^i(q) + \hat{\gamma}_q^{system|i} M_{t-1}, \tag{10}$$

where $\hat{\alpha}_q^i$, $\hat{\gamma}_q^i$, $\hat{\beta}_q^{system|i}$ and $\hat{\gamma}_q^{system|i}$ are coefficients obtained from quantile regressions at the 1% and 5% confidence levels. $\Delta CoVaR_t^i(q)$, which measures the marginal contribution of bank i to the risk of the system at time t, is computed as the difference between $CoVaR_t^i(q)$ conditional on the distress of the institution (i.e., q=5% or 1%) and $CoVaR_t^i(50\%)$ (i.e., the normal state of the institution):

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(50\%). \tag{11}$$

We obtain weekly $\Delta CoVaR_t^i(q)$ from the quantile regressions, and convert it to an annual frequency by first taking the mean of $\Delta CoVaR_t^i(q)$ and then applying a multiplier of 52 for each bank-year. We multiply TAIL5, TAIL1, MES, LRMES, and $\Delta CoVaR_t^i(q)$ by -1 such that higher values correspond to greater risk.

CRI_Bank is defined in Section 2.2. Our point of focus is the coefficient β_1. We control for a list of bank characteristics that are found to be relevant in explaining bank systemic risk (Brunnermeier *et al.*, 2020; Anginer *et al.*, 2018; Laeven *et al.*, 2016; Gauthier *et al.*, 2012). We include bank size (SIZE_Bank), equity ratio (EQRAT_Bank), market-to-book ratio (MTB_Bank), loans-to-assets ratio (LTA_Bank), loan loss provisioning (LLP_Bank), deposit ratio (DEPO_Bank), noninterest income ratio (NII_Bank), return on assets (ROA_Bank), operating expense management (OEM_Bank), and change in cost-to-income ratio (ΔCIR_Bank). Notably, since our *CRI_Bank* has an element of banking lending share, controlling for the book value of loans (LTA) thus allows us to gauge the incremental effect of syndicated lending in addition to bank loan books, on banks' tail risks, and systemic risk contribution.

We also control for a range of borrower firm characteristics that are relevant in explaining lending decisions and loan quality and to control for demand for credit, which include firm size (SIZE_Borrower), market-to-book ratio (MTB_Borrower), cash holding ratio (CASH_Borrower), current ratio (CURRENT_Borrower), interest coverage (COVER_Borrower), debt ratio (DEBT_Borrower), dividend payout (DPO_Borrower), profitability (EBITDA_Borrower), intangible assets ratio (INTAN_Borrower), fixed assets ratio (PPE_Borrower), and annual growth in sales revenue (ΔSALES_Borrower). We control for GDP and GDP growth (ΔGDP) for both lender and borrower states. Variable definitions are detailed in Appendix A. We also include year fixed effects in all regressions to account for economy-wide shocks on bank risk. We include bank fixed effects to control for unobservable time-invariant bank characteristics, and borrower firm fixed effects to control for latent constant characteristics of each borrowers and loan demand around loan origination. With this setup in place, variation in *CRI_Bank* explains the remaining variation. All continuous independent variables are winsorized at the 1^{st} and 99^{th} percentiles of their empirical distribution. Standard errors are adjusted for clustering at the bank-borrower lending relationship level.

3.2. Sample and Descriptive Statistics

We match borrower firms in the Dealscan database with annual financial statement information from Compustat using the linking table provided by Chava and Roberts (2008). We use data from the financial year prior to the year of loan origination to ensure that we use accounting information that is publicly available at the time of loan origination. Using the linking table provided by Schwert (2018), we merge lender banks active in Dealscan with financial statement data from Compustat. We exclude borrower firms that are located within the same state as the lender bank because our primary focus is the cross-state lending as a transmission channel for climate risk exposure, and inclusion of within-state lending would make it difficult to disentangle the impact of climate change on bank risks. We then aggregate all data at lender banks' and borrower firms' parent level to construct the "lender-borrower" sample. This sample contains information on 31 lender banks and 1,778 borrower firms between 1999 and 2017, forming a total of 7,830 lender-borrower-year observations. Table 1 reports sample composition. Panel A reports sample composition by year. Panel B reports sample composition by lender bank state. Panel C reports sample composition by borrower firm state.

[Table 1 about here.]

Table 2 presents descriptive statistics for all variables used in our analysis. For our key dependent variables, the average bank has tail risk at the 5% (−TAIL5) of 3.126%, tail risk at the 1% (−TAIL1) of 5.224%, marginal expected shortfall (−MES) of 3.623%, long-run marginal expected shortfall (−LRMES) of 0.483%, systemic risk contribution at the 5% level (−ΔCoVaR5) of 0.834%, and systemic risk contribution at the 1% level (−ΔCoVaR1) of 0.617%. For the key independent variable, the average value of CRI_Bank is 0.953, with a standard deviation of 10.038. CRI_Bank ranges from −14.893

to 29.634, with a higher value indicating greater climate risk. The average bank in our sample has log of total assets (SIZE_Bank) of 13.538 (mean total assets of $1.134 trillion), equity ratio (EQRAT_Bank) of 8.4%, market-to-book ratio (MTB_Bank) of 1.362, loans-to-assets ratio (LTA_Bank) of 44.2%, deposit ratio (DEPO_Bank) of 55.3%, noninterest income ratio (NII_Bank) of 2.5%, return on assets (ROA_Bank) of 0.9%, operating expense ratio (OEM_Bank) of 5.3%, and growth in cost-to-income ratio (ΔCIR_Bank) of −0.8%. These statistics suggest that the average bank tends to be very large, well-capitalized, and efficient although these averages may mask substantial cross-sectional and time-varying differences. Turning to the borrower controls, we find that the average borrower firm in our sample has a log of total assets (SIZE_Borrower) of 7.377 (mean total assets of $6,572 million), market-to-book ratio (MTB_Borrower) of 1.686, cash holding ratio (CASH_Borrower) of 8.1%, current ratio (CURRENT_Borrower) of 0.44, interest coverage (COVER_Borrower) of 24.172, debt ratio (DEBT_Borrower) of 29.2%, dividend payout ratio (DPO_Borrower) of 1.3%, profitability (EBITDA_Borrower) of 16.6%, intangible assets ratio (INTAN_Borrower) of 20.1%, fixed assets ratio (PPE_Borrower) of 33.4%, and growth in sales (ΔSALES_Borrower) of 14.7%. We also note that the average value of log GDP per capita is 10.871 and 10.812 for lender banks' and borrower firms' states, respectively, and average value of GDP growth (ΔGDP) is 1.315% and 1.285% for lender banks' and borrower firms' states, respectively.

[Table 2 about here.]

4. Results

Table 3 reports the baseline results from regressions of banks' tail and systemic risks on our climate risk measure and control variables. The variable of interest is CRI_Bank. We find that β_1, the coefficient for CRI_Bank, is statistically significant at the 10% level for ΔCoVaR5, at the 5% level for TAIL5 and TAIL1, and at the 1% level for MES, LRMES and ΔCoVaR1. For the purpose of interpretation, we normalize CRI_Bank so that β_1 captures the effect of a unit (one standard deviation) change in CRI_Bank on $Risk$. β_1 thus represents the percentage of additional $Risk$ generated, away from the mean $Risk$, associated with a one standard deviation increase in the pertinent CRI_Bank. A unit increase in CRI_Bank leads to an increase of 3.1% in TAIL5, 8.0% in TAIL1, 8.7% in MES, 2.5% in LRMES, 0.4% in ΔCoVaR5, and 0.9% in ΔCoVaR1. Overall, these results suggest that a higher level of climate risk acquired through the lending channel leads to greater banks' tail risks and their systemic risk contribution. Adjusted R^2 ranges from 90.7% to 96.7%, suggesting that a substantial proportion of the variation in the dependent variables are explained in the models identified.

[Table 3 about here.]

5. Robustness Tests

5.1. Instrumental Variables Approach

The instrumental variables (IV) approach is applicable to address endogeneity concerns arising from omitted variables, measurement errors and simultaneity. The IV approach successfully address endogeneity problems if the following conditions are satisfied: (1) the IV are correlated with endogenous regressors (relevance condition); (2) the IV are uncorrelated with the error term (exogeneity condition); and (3) the IV do not directly affect the dependent variable (exclusion condition). If conditions (2) and (3) are satisfied, the IV are valid. If condition (1) is satisfied but the correlations between the IVs and endogenous regressions are low, the IV are valid but weak.

The choices of IV are therefore important. We select two instruments: foreign loans as a percentage of total loans (FOREIGN) and population density (POP) of the borrower's state. These two instruments are suitable from both a theoretical and empirical perspective. A more stringent home-country climate policy is associated with an increase in banks' cross-border loan share as a means to practise regulatory arbitrage (Benincasa, 2021; Benincasa *et al.*, 2021). Albouy *et al.* (2016) find that population density is negatively correlated with climate risk such that climate risk has both a short- and long-term impact on individuals' cross-state mobility and migration preferences.

Table 4 reports results using the IV approach. *CRI_Bank* is found to have a positive and statistically significant impact on bank tail risks and systemic risk contribution across all model specifications. We perform postestimation tests including underidentification, weak identification, and overidentification tests. All six model specifications reject the under-identifying restrictions test: we reject the null hypothesis that the instruments are uncorrelated with the endogenous regressor at the 1% level. We also reject the null hypothesis of weak instruments at the 1% level, excluding instruments that are weakly correlated with the endogenous regressor. Thus, the instruments are not weak. Since we have two instruments and only one endogenous variable, we perform the Sargan-Hansen test of overidentifying restrictions: under the joint null hypothesis that the instruments are valid (i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation), the test statistic follows a χ^2 distribution in the number of overidentifying restrictions. The test rejects the null hypothesis for overidentifying restrictions across all model specifications, which indicates that the instruments are overall valid. Hence, we conclude that the potential endogeneity problem does not bias our results.

[Table 4 about here.]

5.2. *Alternative Climate Risk Measures*

In this section, we describe our use of several alternative climate risk measures to check the robustness of our results to the choice of climate risk measures. We create three alternative climate risk measures: (1) an adjusted climate risk measure that accounts for borrowers' vulnerability to climate change; (2) a residual climate risk measure that is orthogonal to common risk factors; and (3) a climate risk measure calculated using the Germanwatch method.

5.2.1. *Adjusted Climate Risk Measure*

Climate risk events can inflict damage to physical assets, deprive firms of potential revenue, and disrupt normal operations and lead to operational losses (Huang *et al.*, 2017). Industries operating on nondeployed and long-lived capital assets are more vulnerable to damage to physical assets caused by extreme weather (Wilbanks *et al.*, 2007; McCarthy *et al.*, 2001). Moreover, industries that depend on moderate weather, with a reliance on both infrastructure and an extended supply chain, are likely to experience disruptions in operations due to extreme weather conditions (Challinor *et al.*, 2014; Wilbanks *et al.*, 2007). Huang *et al.* (2017) consider agriculture, energy (including mining and oil extraction), food products, healthcare, communications, business services, and transportation as vulnerable industries. We employ the industry classification developed by ING (2020) that accounts for the extremity in different industries' sensitivity to climate conditions and classifies industries into the three categories of high, medium, and low vulnerability to climate change (Appendix B). Industries such as coal, oil and gas, air and water transportation, and construction are considered as highly vulnerable to climate change.

The varying levels of borrower firms' vulnerability to climate change is expected to affect loan quality and credit risk exposure for lender banks differently. Therefore, we calibrate an adjusted climate risk index that accounts for borrower firms' vulnerability to climate change expressed as follows:

$$CRI\_Bank\_Adj_{i,t} = \sum \frac{L_{i,j,t} W \in \{1,2,3\}}{TL_{i,t}} CRI\_State_{j,t}, \tag{12}$$

where $L_{i,j,t}$, $TL_{i,t}$, and $CRI\_State_{j,t}$ are the same as defined in Equation (1) and (2). W is a re-weighting scheme that accounts for the borrower industry's vulnerability to climate change, as reported in Appendix B. W takes a value of 1, 2, and 3 when a borrower firm's industry presents low, medium, and high vulnerability to climate change, respectively.

Results based on the use of CRI_Bank_Adj are reported in Table 5. Compared to the baseline results reported in Table 3, both the effect size and statistical significance of the climate risk variable increase across all model specifications. These findings confirm that borrowers' vulnerability to climate change has an incremental impact on the positive association between climate risk channeled through lending, and banks' tail risks and systemic risk contribution.

[Table 5 about here.]

5.2.2. Residual Climate Risk Measure

Extreme weather events may systematically influence stock market performance (Lanfear *et al.*, 2019). In order to rule out the possibility that our climate risk measure captures predominantly or acts as a proxy for the systematic effect of climate risk events on the stock market, we create an alternative climate risk measure, CRI_Bank_Res, that is orthogonal to common risk factors identified in prior studies (Fabrizi *et al.*, 2021; Bessler *et al.*, 2015; Bessler and Kurmann, 2014), including interest rate risk, credit risk, commodity risk, foreign exchange risk, market risk, political risk, real estate risk, sovereign risk, and VIX Index. A detailed description of these common risk factors is reported in Appendix C. CRI_Bank_Res is computed as the residual from the regression of CRI_Bank on these common risk factors. We find consistent results based on CRI_Bank_Res and report them in Table 6.

[Table 6 about here.]

5.2.3. Germanwatch Method

Our main construct for the state-level climate risk employs a first principal component of six key climate risk indicators: (1) number of death, (2) number of deaths per 100,000 inhabitants, (3) sum of losses in USD at purchasing power parity (PPP), (4) losses per unit of Gross Domestic Product (GDP), (5) number of events, and (6) loss per event. To check the sensitivity of our results to the method to calibrating climate risk, we apply the Germanwatch method. Each state's climate risk index is the sum of the state's score in the first four indicating categories (i.e., indicators 1 to 4):

$$CRI\_State\_GW = \frac{1}{6} \times Death + \frac{1}{3} \times \frac{Death}{Population} + \frac{1}{6} \times Loss + \frac{1}{3} \times \frac{Loss}{GDP}. \quad (13)$$

We then calculate the bank-level climate risk exposure in the same way detailed in Section 2.2 but based on the above Germanwatch state-level climate risk index. Table 7 reports results based on this alternative climate risk measure. We find consistent results across all model specifications except for the coefficient of TAIL5 (Column 1) being not significant but preserving the correct sign.

[Table 7 about here.]

5.3. Interaction Tests

The climate risk measure used in our main analysis is the sum of weighted outstanding loans by climate risk index of borrowers' states. The fact that banks experience higher tail risks and make greater systemic risk contribution could be driven by lending regardless of the borrowers' exposure to climate risk. To take this into account, we check the robustness of our results to the way bank-level climate risk is constructed by performing analyses that include the bank-level climate risk in the decomposed form (i.e., weighted loan shares; state-level climate risk of the borrower's state) and include them as an interaction term. We first define a dummy variable, CRI_State_High, that takes a value of one if the climate risk index of the borrower's state is in the top quartile of its empirical distribution, and zero otherwise. We then interact CRI_State_High with the lending share of a bank to the specific state in a given year ($Loan\_Share$); the interaction term thus captures the difference in the impact on bank risks between loans issued to borrowers in high- and low-climate risk states. Table 8 reports a positive and statistically significant coefficient for the interaction term across all model specifications, which is consistent with the main inference that loans made to borrowers in states with higher climate risk are associated with larger lender banks' tail risks and systemic risk contribution.

[Table 8 about here.]

5.4. GARCH-$\Delta CoVaR$

Our main systemic risk measure, $\Delta CoVaR$, is computed using the quantile estimation procedure detailed in Section 3. One potential shortcoming of this approach is that it models time-varying moments merely as a function of aggregate state variables (Adrian and Brunnermeier, 2016). We use the bivariate diagonal GARCH model as an alternative method to calculate the time-varying covariance between banks and the financial system, which explicitly captures the dynamic evolution of systemic risk contributions. Table 9 reports regression results based on GARCH-$\Delta CoVaR$, which is consistent with the baseline results. However, the sample size is relatively smaller than the one for the baseline test because the GARCH estimation does not converge for all banks. Our baseline results do not appear to be dependent on the estimation method used to compute $\Delta CoVaR$.

[Table 9 about here.]

5.5. *Weighted Least Squares*

Panel B of Table 1 indicates a substantial variation in the number observations across states where lender banks are headquartered. For this reason, we use state-weighted least squares estimation to control for the different weights of lender bank states in the sample. State Population is used as the weight. Results for this specification tests are reported in Panel A of Table 10. We further employ a capitalization-weighted least squares specification to account for possible greater contributions to systemic risk by larger banks. Laeven *et al.* (2016) find that larger banks have significantly higher systemic risk contributions. The weight is computed as a bank's end-of-year market capitalization divided by the total capitalization of the financial industry at the same point in time. We report results for this specification in Panel B of Table 10. Overall, results using the weighted least squares estimation provide further support for the baseline findings.

[Table 10 about here.]

5.6. *Standard Errors*

We perform two additional tests to check the robustness of our results to the method standard errors are computed. First, we cluster standard errors at borrowers' state level and obtain similar results as reported in Panel A of Table 11, with only TAIL1 being an exception. Second, we follow Newey and West (1987) to compute heteroskedasticity- and autocorrelation-consistent (HAC) standard errors that allow for up to two periods of autocorrelation, and report results in Panel B of Table 11. Overall, these results confirm that our main results are robust to different methods of calculating standard errors.

[Table 11 about here.]

6. Conclusions

This paper provides evidence that more climate risk exposure acquired through the lending channel is associated with greater banks' tail risks and systemic risk contribution. This effect is both statistically and economically significant: An increase by one standard deviation in the bank-level climate risk measure leads to an increase of 3.1% in tail risk at 5%, 8.0% in tail risk at 1%, 8.7% in the marginal expected shortfall, 2.5% in the long-run marginal expected shortfall, 0.4% in systemic risk contribution at 5%, and 0.9% in systemic risk contribution at 1%. Our analysis starts with crafting a bank-level climate risk measure using the NOAA Billion-Dollar Weather and Climate Disasters data and Dealscan syndicated lending data, followed by tests of the impact of banks' climate risk exposure on their tail risks and systemic risk contribution based on a sample of 7,830 lender-borrower-year observations comprised of 31 lender banks and 1,778 borrower firms for the period of 1999–2017. To alleviate endogeneity concerns, we employ an instrumental variables approach that avails of an exogenous source of variation in bank-level climate risk. Our results are robust to several alternative climate risk measures, including an adjusted climate risk measure accounting for borrowers' vulnerability to climate change, a residual climate risk measure that is orthogonal to common risk factors, and an alternative climate risk measure computed following the Germanwatch method. Our results also hold with interaction tests that decompose the climate risk measure, an alternative method to estimate systemic risk, weighted least squares estimators, and alternative methods to compute standard errors.

This paper addresses a recent call for developing methodologies that facilitate a successful assessment of the risks that climate change poses to financial stability (Battiston *et al.*, 2021), and provides validation on central banks' involvement in safeguarding monetary and financial stability against climate risk. We focus on the impact of physical climate risk on bank tail risks and systemic risk contribution, while remaining silent on the effects of transition climate risk. We acknowledge that the latter represents an interesting avenue for future research. Future work could, for instance, attempt to draw the dynamics of the interaction between physical and transition climate risks, and its outcomes at various levels. The major challenge in this respect is designing an identification strategy addressing the feedback effect between climate risk events and climate risk policy. Another aspect that is not considered in our setting is the effect of bank interconnectedness on climate risk transmission, which presents another opportunity for future research to explore: how do banks' climate risks transmit through a network of interconnectedness?

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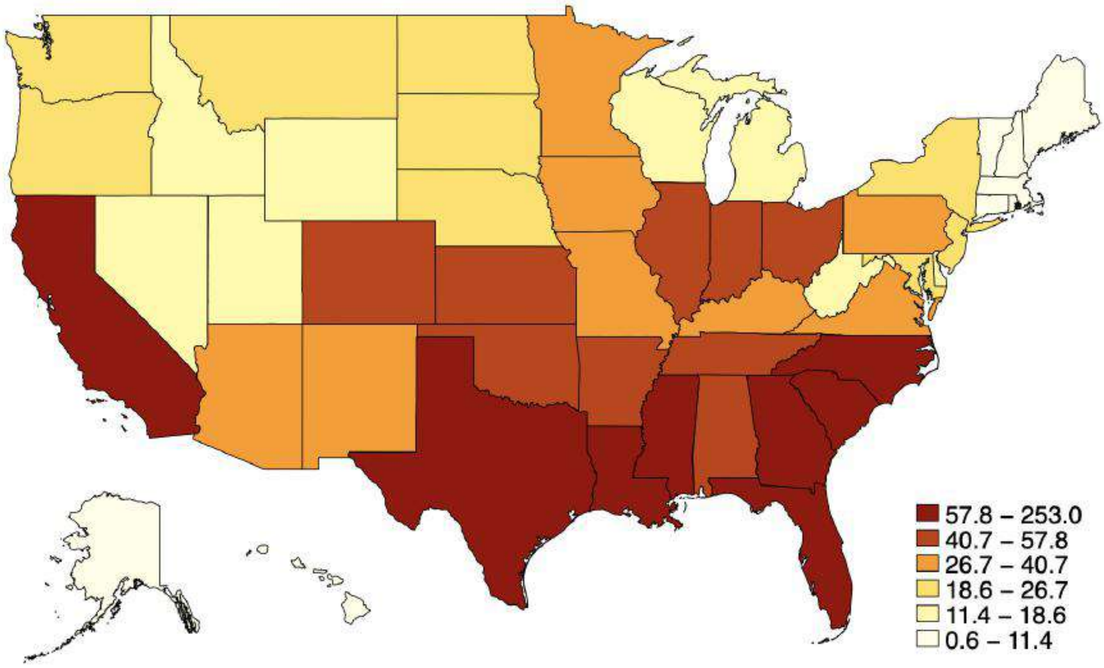

Figure 1: Cumulative Losses (USD bn) of Climate Risk Events 1980–2020

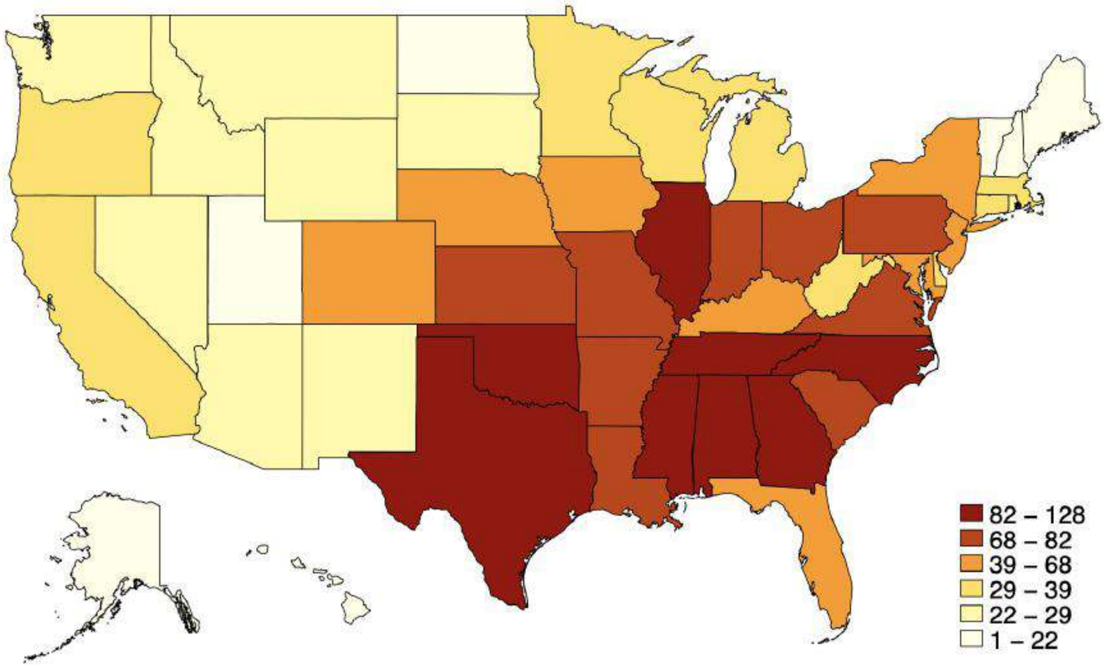

Figure 2: Cumulative Frequency of Climate Risk Events 1980–2020

Table 1: Sample Composition

This table reports the sample composition. Panel A reports the sample composition by year. Panel B reports the sample composition by lender bank state. Panel C reports the sample composition by borrower firm state.

Panel A. Sample Composition by Year

Year	Frequency	Percent	Cumulative
1999	379	4.84	4.84
2000	432	5.52	10.36
2001	491	6.27	16.63
2002	472	6.03	22.66
2003	526	6.72	29.37
2004	579	7.39	36.77
2005	589	7.52	44.29
2006	489	6.25	50.54
2007	444	5.67	56.21
2008	271	3.46	59.67
2009	246	3.14	62.81
2010	376	4.80	67.61
2011	585	7.47	75.08
2012	421	5.38	80.46
2013	408	5.21	85.67
2014	406	5.19	90.86
2015	350	4.47	95.33
2016	305	3.90	99.22
2017	61	0.78	100.00
Total	7,830	100.00	

Panel B. Sample Composition by Lender State

State	Frequency	Percent	Cumulative
Alabama	29	0.37	0.37
California	955	12.20	12.57
Georgia	217	2.77	15.34
Illinois	276	3.52	18.86
Louisiana	8	0.10	18.97
Massachusetts	191	2.44	21.40
Minnesota	156	1.99	23.40
New Jersey	3	0.04	23.44
New York	2,646	33.79	57.23
North Carolina	2,859	36.51	93.74
Ohio	186	2.38	96.12
Pennsylvania	251	3.21	99.32
Rhode Island	10	0.13	99.45
Texas	36	0.46	99.91
Utah	5	0.06	99.97
Wisconsin	2	0.03	100.00
Total	7,830	100.00	

Panel C. Sample Composition by Borrower State

State	Frequency	Percent	Cumulative
Alabama	33	0.42	0.42
Alaska	3	0.04	0.46
Arizona	161	2.06	2.52
Arkansas	76	0.97	3.49
California	509	6.50	9.99
Colorado	263	3.36	13.35
Connecticut	183	2.34	15.68
Delaware	13	0.17	15.85
Florida	390	4.98	20.83
Georgia	284	3.63	24.46
Hawaii	9	0.11	24.57
Idaho	26	0.33	24.90
Illinois	495	6.32	31.23
Indiana	132	1.69	32.91
Iowa	17	0.22	33.13
Kansas	45	0.57	33.70
Kentucky	83	1.06	34.76
Louisiana	85	1.09	35.85
Maine	12	0.15	36.00
Maryland	99	1.26	37.27
Massachusetts	247	3.15	40.42
Michigan	190	2.43	42.85
Minnesota	212	2.71	45.56
Mississippi	3	0.04	45.59
Missouri	225	2.87	48.47
Nebraska	29	0.37	48.84
Nevada	81	1.03	49.87
New Hampshire	20	0.26	50.13
New Jersey	310	3.96	54.09
New Mexico	14	0.18	54.27
New York	204	2.61	56.87
North Carolina	125	1.60	58.47
North Dakota	21	0.27	58.74
Ohio	383	4.89	63.63
Oklahoma	85	1.09	64.71
Oregon	102	1.30	66.02
Pennsylvania	291	3.72	69.73
Rhode Island	46	0.59	70.32
South Carolina	53	0.68	71.00
South Dakota	9	0.11	71.11
Tennessee	185	2.36	73.47
Texas	1,374	17.55	91.02
Utah	48	0.61	91.63
Vermont	10	0.13	91.76
Virginia	260	3.32	95.08
Washington	143	1.83	96.91
West Virginia	14	0.18	97.09
Wisconsin	228	2.91	100.00
Total	7,830	100.00	

Table 2: Descriptive Statistics

This table presents descriptive statistics of the variables studied. N refers to the number of observations. S.D. is the standard deviation. Min and Max refer to the minimum and maximum values, respectively. Variables are defined in Appendix A.

	N	Mean	S.D.	Min	Median	Max
−TAIL5	7,830	3.126	1.911	0.969	2.712	14.354
−TAIL1	7,830	5.224	3.913	1.551	4.328	27.258
−MES	7,830	3.623	2.637	0.567	3.068	14.284
−LRMES	7,830	0.483	0.185	0.100	0.480	0.973
−ΔCoVaR5	7,830	0.834	0.296	0.256	0.775	2.284
−ΔCoVaR1	7,830	0.617	0.331	0.167	0.601	2.675
CRI_Bank	7,830	0.953	10.038	-14.893	-0.849	29.634
SIZE_Bank	7,830	13.538	1.086	8.404	13.920	14.728
EQRAT_Bank	7,830	0.084	0.014	0.040	0.083	0.118
MTB_Bank	7,830	1.362	0.533	0.259	1.339	2.940
LTA_Bank	7,830	0.442	0.120	0.121	0.440	0.740
LLP_Bank	7,830	0.005	0.005	0.000	0.004	0.022
DEPO_Bank	7,830	0.553	0.094	0.247	0.552	0.864
NII_Bank	7,830	0.025	0.006	0.010	0.024	0.050
ROA_Bank	7,830	0.009	0.005	-0.006	0.010	0.019
OEM_Bank	7,830	0.053	0.015	0.028	0.054	0.134
ΔCIR_Bank	7,830	-0.008	0.096	-0.192	-0.016	0.246
GDP_Bank	7,830	10.871	0.147	10.647	10.845	11.155
ΔGDP_Bank	7,830	1.315	2.022	-5.546	1.454	5.207
SIZE_Borrower	7,830	7.337	1.662	2.015	7.312	10.929
MTB_Borrower	7,830	1.686	0.868	0.690	1.422	6.305
CASH_Borrower	7,830	0.081	0.100	0.000	0.042	0.598
CURRENT_Borrower	7,830	0.441	0.395	0.000	0.339	2.617
COVER_Borrower	7,830	24.172	60.542	-28.588	7.660	429.051
DEBT_Borrower	7,830	0.292	0.190	0.000	0.278	1.111
DPO_Borrower	7,830	0.013	0.022	0.000	0.003	0.173
EBITDA_Borrower	7,830	0.166	0.153	-0.697	0.137	0.683
INTAN_Borrower	7,830	0.201	0.198	0.000	0.139	0.750
PPE_Borrower	7,830	0.334	0.249	0.010	0.263	0.911
ΔSALES_Borrower	7,830	0.147	0.432	-0.699	0.076	4.956
GDP_Borrower	7,830	10.812	0.134	10.476	10.809	11.131
ΔGDP_Borrower	7,830	1.285	2.164	-5.463	1.407	6.020

Table 3: Baseline Results

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	0.031**	0.080**	0.087***	0.025***	0.004*	0.009***
	(2.077)	(2.152)	(4.547)	(15.156)	(1.859)	(2.744)
SIZE_Bank	-0.610***	-1.259***	-0.621***	-0.024**	-0.035***	0.094***
	(-6.454)	(-4.658)	(-4.383)	(-2.355)	(-2.609)	(5.501)
EQRAT_Bank	-13.531***	-6.218	-7.716***	-1.004***	1.461***	2.482***
	(-7.469)	(-1.478)	(-3.018)	(-4.178)	(8.201)	(9.136)
MTB_Bank	-0.753***	-1.763***	-0.661***	-0.040***	-0.020***	0.035***
	(-9.311)	(-8.266)	(-6.838)	(-5.231)	(-2.752)	(3.028)
LTA_Bank	0.583*	-1.680**	1.515***	0.010	0.316***	0.424***
	(1.741)	(-2.151)	(4.061)	(0.335)	(8.266)	(7.752)
LLP_Bank	5.293	120.632***	38.338***	7.157***	3.411***	-6.372***
	(0.561)	(6.269)	(3.491)	(7.383)	(3.380)	(-3.906)
DEPO_Bank	-1.760***	-2.806***	-1.733***	-0.093***	-0.062	0.057
	(-4.580)	(-2.704)	(-3.695)	(-2.909)	(-1.386)	(0.884)
NII_Bank	30.917***	9.567	60.605***	3.200***	4.444***	7.083***
	(5.853)	(0.836)	(9.637)	(6.610)	(8.794)	(9.274)
ROA_Bank	-67.935***	-49.993***	-107.255***	-5.330***	-5.181***	-10.009***
	(-8.777)	(-2.929)	(-11.679)	(-8.638)	(-7.529)	(-9.076)
OEM_Bank	7.071*	28.508***	-24.250***	-1.344***	-2.923***	-3.885***
	(1.709)	(2.937)	(-5.245)	(-4.847)	(-8.626)	(-6.138)
ΔCIR_Bank	-0.230	-0.458	-0.833***	-0.051***	0.023	0.082***
	(-1.582)	(-1.324)	(-4.438)	(-4.072)	(1.461)	(2.623)
GDP_Bank	5.040***	11.439***	6.702***	-0.202***	0.739***	0.448***
	(7.656)	(7.302)	(7.825)	(-3.169)	(10.515)	(4.549)
ΔGDP_Bank	0.064***	0.041**	-0.000	-0.003***	-0.006***	-0.010***
	(8.233)	(2.164)	(-0.046)	(-4.068)	(-8.257)	(-8.789)
SIZE_Borrower	0.005	-0.052	-0.017	-0.003*	-0.001	-0.004
	(0.298)	(-1.142)	(-0.764)	(-1.938)	(-0.357)	(-1.215)
MTB_Borrower	-0.015	-0.066*	-0.037**	-0.002**	-0.000	-0.003
	(-1.117)	(-1.911)	(-2.071)	(-1.988)	(-0.231)	(-1.359)
CASH_Borrower	0.030	0.354	0.313	0.021*	0.006	-0.010
	(0.190)	(0.881)	(1.535)	(1.751)	(0.370)	(-0.413)
CURRENT_Borrower	-0.001	-0.003	0.003	0.000	-0.001	-0.001
	(-0.036)	(-0.048)	(0.119)	(0.045)	(-0.406)	(-0.265)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.635)	(1.232)	(1.676)	(0.717)	(0.306)	(0.244)
DEBT_Borrower	-0.086	-0.344**	-0.076	0.000	-0.003	-0.001
	(-1.485)	(-2.149)	(-1.012)	(0.014)	(-0.352)	(-0.069)
DPO_Borrower	-0.246	0.462	-0.149	0.037	-0.077	-0.089
	(-0.558)	(0.358)	(-0.219)	(0.808)	(-1.395)	(-1.006)
EBITDA_Borrower	-0.269**	-0.549*	-0.287**	-0.006	-0.016	-0.032*
	(-2.357)	(-1.808)	(-2.074)	(-0.841)	(-1.533)	(-1.744)
INTAN_Borrower	0.068	0.226	0.177	0.020**	0.005	0.005
	(0.587)	(0.788)	(1.276)	(2.077)	(0.366)	(0.264)
PPE_Borrower	0.012	-0.003	0.141	0.016	-0.003	-0.003
	(0.078)	(-0.008)	(0.786)	(1.391)	(-0.177)	(-0.116)
ΔSALES_Borrower	0.018	0.056	0.047**	0.001	0.002	0.001
	(1.076)	(1.350)	(2.216)	(0.563)	(0.841)	(0.302)
GDP_Borrower	-0.012	0.468	-0.128	-0.038**	-0.005	-0.009
	(-0.055)	(0.844)	(-0.535)	(-2.234)	(-0.196)	(-0.215)
ΔGDP_Borrower	0.008*	0.013	0.012**	0.000	0.000	-0.000
	(1.695)	(0.987)	(2.017)	(0.729)	(0.068)	(-0.297)
Constant	-41.018***	-103.337***	-56.918***	3.626***	-6.773***	-5.699***
	(-5.909)	(-6.312)	(-6.436)	(5.663)	(-9.410)	(-5.255)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Table 4: Instrumental Variables Approach Results

This table reports instrumental variables two-stage least squares regression results of the impact of the banks' climate risk exposure on their tail and systemic risks. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	2.891***	4.324***	2.397***	0.135***	0.067**	0.589***
	(4.550)	(4.027)	(4.265)	(4.394)	(2.184)	(4.666)
SIZE_Bank	-2.897***	-4.652***	-2.468***	-0.112***	-0.086***	-0.826***
	(-5.429)	(-5.160)	(-5.228)	(-4.347)	(-3.319)	(-4.762)
EQRAT_Bank	-18.658***	-13.826**	-11.856***	-1.201***	1.347***	3.540***
	(-5.351)	(-2.346)	(-3.844)	(-7.128)	(7.974)	(4.760)
MTB_Bank	-1.528***	-2.913***	-1.286***	-0.070***	-0.038***	-0.177***
	(-7.163)	(-8.083)	(-6.818)	(-6.761)	(-3.646)	(-3.190)
LTA_Bank	2.895***	1.750	3.382***	0.098***	0.368***	-0.085
	(3.807)	(1.362)	(5.026)	(2.671)	(9.981)	(-0.553)
LLP_Bank	82.138***	234.644***	100.395***	10.102***	5.121***	-28.318***
	(3.666)	(6.198)	(5.066)	(9.332)	(4.719)	(-6.862)
DEPO_Bank	-9.516***	-14.313***	-7.996***	-0.390***	-0.235***	-0.843***
	(-5.140)	(-4.576)	(-4.883)	(-4.361)	(-2.621)	(-2.932)
NII_Bank	28.143***	5.451	58.364***	3.094***	4.383***	15.726***
	(3.430)	(0.393)	(8.041)	(7.804)	(11.026)	(7.702)
ROA_Bank	-6.901	40.561	-57.967***	-2.991***	-3.823***	-21.512***
	(-0.381)	(1.324)	(-3.615)	(-3.415)	(-4.354)	(-7.661)
OEM_Bank	-41.025***	-42.851**	-63.091***	-3.187***	-3.993***	-18.673***
	(-3.306)	(-2.044)	(-5.748)	(-5.315)	(-6.643)	(-7.059)
ΔCIR_Bank	4.108***	5.979***	2.670***	0.115**	0.120**	0.761***
	(4.085)	(3.518)	(3.002)	(2.373)	(2.460)	(4.032)
GDP_Bank	3.401***	9.007***	5.378***	-0.264***	0.702***	3.153***
	(3.069)	(4.811)	(5.488)	(-4.940)	(13.085)	(8.436)
ΔGDP_Bank	0.146***	0.163***	0.066***	-0.000	-0.004***	-0.011***
	(6.217)	(4.114)	(3.178)	(-0.280)	(-3.594)	(-2.882)
SIZE_Borrower	0.020	-0.030	-0.005	-0.002	-0.000	-0.007
	(0.452)	(-0.410)	(-0.133)	(-1.140)	(-0.206)	(-0.924)
MTB_Borrower	0.012	-0.026	-0.015	-0.001	0.000	-0.006
	(0.374)	(-0.472)	(-0.530)	(-0.893)	(0.170)	(-1.085)
CASH_Borrower	0.638*	1.256**	0.804***	0.045***	0.019	0.019
	(1.813)	(2.114)	(2.584)	(2.633)	(1.142)	(0.314)
CURRENT_Borrower	-0.056	-0.084	-0.041	-0.002	-0.003	-0.008
	(-0.982)	(-0.877)	(-0.818)	(-0.733)	(-0.915)	(-0.824)
COVER_Borrower	0.001	0.001	0.000	0.000	0.000	-0.000
	(1.356)	(1.173)	(1.397)	(0.794)	(0.495)	(-0.272)
DEBT_Borrower	-0.176	-0.477*	-0.148	-0.003	-0.005	-0.017
	(-1.136)	(-1.822)	(-1.083)	(-0.449)	(-0.606)	(-0.630)
DPO_Borrower	-2.684**	-3.156	-2.118*	-0.057	-0.131**	-0.446**
	(-2.101)	(-1.462)	(-1.874)	(-0.918)	(-2.113)	(-2.002)
EBITDA_Borrower	-0.365*	-0.692**	-0.364**	-0.010	-0.018*	-0.021
	(-1.870)	(-2.096)	(-2.106)	(-1.049)	(-1.910)	(-0.606)
INTAN_Borrower	0.485*	0.846*	0.514**	0.036***	0.014	0.017
	(1.809)	(1.865)	(2.167)	(2.772)	(1.067)	(0.367)
PPE_Borrower	0.480	0.693	0.520*	0.034**	0.008	0.027
	(1.466)	(1.251)	(1.792)	(2.176)	(0.486)	(0.470)
ΔSALES_Borrower	-0.014	0.009	0.021	-0.000	0.001	-0.004
	(-0.315)	(0.125)	(0.553)	(-0.115)	(0.581)	(-0.497)
GDP_Borrower	-0.282	0.068	-0.346	-0.048*	-0.011	-0.049
	(-0.514)	(0.073)	(-0.714)	(-1.823)	(-0.428)	(-0.503)
ΔGDP_Borrower	0.012	0.018	0.015	0.000	0.000	-0.000
	(1.063)	(0.977)	(1.534)	(0.844)	(0.212)	(-0.174)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Underidentification (P-value)	0.000	0.000	0.000	0.000	0.000	0.000
Weak identification (F-statistic)	11.751***	11.751***	11.751***	11.751***	11.751***	11.751***
Overidentification (P-value)	0.843	0.681	0.733	0.252	0.230	0.303
Observations	7,830	7,830	7,830	7,830	7,830	7,830

Table 5: Alternative Climate Risk Measure: Adjusting for Borrowers' Vulnerability to Climate Change

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks based on the use of an alternative climate risk measure adjusting for borrowers' vulnerability to climate change. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank_Adj	0.064***	0.122***	0.112***	0.025***	0.006***	0.012***
	(4.076)	(3.143)	(5.576)	(15.451)	(2.919)	(3.512)
SIZE_Bank	-0.634***	-1.289***	-0.637***	-0.023**	-0.036***	0.092***
	(-6.687)	(-4.761)	(-4.480)	(-2.233)	(-2.715)	(5.378)
EQRAT_Bank	-13.702***	-6.507	-7.955***	-1.046***	1.447***	2.455***
	(-7.535)	(-1.544)	(-3.106)	(-4.307)	(8.128)	(9.046)
MTB_Bank	-0.764***	-1.780***	-0.672***	-0.041***	-0.021***	0.034***
	(-9.409)	(-8.311)	(-6.918)	(-5.289)	(-2.844)	(2.895)
LTA_Bank	0.598*	-1.668**	1.514***	0.005	0.317***	0.424***
	(1.795)	(-2.142)	(4.064)	(0.160)	(8.271)	(7.756)
LLP_Bank	6.737	122.829***	39.976***	7.353***	3.519***	-6.185***
	(0.710)	(6.385)	(3.633)	(7.521)	(3.484)	(-3.778)
DEPO_Bank	-1.857***	-2.935***	-1.813***	-0.094***	-0.069	0.047
	(-4.845)	(-2.828)	(-3.863)	(-2.946)	(-1.519)	(0.730)
NII_Bank	30.547***	8.879	59.989***	3.071***	4.412***	7.015***
	(5.795)	(0.774)	(9.575)	(6.365)	(8.724)	(9.166)
ROA_Bank	-66.604***	-47.896***	-105.633***	-5.104***	-5.079***	-9.825***
	(-8.602)	(-2.797)	(-11.513)	(-8.219)	(-7.372)	(-8.867)
OEM_Bank	6.430	27.634***	-24.816***	-1.366***	-2.967***	-3.952***
	(1.544)	(2.832)	(-5.326)	(-4.913)	(-8.763)	(-6.218)
ΔCIR_Bank	-0.166	-0.366	-0.771***	-0.046***	0.028*	0.090***
	(-1.114)	(-1.034)	(-4.003)	(-3.651)	(1.724)	(2.809)
GDP_Bank	4.940***	11.259***	6.546***	-0.233***	0.730***	0.431***
	(7.475)	(7.141)	(7.645)	(-3.644)	(10.352)	(4.347)
ΔGDP_Bank	0.065***	0.043**	0.001	-0.003***	-0.006***	-0.010***
	(8.359)	(2.273)	(0.113)	(-3.823)	(-8.084)	(-8.562)
SIZE_Borrower	0.006	-0.051	-0.016	-0.003*	-0.001	-0.004
	(0.318)	(-1.131)	(-0.746)	(-1.894)	(-0.345)	(-1.198)
MTB_Borrower	-0.015	-0.066*	-0.037**	-0.002**	-0.000	-0.003
	(-1.101)	(-1.906)	(-2.069)	(-2.007)	(-0.221)	(-1.352)
CASH_Borrower	0.038	0.364	0.319	0.021*	0.006	-0.009
	(0.238)	(0.906)	(1.567)	(1.750)	(0.401)	(-0.384)
CURRENT_Borrower	-0.001	-0.004	0.003	0.000	-0.001	-0.001
	(-0.064)	(-0.062)	(0.101)	(0.050)	(-0.419)	(-0.277)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.662)	(1.249)	(1.703)	(0.777)	(0.321)	(0.266)
DEBT_Borrower	-0.088	-0.346**	-0.077	0.000	-0.003	-0.001
	(-1.508)	(-2.161)	(-1.027)	(0.008)	(-0.363)	(-0.079)
DPO_Borrower	-0.269	0.436	-0.162	0.039	-0.078	-0.090
	(-0.609)	(0.337)	(-0.237)	(0.865)	(-1.422)	(-1.025)
EBITDA_Borrower	-0.269**	-0.549*	-0.285**	-0.006	-0.016	-0.031*
	(-2.347)	(-1.802)	(-2.061)	(-0.773)	(-1.528)	(-1.738)
INTAN_Borrower	0.073	0.232	0.181	0.020**	0.005	0.005
	(0.630)	(0.809)	(1.302)	(2.059)	(0.389)	(0.286)
PPE_Borrower	0.017	0.003	0.144	0.016	-0.002	-0.002
	(0.113)	(0.009)	(0.806)	(1.372)	(-0.156)	(-0.098)
ΔSALES_Borrower	0.017	0.055	0.046**	0.001	0.002	0.001
	(1.044)	(1.328)	(2.186)	(0.517)	(0.823)	(0.281)
GDP_Borrower	-0.012	0.471	-0.125	-0.037**	-0.005	-0.008
	(-0.055)	(0.851)	(-0.523)	(-2.168)	(-0.192)	(-0.207)
ΔGDP_Borrower	0.008*	0.013	0.012**	0.000	0.000	-0.000
	(1.688)	(0.980)	(2.000)	(0.657)	(0.059)	(-0.311)
Constant	-39.505***	-100.868***	-54.939***	3.938***	-6.654***	-5.477***
	(-5.657)	(-6.104)	(-6.189)	(6.112)	(-9.181)	(-4.984)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Table 6: Alternative Climate Risk Measure: Residual Climate Risk

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks based on the use of an alternative climate risk measure computed as a residual of common risk factors. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank_Res	0.015**	0.040**	0.043***	0.013***	0.002*	0.005***
	(2.077)	(2.152)	(4.547)	(15.156)	(1.859)	(2.744)
SIZE_Bank	-0.610***	-1.259***	-0.621***	-0.024**	-0.035***	0.094***
	(-6.454)	(-4.658)	(-4.383)	(-2.355)	(-2.609)	(5.501)
EQRAT_Bank	-13.531***	-6.218	-7.716***	-1.004***	1.461***	2.482***
	(-7.469)	(-1.478)	(-3.018)	(-4.178)	(8.201)	(9.136)
MTB_Bank	-0.753***	-1.763***	-0.661***	-0.040***	-0.020***	0.035***
	(-9.311)	(-8.266)	(-6.838)	(-5.231)	(-2.752)	(3.028)
LTA_Bank	0.583*	-1.680**	1.515***	0.010	0.316***	0.424***
	(1.741)	(-2.151)	(4.061)	(0.335)	(8.266)	(7.752)
LLP_Bank	5.293	120.632***	38.338***	7.157***	3.411***	-6.372***
	(0.561)	(6.269)	(3.491)	(7.383)	(3.380)	(-3.906)
DEPO_Bank	-1.760***	-2.806***	-1.733***	-0.093***	-0.062	0.057
	(-4.580)	(-2.704)	(-3.695)	(-2.909)	(-1.386)	(0.884)
NII_Bank	30.917***	9.567	60.605***	3.200***	4.444***	7.083***
	(5.853)	(0.836)	(9.637)	(6.610)	(8.794)	(9.274)
ROA_Bank	-67.935***	-49.993***	-107.255***	-5.330***	-5.181***	-10.009***
	(-8.777)	(-2.929)	(-11.679)	(-8.638)	(-7.529)	(-9.076)
OEM_Bank	7.071*	28.508***	-24.250***	-1.344***	-2.923***	-3.885***
	(1.709)	(2.937)	(-5.245)	(-4.847)	(-8.626)	(-6.138)
ΔCIR_Bank	-0.230	-0.458	-0.833***	-0.051***	0.023	0.082***
	(-1.582)	(-1.324)	(-4.438)	(-4.072)	(1.461)	(2.623)
GDP_Bank	5.040***	11.439***	6.702***	-0.202***	0.739***	0.448***
	(7.656)	(7.302)	(7.825)	(-3.169)	(10.515)	(4.549)
ΔGDP_Bank	0.064***	0.041**	-0.000	-0.003***	-0.006***	-0.010***
	(8.233)	(2.164)	(-0.046)	(-4.068)	(-8.257)	(-8.789)
SIZE_Borrower	0.005	-0.052	-0.017	-0.003*	-0.001	-0.004
	(0.298)	(-1.142)	(-0.764)	(-1.938)	(-0.357)	(-1.215)
MTB_Borrower	-0.015	-0.066*	-0.037**	-0.002**	-0.000	-0.003
	(-1.117)	(-1.911)	(-2.071)	(-1.988)	(-0.231)	(-1.359)
CASH_Borrower	0.030	0.354	0.313	0.021*	0.006	-0.010
	(0.190)	(0.881)	(1.535)	(1.751)	(0.370)	(-0.413)
CURRENT_Borrower	-0.001	-0.003	0.003	0.000	-0.001	-0.001
	(-0.036)	(-0.048)	(0.119)	(0.045)	(-0.406)	(-0.265)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.635)	(1.232)	(1.676)	(0.717)	(0.306)	(0.244)
DEBT_Borrower	-0.086	-0.344**	-0.076	0.000	-0.003	-0.001
	(-1.485)	(-2.149)	(-1.012)	(0.014)	(-0.352)	(-0.069)
DPO_Borrower	-0.246	0.462	-0.149	0.037	-0.077	-0.089
	(-0.558)	(0.358)	(-0.219)	(0.808)	(-1.395)	(-1.006)
EBITDA_Borrower	-0.269**	-0.549*	-0.287**	-0.006	-0.016	-0.032*
	(-2.357)	(-1.808)	(-2.074)	(-0.841)	(-1.533)	(-1.744)
INTAN_Borrower	0.068	0.226	0.177	0.020**	0.005	0.005
	(0.587)	(0.788)	(1.276)	(2.077)	(0.366)	(0.264)
PPE_Borrower	0.012	-0.003	0.141	0.016	-0.003	-0.003
	(0.078)	(-0.008)	(0.786)	(1.391)	(-0.177)	(-0.116)
ΔSALES_Borrower	0.018	0.056	0.047**	0.001	0.002	0.001
	(1.076)	(1.350)	(2.216)	(0.563)	(0.841)	(0.302)
GDP_Borrower	-0.012	0.468	-0.128	-0.038**	-0.005	-0.009
	(-0.055)	(0.844)	(-0.535)	(-2.234)	(-0.196)	(-0.215)
ΔGDP_Borrower	0.008*	0.013	0.012**	0.000	0.000	-0.000
	(1.695)	(0.987)	(2.017)	(0.729)	(0.068)	(-0.297)
Constant	-41.018***	-103.337***	-56.918***	3.626***	-6.773***	-5.699***
	(-5.909)	(-6.312)	(-6.436)	(5.663)	(-9.410)	(-5.255)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Table 7: Alternative Climate Risk Measure: Germanwatch Method

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks based on the use of an alternative climate risk measure computed using the Germanwatch method. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank_GW	0.025	0.122*	0.206***	0.016***	0.019***	0.024***
	(0.970)	(1.723)	(5.642)	(5.792)	(5.899)	(4.287)
SIZE_Bank	-0.604***	-1.286***	-0.705***	-0.016	-0.046***	0.083***
	(-6.266)	(-4.461)	(-4.772)	(-1.621)	(-3.389)	(4.736)
EQRAT_Bank	-13.437***	-5.886	-7.241***	-0.935***	1.497***	2.536***
	(-7.437)	(-1.398)	(-2.829)	(-3.873)	(8.352)	(9.245)
MTB_Bank	-0.742***	-1.729***	-0.616***	-0.032***	-0.017**	0.040***
	(-9.291)	(-8.142)	(-6.389)	(-4.143)	(-2.354)	(3.539)
LTA_Bank	0.556*	-1.757**	1.423***	-0.012	0.311***	0.414***
	(1.659)	(-2.254)	(3.845)	(-0.428)	(7.862)	(7.401)
LLP_Bank	5.671	124.453***	46.045***	7.237***	4.241***	-5.436***
	(0.591)	(6.283)	(4.220)	(7.283)	(4.178)	(-3.253)
DEPO_Bank	-1.756***	-2.983***	-2.159***	-0.074**	-0.114**	0.004
	(-4.385)	(-2.615)	(-4.236)	(-2.327)	(-2.413)	(0.056)
NII_Bank	30.590***	7.882	57.726***	3.001***	4.175***	6.742***
	(5.848)	(0.690)	(9.324)	(6.044)	(8.008)	(8.652)
ROA_Bank	-68.528***	-51.364***	-108.542***	-5.826***	-5.204***	-10.139***
	(-8.889)	(-3.025)	(-11.841)	(-9.167)	(-7.622)	(-9.327)
OEM_Bank	7.333*	28.576***	-24.937***	-1.081***	-3.061***	-3.983***
	(1.761)	(2.928)	(-5.352)	(-3.961)	(-9.251)	(-6.369)
ΔCIR_Bank	-0.275**	-0.568*	-0.947***	-0.088***	0.020	0.071**
	(-2.030)	(-1.776)	(-5.381)	(-7.375)	(1.286)	(2.379)
GDP_Bank	5.053***	11.464***	6.716***	-0.190***	0.738***	0.449***
	(7.710)	(7.368)	(7.893)	(-2.958)	(10.582)	(4.591)
ΔGDP_Bank	0.062***	0.037**	-0.005	-0.004***	-0.006***	-0.010***
	(8.175)	(1.977)	(-0.525)	(-5.089)	(-8.775)	(-9.562)
SIZE_Borrower	0.005	-0.053	-0.018	-0.003**	-0.001	-0.004
	(0.282)	(-1.166)	(-0.833)	(-2.025)	(-0.410)	(-1.269)
MTB_Borrower	-0.015	-0.066*	-0.036**	-0.003**	-0.000	-0.003
	(-1.117)	(-1.895)	(-2.006)	(-2.003)	(-0.108)	(-1.282)
CASH_Borrower	0.024	0.340	0.299	0.016	0.006	-0.012
	(0.152)	(0.845)	(1.469)	(1.309)	(0.346)	(-0.474)
CURRENT_Borrower	-0.000	-0.001	0.004	0.001	-0.001	-0.001
	(-0.013)	(-0.025)	(0.160)	(0.255)	(-0.398)	(-0.241)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.632)	(1.233)	(1.703)	(0.665)	(0.355)	(0.283)
DEBT_Borrower	-0.086	-0.342**	-0.074	0.001	-0.003	-0.001
	(-1.468)	(-2.135)	(-0.990)	(0.141)	(-0.350)	(-0.053)
DPO_Borrower	-0.227	0.491	-0.141	0.053	-0.080	-0.089
	(-0.516)	(0.381)	(-0.207)	(1.147)	(-1.442)	(-1.005)
EBITDA_Borrower	-0.270**	-0.556*	-0.299**	-0.007	-0.017*	-0.033*
	(-2.370)	(-1.833)	(-2.176)	(-0.871)	(-1.679)	(-1.849)
INTAN_Borrower	0.066	0.225	0.183	0.018*	0.006	0.006
	(0.568)	(0.787)	(1.326)	(1.832)	(0.452)	(0.304)
PPE_Borrower	0.007	-0.012	0.133	0.013	-0.003	-0.003
	(0.049)	(-0.033)	(0.747)	(1.076)	(-0.175)	(-0.147)
ΔSALES_Borrower	0.018	0.054	0.043**	0.001	0.002	0.001
	(1.061)	(1.307)	(2.077)	(0.511)	(0.688)	(0.184)
GDP_Borrower	-0.013	0.456	-0.154	-0.038**	-0.008	-0.012
	(-0.060)	(0.821)	(-0.639)	(-2.163)	(-0.292)	(-0.290)
ΔGDP_Borrower	0.008*	0.013	0.012*	0.000	-0.000	-0.000
	(1.675)	(0.958)	(1.932)	(0.557)	(-0.024)	(-0.381)
Constant	-41.237***	-102.947***	-55.299***	3.371***	-6.534***	-5.488***
	(-5.962)	(-6.394)	(-6.313)	(5.166)	(-9.036)	(-5.029)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.944	0.907	0.953	0.951	0.967	0.938

Table 8: Interaction Tests

The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
Loan Share	-0.015	-0.026	0.012	-0.004***	-0.000	0.000
	(-1.389)	(-0.907)	(0.946)	(-4.720)	(-0.291)	(0.074)
CRI_State_High	-0.074***	-0.215***	-0.102***	-0.009***	-0.002	-0.005
	(-3.309)	(-3.680)	(-3.748)	(-4.568)	(-0.895)	(-1.287)
Loan Share×CRI_State_High	0.065***	0.151***	0.081***	0.011***	0.006***	0.007***
	(7.559)	(6.966)	(7.444)	(12.032)	(5.406)	(4.642)
SIZE_Bank	-0.591***	-1.205***	-0.562***	-0.005	-0.033**	0.100***
	(-6.434)	(-4.499)	(-4.125)	(-0.559)	(-2.534)	(6.233)
EQRAT_Bank	-13.662***	-6.518	-7.995***	-0.983***	1.438***	2.460***
	(-7.526)	(-1.545)	(-3.077)	(-3.986)	(8.031)	(9.029)
MTB_Bank	-0.746***	-1.742***	-0.636***	-0.034***	-0.020***	0.037***
	(-9.350)	(-8.230)	(-6.606)	(-4.357)	(-2.670)	(3.286)
LTA_Bank	0.585*	-1.688**	1.493***	-0.007	0.318***	0.421***
	(1.746)	(-2.157)	(3.997)	(-0.227)	(8.242)	(7.592)
LLP_Bank	5.544	121.047***	37.665***	6.644***	3.428***	-6.475***
	(0.589)	(6.249)	(3.422)	(6.685)	(3.387)	(-4.001)
DEPO_Bank	-1.739***	-2.727***	-1.603***	-0.034	-0.061	0.071
	(-4.540)	(-2.626)	(-3.449)	(-1.110)	(-1.357)	(1.130)
NII_Bank	30.514***	8.565	59.674***	3.173***	4.386***	7.008***
	(5.817)	(0.753)	(9.550)	(6.445)	(8.628)	(9.122)
ROA_Bank	-68.241***	-50.850***	-108.328***	-5.823***	-5.206***	-10.139***
	(-8.888)	(-3.008)	(-11.848)	(-9.182)	(-7.579)	(-9.251)
OEM_Bank	7.437*	29.592***	-22.717***	-0.960***	-2.871***	-3.733***
	(1.828)	(3.100)	(-5.067)	(-3.501)	(-8.552)	(-6.050)
ΔCIR_Bank	-0.290**	-0.619*	-0.991***	-0.090***	0.017	0.067**
	(-2.141)	(-1.933)	(-5.679)	(-7.624)	(1.112)	(2.236)
GDP_Bank	4.958***	11.237***	6.526***	-0.199***	0.727***	0.435***
	(7.586)	(7.273)	(7.691)	(-3.045)	(10.311)	(4.424)
ΔGDP_Bank	0.064***	0.041**	-0.001	-0.004***	-0.006***	-0.010***
	(8.312)	(2.159)	(-0.138)	(-4.600)	(-8.254)	(-9.019)
SIZE_Borrower	0.001	-0.063	-0.028	-0.004**	-0.001	-0.005
	(0.037)	(-1.373)	(-1.235)	(-2.269)	(-0.653)	(-1.489)
MTB_Borrower	-0.017	-0.072**	-0.042**	-0.003**	-0.001	-0.004
	(-1.269)	(-2.065)	(-2.319)	(-2.245)	(-0.378)	(-1.514)
CASH_Borrower	0.034	0.361	0.310	0.018	0.006	-0.011
	(0.216)	(0.900)	(1.523)	(1.411)	(0.399)	(-0.432)
CURRENT_Borrower	0.001	0.002	0.007	0.001	-0.001	-0.001
	(0.046)	(0.043)	(0.256)	(0.354)	(-0.364)	(-0.204)
COVER_Borrower	0.000***	0.001	0.000*	0.000	0.000	0.000
	(2.761)	(1.298)	(1.776)	(0.771)	(0.394)	(0.317)
DEBT_Borrower	-0.087	-0.346**	-0.072	0.000	-0.002	-0.000
	(-1.506)	(-2.171)	(-0.961)	(0.074)	(-0.330)	(-0.033)
DPO_Borrower	-0.206	0.569	-0.043	0.060	-0.072	-0.079
	(-0.467)	(0.441)	(-0.063)	(1.277)	(-1.312)	(-0.892)
EBITDA_Borrower	-0.267**	-0.548*	-0.290**	-0.005	-0.016	-0.032*
	(-2.336)	(-1.799)	(-2.114)	(-0.632)	(-1.528)	(-1.746)
INTAN_Borrower	0.076	0.240	0.185	0.018*	0.006	0.006
	(0.658)	(0.838)	(1.335)	(1.884)	(0.471)	(0.311)
PPE_Borrower	0.006	-0.025	0.116	0.013	-0.003	-0.004
	(0.043)	(-0.067)	(0.651)	(1.099)	(-0.195)	(-0.183)
ΔSALES_Borrower	0.018	0.058	0.048**	0.001	0.002	0.001
	(1.108)	(1.396)	(2.291)	(0.696)	(0.829)	(0.316)
GDP_Borrower	-0.040	0.463	-0.167	-0.044**	-0.016	-0.018
	(-0.176)	(0.805)	(-0.668)	(-2.467)	(-0.559)	(-0.456)
ΔGDP_Borrower	0.008	0.011	0.011*	0.000	-0.000	-0.000
	(1.584)	(0.851)	(1.795)	(0.542)	(-0.001)	(-0.389)
Constant	-40.047***	-101.762***	-55.410***	3.374***	-6.552***	-5.532***
	(-5.777)	(-6.255)	(-6.286)	(5.039)	(-8.946)	(-5.077)
Loan Share +	0.050***	0.125***	0.093***	0.007***	0.005***	0.007***
Loan Share×CRI_State_High	(4.020)	(3.810)	(5.950)	(5.930)	(3.450)	(3.190)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.951	0.967	0.938

Table 9: Alternative Systemic Risk Measures: GARCH–ΔCoVaR

This table reports test results of the impact of the banks' climate risk exposure on their systemic risks estimated using the bivariate diagonal GARCH model. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust *t*-statistics are reported in parentheses. Variables are defined in Appendix A.

	(1) GARCH−ΔCoVaR5	(2) GARCH−ΔCoVaR1
CRI_Bank	0.016**	0.023**
	(2.353)	(2.353)
SIZE_Bank	0.043	0.061
	(1.204)	(1.204)
EQRAT_Bank	0.024	0.034
	(0.026)	(0.026)
MTB_Bank	0.127***	0.180***
	(4.104)	(4.104)
LTA_Bank	0.128	0.181
	(1.309)	(1.309)
LLP_Bank	-0.175	-0.247
	(-0.049)	(-0.049)
DEPO_Bank	-0.034	-0.048
	(-0.146)	(-0.146)
NII_Bank	-2.457*	-3.475*
	(-1.652)	(-1.652)
ROA_Bank	-5.875	-8.309
	(-1.575)	(-1.575)
OEM_Bank	-8.135***	-11.506***
	(-5.759)	(-5.759)
ΔCIR_Bank	0.049	0.069
	(0.631)	(0.631)
GDP_Bank	-1.165***	-1.647***
	(-4.509)	(-4.509)
ΔGDP_Bank	-0.003	-0.005
	(-0.824)	(-0.824)
SIZE_Borrower	-0.001	-0.002
	(-0.172)	(-0.172)
MTB_Borrower	-0.003	-0.004
	(-0.386)	(-0.386)
CASH_Borrower	0.068	0.096
	(1.258)	(1.258)
CURRENT_Borrower	-0.012	-0.018
	(-1.349)	(-1.349)
COVER_Borrower	0.000	0.000
	(0.562)	(0.562)
DEBT_Borrower	0.031	0.044
	(1.119)	(1.119)
DPO_Borrower	-0.077	-0.109
	(-0.512)	(-0.512)
EBITDA_Borrower	-0.022	-0.031
	(-0.561)	(-0.561)
INTAN_Borrower	0.031	0.044
	(0.659)	(0.659)
PPE_Borrower	-0.028	-0.040
	(-0.534)	(-0.534)
ΔSALES_Borrower	0.004	0.006
	(1.005)	(1.005)
GDP_Borrower	0.100	0.141
	(0.965)	(0.965)
ΔGDP_Borrower	-0.001	-0.001
	(-0.521)	(-0.521)
Constant	12.691***	17.949***
	(4.743)	(4.743)
Bank FE	Yes	Yes
Borrower FE	Yes	Yes
Year FE	Yes	Yes
Observations	1,983	1,983
Adjusted R^2	0.975	0.975

Table 10: Weighted Least Squares

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks using Weighted Least Squares (WLS) estimation. Panel A reports results using state population of lender banks as the weight in WLS estimation. Panel B reports results using banks' market capitalization as the weight in WLS estimation. The regressions include bank, borrower and year fixed effects (not reported). Standard errors are adjusted for clustering at the bank-borrower (lending relationship) level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

Panel A. Weighted Least Squares (by State Population of Lender Banks)

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	0.031**	0.080**	0.087***	0.025***	0.004**	0.010***
	(2.044)	(2.138)	(4.495)	(15.015)	(1.980)	(2.853)
Constant	-41.787***	-105.039***	-57.162***	3.650***	-6.829***	-5.787***
	(-6.135)	(-6.444)	(-6.520)	(5.790)	(-9.546)	(-5.365)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Panel B. Weighted Least Squares (by Bank Market Capitalization)

	(1) −TAIL5	(2) −TAIL1	(3) −MES	(4) −LRMES	(5) −ΔCoVaR5	(6) −ΔCoVaR1
CRI_Bank	0.029**	0.086**	0.091***	0.026***	0.003*	0.008**
	(1.968)	(2.365)	(4.850)	(16.021)	(1.815)	(2.506)
Constant	-45.707***	-111.530***	-61.885***	3.608***	-7.233***	-6.618***
	(-6.677)	(-6.902)	(-7.370)	(6.255)	(-10.271)	(-6.266)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.947	0.909	0.954	0.956	0.968	0.938

Table 11: Standard Errors

This table reports test results of the impact of the banks' climate risk exposure on their tail and systemic risks. Panel A reports results with standard errors adjusted for clustering at the borrower state level. Panel B reports results with heteroskedasticity- and autocorrelation-consistent (HAC) standard errors computed following the Newey and West (1987) procedure that allows for up to two periods of autocorrelation. The regressions include bank, borrower and year fixed effects (not reported). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Robust t-statistics are reported in parentheses. Variables are defined in Appendix A.

Panel A. Standard Errors Clustered at Borrower State Level

	(1) $-$TAIL5	(2) $-$TAIL1	(3) $-$MES	(4) $-$LRMES	(5) $-\Delta$CoVaR5	(6) $-\Delta$CoVaR1
CRI_Bank	0.031*	0.080	0.087***	0.025***	0.004*	0.009***
	(1.819)	(1.405)	(3.302)	(9.558)	(1.936)	(2.858)
Constant	-41.018***	-103.337***	-56.918***	3.626***	-6.773***	-5.699***
	(-4.750)	(-5.230)	(-5.097)	(5.485)	(-5.824)	(-3.649)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Panel B. Newey-West Standard Errors

	(1) $-$TAIL5	(2) $-$TAIL1	(3) $-$MES	(4) $-$LRMES	(5) $-\Delta$CoVaR5	(6) $-\Delta$CoVaR1
CRI_Bank	0.031**	0.080**	0.087***	0.025***	0.004**	0.009***
	(2.219)	(2.288)	(4.855)	(15.855)	(1.988)	(3.080)
Constant	-40.371***	-102.868***	-55.688***	3.568***	-6.926***	-5.434***
	(-6.863)	(-6.963)	(-7.594)	(6.629)	(-10.761)	(-5.659)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,830	7,830	7,830	7,830	7,830	7,830
Adjusted R^2	0.945	0.907	0.953	0.953	0.967	0.938

Appendix A. Variable Definition

Variable	Definition	Source
Climate Risk Measures		
CRI_State	State-level climate risk calculated based on the Billion-Dollar Weather and Climate Disasters data by the National Centers for Environmental Information (NOAA). It is defined as the first principal component of six key climate risk indicators: (1) number of death, (2) number of deaths per 100,000 inhabitants, (3) sum of losses in USD at purchasing power parity (PPP), (4) losses per unit of Gross Domestic Product (GDP), (5) number of events, and (6) loss per event.	BEA NOAA
CRI_State_GW	State-level climate risk calculated using the Germanwatch method. It is defined as the sum of the state's score in all four indicating categories: (1) number of deaths, (2)number of deaths per 100,000 inhabitants, (3) sum of losses in USD at PPP, (4) losses per unit of GDP, (5) number of events, and (6) loss per event.	As above
CRI_Bank	Bank-level climate risk. The sum of a bank's lending to individual state as a percentage of its total lending weighted by CRI_State of the specific state for each year.	BEA NOAA Dealscan
CRI_Bank_Adj	Bank-level climate risk adjusting for borrower firms' vulnerability to climate change.	As above
CRI_Bank_Res	Bank-level residual climate risk. The residual imputed from regressing CRI_Bank on a set of market-based common risk factors including market risk, market risk for banking industry, credit risk, commodity risk, political risk, real estate risk, and sovereign risk.	As above
CRI_Bank_GW	Bank-level climate risk calculated based on CRI_State_GW.	As above
Dependent Variables		
TAIL5	The average return for a bank during the 5% worst return days for the bank in a year.	CRSP
TAIL1	The average return for a bank during the 1% worst return days for the bank in a year.	As above
MES	Marginal expected shortfall. The average return for a bank during the 5% worst return days for the banking industry in a year.	As above
LRMES	Long-run marginal expected shortfall during the 2% worst return days for the banking industry in a year.	As above

Variable	Definition	Source
ΔCoVaR5	A measure of a bank's marginal contribution to the risk of the system, computed as the difference between the value at risk of the system when the institution's return is at the 5^{th} percentile and the value at risk of the system when the institution' return is at the median.	As above
ΔCoVaR1	A measure of a bank's marginal contribution to the risk of the system, computed as the difference between the value at risk of the system when the institution's return is at the 1^{st} percentile and the value at risk of the system when the institution' return is at the median.	As above
Lender Characteristics		
SIZE_Bank	Bank size. Natural logarithm of total assets (*at*).	Compustat
EQRAT_Bank	Equity ratio. Book value of equity (*ceq*) divided by total assets (*at*).	As above
MTB_Bank	Market-to-book ratio. Market value of equity (*prccm*× *cshom*) divided by book value of equity (*ceq*).	As above
LTA_Bank	Loans-to-assets ratio. Loans net of total allowance for loan losses (*lntal*) divided by total assets (*at*).	As above
LLP_Bank	Loan loss provisioning. Provisions for loan or asset losses (*pll*) divided by total assets (*at*).	As above
DEPO_Bank	Deposit ratio. Total deposits (*dptc*) divided by total assets (*at*).	As above
NII_Bank	Noninterest income ratio. Total noninterest income (*tnii*) divided by total assets (*at*).	As above
ROA_Bank	Return on assets. Net income (*ni*) divided by total assets (*at*).	As above
OEM_Bank	Operating expense management. Total current operating expenses (*tcoe*) divided by total assets (*at*).	As above
ΔCIR_Bank	Change in cost-to-income ratio. Cost to income ratio is calculate as dividing total current operating expenses (*tcoe*) by gross total revenue (*tcor*).	As above
Borrower Characteristics		
SIZE_Borrower	Firm size. Natural logarithm of total assets (*at*).	Compustat
MTB_Borrower	Market-to-book ratio. Market value of equity (*prcc_f*× *csho*) divided by book value of equity (*ceq*).	As above
CASH_Borrower	Cash holding ratio. Cash and short-term investments (*che*) divided by total assets (*at*).	As above
CURRENT_Borrower	Current ratio. Current assets (*aco*) divided by current liabilities (*lco*).	As above

Variable	Definition	Source
COVER_Borrower	Interest coverage. Earnings before interest (*ebitda*) divided by total interest expense (*xint*).	As above
DPO_Borrower	Dividend payout ratio. The sum of dividends paid to ordinary shares (*dvc*) and dividends paid to preferred shares (*dvp*) divided by total assets (*at*).	As above
EBIDTDA_Borrower	Earnings before interest, taxes, depreciation, and amortization (*ebidtda*) divided by sales (*sale*).	As above
INTAN_Borrower	Intangible assets ratio. Intangible assets (*intan*) divided by total assets (*at*).	As above
PPE_Borrower	Fixed assets ratio. Property, plant and equipment (*ppent*) divided by total assets (*at*).	As above
ΔSALES_Borrower	Annual growth in sales revenue (*sale*).	As above
State-Level Variables		
GDP_Bank	Natural logarithm of annual gross domestic product (GDP) per capita of the bank's state.	BEA
ΔGDP_Bank	Annual growth rate of GDP per capita of the bank's state.	As above
GDP_Borrower	Natural logarithm of annual GDP per capita of the firm's state.	As above
ΔGDP_Borrower	Annual growth rate of GDP per capita of the firm's state.	As above
Instrumental Variables		
FOREIGN	Foreign loans. Foreign loans (*lft*) divided by total loans (*lntal*).	Compustat
POP	Population density. The population of a state in a given year divided by the land area of the state.	St. Louis Fed

Appendix B. Industry Classification by Climate Change Vulnerability

High	Medium	Low
Coal	Agriculture	Real estate
Oil and gas	Automotive	Telecommunication carriers
Shipping and aviation	Electronics	Rail systems
Construction (incl. cement)	Retail stores (incl. warehouses)	Renewable power generation
Freight transport	Metal mining	Natural gas extraction
Livestock	Iron and steel production	
Aluminium production		

Source: ING (2020)

Appendix C. Common Risk Factors

Risk Factor	Description	Source
Interest rate risk	Percentage changes in the market value of long-term assets. The factor is based on market prices of 10–year government bonds.	Datastream
Credit risk	Changes in the default premium between BAA– and AAA–rated corporate bonds. The factor is based on time series maintained by Moody's.	Datastream
Commodity risk	Percentage changes in the S&P GSCI Total Return Index.	Datastream
Foreign exchange risk	Percentage changes in the trade-weighted currency baskets. The factor measures the currency value with respect to the currency values of the major trade partners.	Bank of England
Market risk	Percentage changes in the market value of S&P 500.	Datastream
Market risk (banking industry)	Percentage changes in the market value of the banking sector stock market portfolios.	Datastream
Political risk	Percentage changes in gold price against U.S. dollars.	Bank of England
Real estate risk	Percentage changes in the market value of the REIT investments.	Datastream
Sovereign risk	Changes in the difference of the (mean) of yields on the 10–year government bonds (Greece, Portugal, Spain, Italy) and 10–year German Government bonds.	Datastream
VIX	Chicago Board Options Exchange volatility index. The index measures market expectations of short-term volatility based on S&P 500 stock-index option prices.	Datastream

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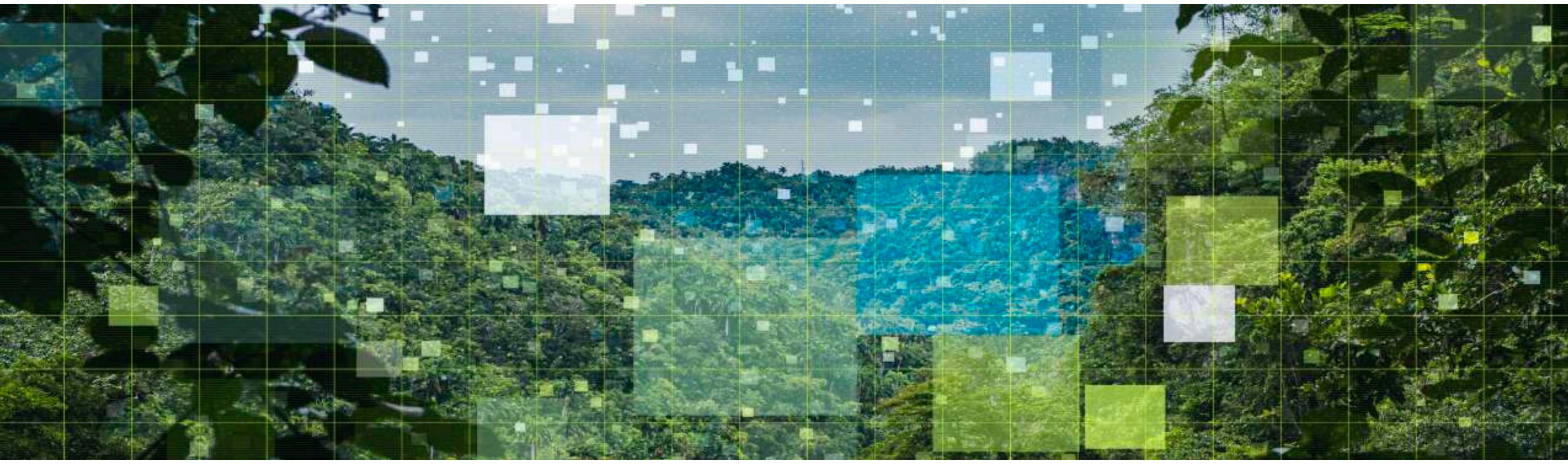

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Integrating Climate Risk Into an Insurer's Strategic Asset Allocation

When practitioners apply climate considerations into strategic models such as strategic asset allocation (SAA), they tend to apply climate-impact adjustments at the security level *after* the portfolio optimization is complete.

Neuberger Berman has developed a proprietary framework to estimate the potential impact of climate change at the asset-class level, which can then be used to generate climate-adjusted capital market assumptions to serve as inputs in an SAA. We believe there are considerable advantages to this *ex-ante* adjustment for climate-related effects because SAA determines a meaningful portion of the variation of portfolio returns over time. Substantial variation exists in our estimated climate effects for asset classes, sectors and regions, suggesting the availability of abundant "climate asset-allocation alpha."

In previous work, we showed that this "Climate SAA" process could "recover" some of the estimated return "lost" when climate-related effects are applied *ex post*.

In this paper, we apply the same Climate SAA framework with constraints and objectives, such as solvency capital requirements and asset-liability matching, designed to reflect those of European insurance investors.

Executive Summary

- We use a proprietary framework that incorporates "Climate Value at Risk" (Climate VaR) and an equivalent proprietary sovereign bonds model to estimate the potential impact of climate change on the present value of assets and securities, which we then aggregate up to the benchmark index level to use as inputs into the strategic asset allocation (SAA) process.
- Under a 2°C warming scenario, we subject the optimized asset allocations of a typical UK general insurer and Continental European life insurer to these climate-related adjustments to estimated returns: these *ex-post* adjustments lower the portfolios' estimated returns, revealing them to be sub-optimal.
- We run an optimization for each insurer that integrates climate-related effects into the SAA by subjecting the portfolio constituents to climate-cost adjustments *ex ante.*
  - This "Climate SAA" process "recovers" a large portion of the estimated return "lost" to the *ex-post* adjustment for climate adjustments.
  - The process also lowers the solvency capital requirements (SCR) of the portfolios on the efficient frontier, as it results in allocations away from equities and extended fixed income and toward core fixed income.
- Climate SAA also lowers the financed emissions of the portfolios; introducing financed emissions as a constraint in the Climate SAA optimization can lower them even further, with minimal effect on estimated return and volatility (but with some sacrifice of solvency-capital efficiency).

Traditional ESG analyses have tended to focus on fundamental or "bottom-up" factors. That means climate considerations are generally addressed at the sector and company level only after a portfolio's strategic asset allocation (SAA) has been set. This leaves climate risk exposure unrecognized and unmanaged at the SAA level.

At Neuberger Berman, we believe that this is a significant decision, given that SAA can drive up to 90% of the variation in portfolio returns over time. We believe that fully integrating climate considerations into SAA can identify portfolio-level return potential that is missed when climate-related impact is considered only afterwards, at the issuer level. That belief was reinforced when we applied our climate-related adjustments to the expected returns of our universes of corporate bonds and equities, and found very wide dispersion at the regional, asset-class and sector levels. This suggests to us an abundant availability of top-down "climate asset-allocation alpha."

Neuberger Berman developed its proprietary "Climate SAA" model to test this hypothesis, and set out its findings in its 2022 paper, *Integrating Climate Risk into Strategic Asset Allocation*. We found that, when we adjusted asset-class expected returns for climate-related effects *after* conducting a standard SAA optimization, it lowered the efficient frontier relative to the standard SAA output. When we adjusted asset-class estimated returns *before* conducting the optimization, however, we found that it "recovered" some of that lost estimated return.

In other words, integrating climate-related effects *ex ante* into the SAA optimization process achieved higher levels of estimated return with no additional portfolio volatility, relative to imposing the effects after a standard SAA.[1]

[1] Charles Nguyen, Tully Cheng, et al, Integrating Climate Risk into Strategic Asset Allocation (May 2022), at https://www.nb.com/en/gb/insights/integrating-climate-risk-into-strategic-asset-allocation.

Climate VaR

How do we estimate climate effects and integrate them into an SAA?

We use a "Climate Value at Risk" (Climate VaR) model to estimate the impact of climate change on most equity and corporate bond securities. Climate VaR is defined as the present value of aggregated future policy risk costs, technology opportunity profits, and extreme weather event costs and profits, under a given warming scenario, expressed as a percentage of a security or portfolio's market value. This initial analytical step can be useful in itself, in that it reveals where climate-related risks and opportunities may lie in an existing portfolio or asset allocation. To get the most out of the information, however, we think it is best to bring it into the investment process before the risks are allowed into the portfolio.

To that end, we use a proprietary methodology to convert this present value of costs into a change in return expectation, and then aggregate these security-level Climate VaR return adjustments, using the relevant index's security weights, to create a climate risk-adjusted, index-level estimated return to use in the Climate SAA process.

In this paper, we aim to apply Climate SAA to portfolios typical of insurance investors. European insurance portfolios tend to have meaningful allocations to sovereign bonds, requiring us to apply an "apples-to-apples" equivalent of Climate VaR to those assets. Our estimates of climate impact on sovereign bonds are calculated by taking the same future policy risks, technology opportunities and extreme weather events that go into the Climate VaR model, and applying them to macro-financial factors such as GDP growth, debt-to-GDP ratios and inflation.[2]

As in our previous work, to test the benefit of integrating these climate-related effects into the SAA process, we first apply them *ex-post* to the estimated returns of illustrative UK and Continental European insurance portfolios, before re-optimizing them with the climate effects applied *ex ante.* We can then quantify how much of the "lost" estimated return has been "recovered" by this Climate SAA process.

Climate SAA for a Typical UK General Insurer

In the Appendix, we describe a typical UK insurer's balance sheet and asset allocation, based on what we see in the current market.

While this asset allocation reflects what is typical for the sector, it is not an optimized portfolio. Therefore, to provide a more robust starting point, we optimize for estimated return and surplus volatility (reflecting the illustrative insurer's asset-liability matching), with constraints based on the illustrative insurer's estimated solvency capital requirements (SCR), and on asset weights that would be reasonable for such an insurer to consider.

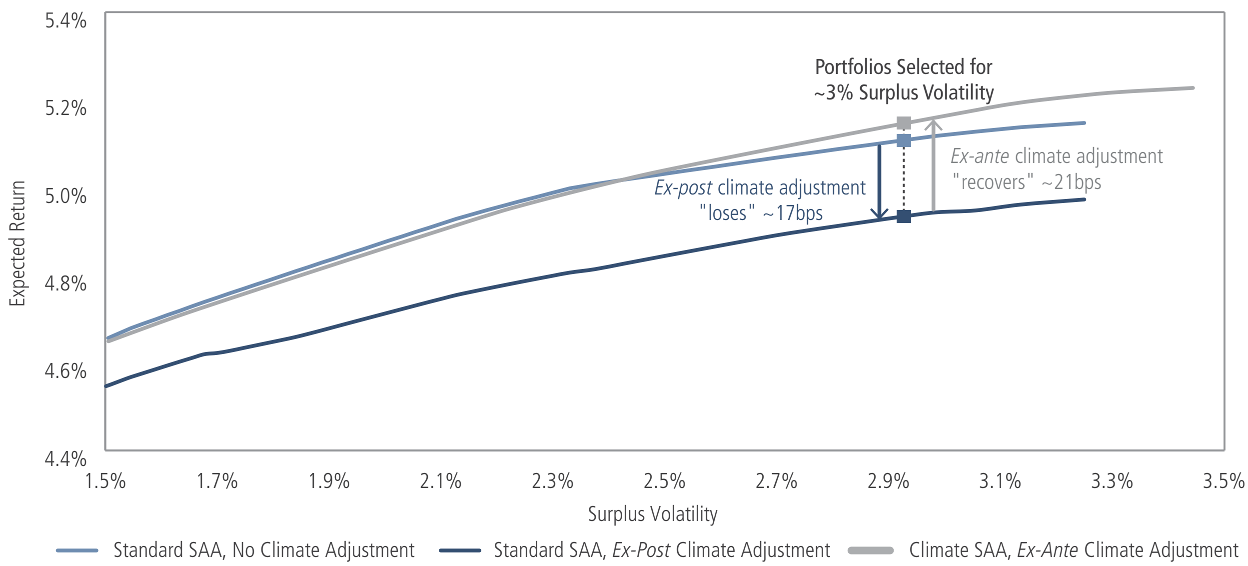
This provides us with an efficient frontier from which we can select the portfolio that has similar surplus volatility to that of our illustrative UK insurer, around 3%. That portfolio has an estimated return of 5.11%.

We then take the standard approach to climate-related costs: applying Climate VaR and its equivalents to the constituents of the portfolio, assuming a 2°C warming scenario, after the optimization is complete. For a surplus volatility level around 3%, the estimated return falls from 5.11% to 4.94%, a loss of 17 basis points. The efficient frontiers for these optimizations are shown light and dark blue in figure 1.

[2] Our illustrative Continental European life insurer asset allocations include private equity and hedge funds. As we are still developing a Climate VaR equivalent for these asset classes, in this paper their estimated returns remain unadjusted for climate effects.

FIGURE 1. CLIMATE EFFECTS CAN BE MITIGATED BY INTEGRATING THEM INTO AN SAA

Standard and Climate SAA efficient frontiers for a typical UK general insurer



Source: Bloomberg, MSCI, JP Morgan, S&P Global, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, and US Equities; MSCI Indices for UK Equity and Global Equity; JPM EMBI for Emerging Markets Sovereign Debt; JPM CEMBI for Emerging Markets Corporate Bonds; MSCI and S&P Global Indices for Real Estate. **Past performance is no guarantee of future results.** Please note that estimated returns data is based on NB's capital markets assumptions and are provided for information purposes only. There is no guarantee that estimated returns will be realized or achieved nor that an investment strategy will be successful, and may be significantly different than shown here. Investors should keep in mind that the securities markets are volatile and unpredictable. There are no guarantees that historical performance of an investment, portfolio, or asset class will have a direct correlation with its future performance. Net returns will be lower.

How much of this "lost" estimated return can be "recovered" by adjusting for climate-related effects before optimizing the portfolio, rather than afterwards? That is shown by the gray efficient frontier in figure 1. The selected Climate SAA portfolio, with the same level of surplus volatility as the Standard portfolios, has an estimated return of 5.15%. Climate SAA has recovered 21 basis points, more than the 17 basis points lost when we made *ex-post* adjustments for climate-related effects.

This recovered loss represents asset-allocation alpha. But it also represents something even more interesting: "climate asset-allocation alpha." To understand what we mean by that, let's take a closer look at how this Climate SAA process changes both the portfolio's asset allocation and its general risk profile, in figure 2. This shows the profiles of the Standard and Climate portfolios selected from the efficient frontiers for 2.9% surplus volatility.

FIGURE 2. INTEGRATING CLIMATE EFFECTS INTO AN SAA CAN PROFOUNDLY CHANGE A PORTFOLIO'S RETURN-RISK PROFILE

Effect of *ex-ante* Climate SAA at asset class level, and on portfolio risk profile

	Standard SAA, Ex-Post Climate Adj.	Climate SAA	Δ (Climate – Standard)
Sterling Gov/Agency	15.9%	16.4%	0.5%
Sterling IG Corp	32.5%	31.5%	-1.0%
Euro Gov/Agency	8.5%	9.0%	0.5%
Euro IG Corp	13.1%	16.6%	3.5%
US Gov/Agency	8.5%	8.7%	0.2%
US IG Corp	6.5%	6.3%	-0.2%
Core Fixed Income	**85.1%**	**88.5%**	**3.4%**
HY BB	5.0%	5.0%	0.0%
EMD	1.5%	0.0%	-1.5%
Extended Fixed Income	**6.5%**	**5.0%**	**-1.5%**
Real Estate	2.0%	2.0%	0.0%
UK Equity	3.8%	2.6%	-1.1%
US Equity	0.8%	0.5%	-0.2%
Global Equity	1.9%	1.3%	-0.6%
Equity & Alternatives	**8.4%**	**6.5%**	**-1.9%**
Expected Return	4.94%	5.15%	0.21%
Surplus Volatility	2.9%	2.9%	0.0%
Asset Volatility	3.0%	3.0%	0.0%
Asset Duration	2.0	2.0	0.0
Surplus Duration	0.4	0.4	0.0
Carbon Intensity	96	61	-35
Carbon Footprint	52	31	-21
Total SCR	**6.1%**	**5.4%**	**-0.7%**

Asset re-allocation effect of *ex-ante* Climate SAA at industry sector level

	Sterling Core FI	Euro Core FI	US Core FI	Extended FI	Equity
Basic Materials	0.0%	-1.3%	-1.2%	-2.4%	-3.7%
Communications	-1.3%	-2.6%	-2.8%	9.4%	3.1%
Consumer, Cyclical	-6.6%	-4.4%	-4.2%	-22.1%	0.0%
Consumer, Non-cyclical	-5.6%	-0.5%	-2.8%	1.0%	15.8%
Energy	-0.7%	-1.5%	-3.2%	-1.4%	-5.3%
Financial	18.2%	17.0%	24.4%	3.6%	-9.0%
Industrial	-2.1%	-2.6%	-3.9%	-0.1%	-3.4%
Technology	0.0%	-0.9%	-3.7%	0.2%	1.6%
Utilities	-2.0%	-3.3%	-2.7%	11.8%	0.9%

Source: Bloomberg, MSCI, JP Morgan, S&P Global, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, and US Equities; MSCI Indices for UK Equity and Global Equity; JPM EMBI for Emerging Markets Sovereign Debt; JPM CEMBI for Emerging Markets Corporate Bonds; MSCI and S&P Global Indices for Real Estate. Carbon Intensity and Carbon Footprint data are calculated on Scope 1 and 2 emissions. **Past performance is no guarantee of future results.** Please note that estimated returns data is based on NB's capital markets assumptions and are provided for information purposes only. There is no guarantee that estimated returns will be realized or achieved nor that an investment strategy will be successful, and may be significantly different than shown here. Investors should keep in mind that the securities markets are volatile and unpredictable. There are no guarantees that historical performance of an investment, portfolio, or asset class will have a direct correlation with its future performance. Net returns will be lower.

The first thing to note is the improvement in the portfolio's Scope 1 and 2 carbon intensity and carbon footprint. Carbon intensity is defined as the number of tons of CO_2 equivalents emitted for every million dollars of each constituent company's revenue. The carbon footprint of the portfolio is the absolute apportioned emissions financed by the portfolio itself—that is, the emissions attributed to the portfolio based on its ownership share of an emitter's total invested capital, further normalized by the investment value.

This is an intuitive result, as the optimizer now penalizes the assets whose estimated returns are most affected by climate-related costs, and those assets tend to be issued by entities with relatively large carbon emissions.

More strikingly and counterintuitively, the Climate SAA process reduces the portfolio's solvency capital requirement (SCR) even as it adds 21 basis points of estimated return.

It might be assumed that taking allocation away from equities, high yield bonds and emerging markets debt and giving it to core fixed income, especially EUR-denominated investment grade bonds, would reduce estimated return, not raise it. The fact that it raises estimated return reflects the extent to which the traditionally higher-return asset classes are hit by bigger adjustments for climate-related costs. For example, as we can see in the table in the Appendix, even short-duration US high yield bonds receive a 163-basis-point-per-annum penalty, and UK equities get hit by 77 basis points per annum. With Climate SAA, all of these adjustments are fed into the optimizer *ex ante*, in a way they were not with the Standard efficient frontier.

Finally, it is also worth noting that, like any SAA, the Climate SAA process provides no insight into the additional benefits that can be achieved with security selection, below the levels of asset classes, regions and sectors. At Neuberger Berman, we believe that climate risk-awareness and sustainable business practices tend to be rewarded by the market, and therefore can and should inform bottom-up security selection. In our view, ESG-integrated, sustainable and impact investment strategies that build these factors into their processes or objectives have the potential to squeeze further return from each unit of portfolio risk.

Climate SAA for a Typical Continental European Life Insurer

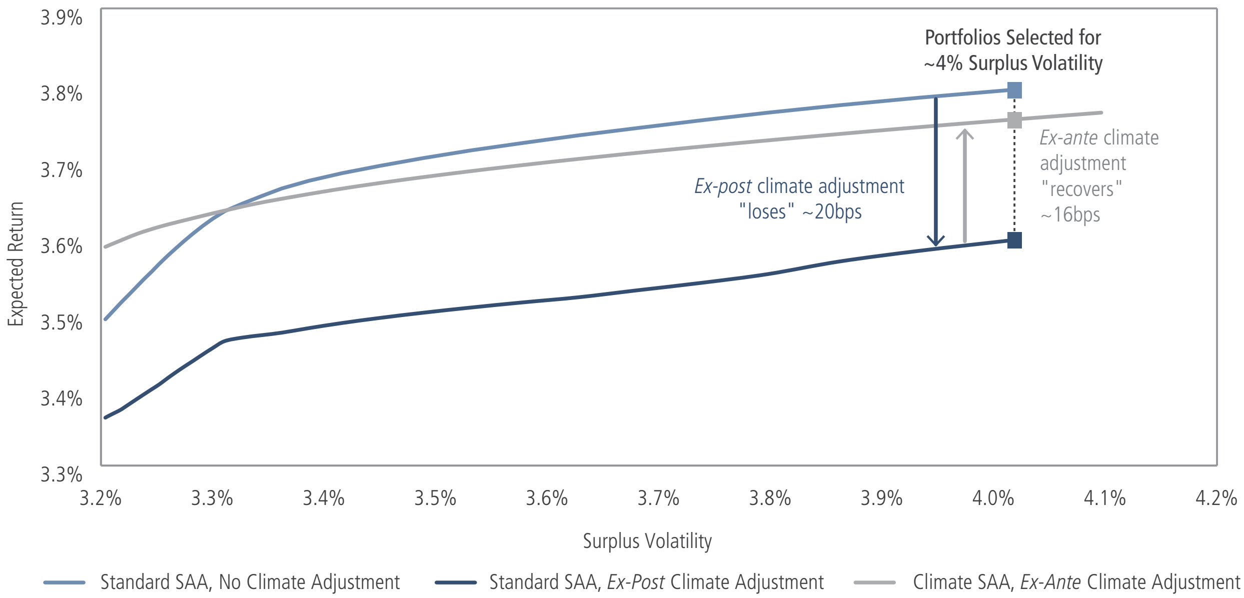
With our Continental European life insurer, we again optimize an efficient frontier with constraints related to the illustrative profile shown in the Appendix. When we select the portfolio that has similar surplus volatility to that of our illustrative asset allocation, around 4%, we find an estimated return of 3.79%.

We apply Climate VaR and its equivalents to the constituents of this efficient frontier and the selected portfolio to find the dark-blue efficient frontier and portfolio shown in figure 3. For a surplus volatility level around 4%, the estimated return falls from 3.79% to 3.59%, a loss of 20 basis points.

A Climate SAA generates the gray efficient frontier. The selected Climate SAA portfolio, with the same level of surplus volatility as the Standard portfolios, has an estimated return of 3.75%, recovering 16 basis points of the total 20 basis points lost by the *ex-post* adjustment for climate-related effects.

FIGURE 3. INTEGRATING CLIMATE EFFECTS INTO AN SAA CAN ENHANCE ESTIMATED RETURN

Standard and Climate SAA efficient frontiers for a typical Continental European life insurer



Source: Bloomberg, MSCI, JP Morgan, S&P Global, Cambridge Associates, HFRI, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, US Equities and Europe Equities; JPM EMBI for Emerging Markets Sovereign Debt; JPM CEMBI for Emerging Markets Corporate Bonds; Cambridge Associates Indices for Private Equity; HFRI Indices for Hedge Funds; MSCI and S&P Global Indices for Real Estate. **Past performance is no guarantee of future results.** Please note that estimated returns data is based on NB's capital markets assumptions and are provided for information purposes only. There is no guarantee that estimated returns will be realized or achieved nor that an investment strategy will be successful, and may be significantly different than shown here. Investors should keep in mind that the securities markets are volatile and unpredictable. There are no guarantees that historical performance of an investment, portfolio, or asset class will have a direct correlation with its future performance. Net returns will be lower.

Figure 4 confirms, once again, that the Climate SAA process can substantially reduce an insurance portfolio's carbon intensity and carbon footprint while simultaneously lowering its SCR and raising estimated return, due to the *ex-ante* penalization of traditionally higher-return assets.

FIGURE 4. INTEGRATING CLIMATE COSTS INTO AN SAA CAN IMPROVE SOLVENCY CAPITAL EFFICIENCY

Effect of *ex-ante* Climate SAA at asset class level, and on portfolio risk profile

	Standard SAA, Ex-Post Climate Adj.	Climate SAA	Δ (Climate – Standard)
Euro Gov/Agency	20.7%	21.0%	0.3%
Euro IG Corp	60.4%	61.1%	0.6%
US IG Corp	0.0%	0.0%	0.0%
Core Fixed Income	**81.2%**	**82.1%**	**0.9%**
HY BB&B	5.0%	5.0%	0.0%
EMD	5.0%	4.5%	-0.5%
Extended Fixed Income	**10.0%**	**9.5%**	**-0.5%**
US Equity	0.0%	0.0%	0.0%
Europe Equity	5.9%	5.5%	-0.4%
Private Equity	0.5%	0.5%	0.0%
Hedge Funds	0.4%	0.4%	0.0%
Real Estate	2.0%	2.0%	0.0%
Equity & Alternatives	**8.8%**	**8.5%**	**-0.4%**
Expected Return	3.59%	3.75%	0.16%
Surplus Volatility	4.0%	4.0%	0.0%
Asset Volatility	7.1%	7.1%	0.0%
Asset Duration	9.0	9.0	0.0
Surplus Duration	-0.9	-0.9	0.0
Carbon Intensity	170	106	-64
Carbon Footprint	111	67	-43
Total SCR	**13.6%**	**13.4%**	**-0.2%**

Asset re-allocation effect of *ex-ante* Climate SAA at industry sector level

	Euro Core FI	US Core FI	Extended FI	Equity
Basic Materials	-0.4%	-0.1%	-3.3%	-3.1%
Communications	6.2%	2.1%	4.2%	2.2%
Consumer, Cyclical	-0.7%	0.3%	-5.2	-5.2%
Consumer, Non-cyclical	-0.2%	-1.0%	2.7%	15.9%
Energy	0.4%	-1.8%	1.5%	-3.5%
Financial	4.6%	0.3%	9.0%	-0.6%
Industrial	-1.4%	-0.3%	-6.5%	-6.4%
Technology	0.2%	0.1%	1.0%	2.8%
Utilities	-8.7%	0.4%	-3.5%	-2.2%

Source: Bloomberg, MSCI, JP Morgan, S&P Global, Cambridge Associates, HFRI, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, US Equities and Europe Equities; JPM EMBI for Emerging Markets Sovereign Debt; JPM CEMBI for Emerging Markets Corporate Bonds; Cambridge Associates Indices for Private Equity; HFRI Indices for Hedge Funds; MSCI and S&P Global Indices for Real Estate. Carbon Intensity and Carbon Footprint data are calculated on Scope 1 and 2 emissions. **Past performance is no guarantee of future results.** Please note that estimated returns data is based on NB's capital markets assumptions and are provided for information purposes only. There is no guarantee that estimated returns will be realized or achieved nor that an investment strategy will be successful, and may be significantly different than shown here. Investors should keep in mind that the securities markets are volatile and unpredictable. There are no guarantees that historical performance of an investment, portfolio, or asset class will have a direct correlation with its future performance. Net returns will be lower.

Integrating Financed Emissions into the SAA Process

In both the UK and Continental European insurer case studies, we found that the Climate SAA process substantially reduced carbon intensity and carbon footprint while simultaneously lowering SCR and raising estimated return.

We think this is notable, especially in light of the recent approval, by the European Parliament's Committee on Economic and Monetary Affairs, of draft amendments to Solvency II that would require insurers to publish quantifiable plans for achieving net-zero portfolio emissions by 2050, as well as the processes by which they monitor and address carbon-transition risks.[3]

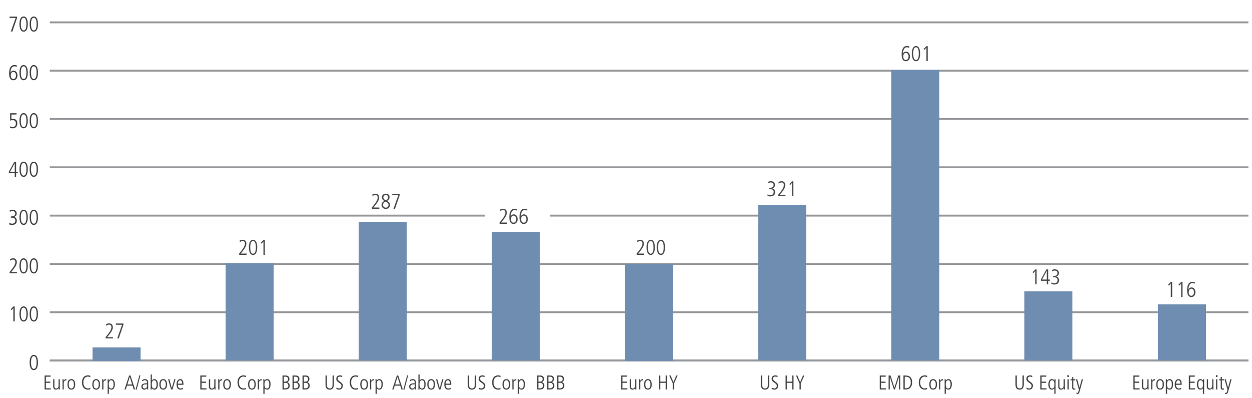
The Climate SAA process reduces financed emissions because they are important inputs into the Climate VaR model and its equivalents that are used to calculate estimated returns. All other things being equal, the Climate SAA therefore prefers assets with lower financed emissions. Investors can choose to "dial-up" the effect of financed emissions, however, by adding them as constraints to the Climate SAA.[4]

As a reminder, carbon intensity is defined as the number of tons of CO_2 equivalents emitted for every million dollars of each constituent company's revenue. The carbon footprint of the portfolio is the absolute apportioned emissions financed by the portfolio itself—that is, the emissions attributed to the portfolio based on its ownership share of an emitter's total invested capital, further normalized by the investment value.

Like the impact of Climate VaR on estimated returns, and for much the same reason, carbon intensity and carbon footprint vary widely at the asset-class level (figure 5). In general, fixed income assets generate more financed emissions than equities, due to their lower sector exposures in technology and higher exposures in utilities and energy; and EUR fixed income generates fewer financed emissions than USD fixed income due to its higher exposure to financials.

FIGURE 5. FINANCED EMISSIONS VARY WIDELY AT BOTH ASSET CLASS AND SECTOR LEVEL

Carbon intensity, tons of CO_2 equivalents per million dollars of issuer revenue, by asset class



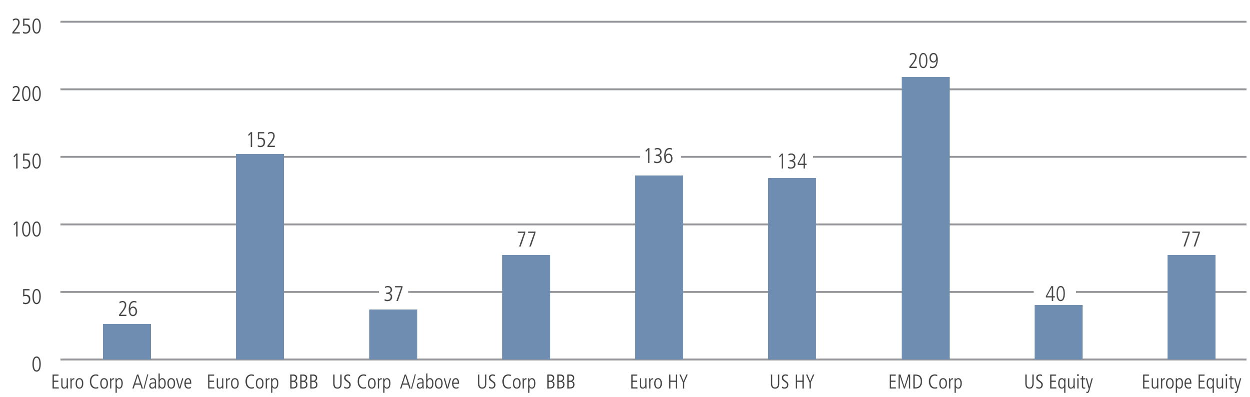
[3] https://emeeting.europarl.europa.eu/emeeting/committee/en/agenda/202307/ECON?meeting=ECON-2023-0718_1&session=07-18-08-00; https://www.europarl.europa.eu/cmsdata/273462/RCVs_18%20July%202023.pdf

[4] While we have used them for simple illustration in this paper, we regard metrics such as carbon intensity and carbon footprint as somewhat blunt instruments for assessing issuer and portfolio emissions, and particularly future emissions. As an example of some of the issues they present, note how, in figure 5, while carbon intensity and carbon footprint are generally positive correlated, EUR BBB corporate bonds and high yield have a higher carbon footprint than their US counterparts, despite exhibiting lower carbon intensity; and the same is the case with European versus US equities. This apparent anomaly occurs because the macroeconomic environment can effect these metrics via both their numerators (carbon output) and, especially, their denominators (revenue or enterprise value), without their being a real change in a company or sector's overall emissions profile. That is one reason why we regard metrics such as these as necessary but not sufficient to determine net-zero alignment, a subject we address in more detail in a recent paper, which also sets out a proprietary Net Zero Alignment Indicator, designed to assign a net-zero alignment score and status to security issuers based on what we believe to be a richer, more forward-looking set of data and metrics. See Jonathan Bailey, Sarah Peasey and Laura Kunstler-Brooks, *Net-Zero Alignment: Beyond the Numbers (July 2023)*, at https://www.nb.com/en/link?type=article&name=whitepaper-net-zero-alignment-beyond-the-numbers.

Carbon intensity, tons of CO_2 equivalents per million dollars of issuer revenue, by sector

	Euro Corp A/above	Euro Corp BBB	US Corp A/above	US Corp BBB	Euro HY	US HY	EMD Corp	US Equity	Europe Equity
Basic Materials	568	441	713	535	600	677	1136	631	461
Communications	47	29	25	31	25	27	73	18	18
Consumer, Cyclical	25	112	42	76	167	273	387	56	22
Consumer, Non-cyclical	26	44	25	31	45	53	112	24	29
Energy	291	337	369	735	207	691	661	447	273
Financial	4	28	10	30	23	46	13	51	8
Industrial	46	788	192	203	294	194	615	132	206
Technology	9	22	23	23	44	39	152	20	18
Utilities	389	589	2497	1787	1030	3121	3805	2227	627
Index	27	201	287	266	200	321	601	143	116

Carbon footprint, tons of CO_2 equivalents per million dollars of portfolio investment, by asset class



Carbon footprint, tons of CO_2 equivalents per million dollars of portfolio investment, by sector

	Euro Corp A/above	Euro Corp BBB	US Corp A/above	US Corp BBB	Euro HY	US HY	EMD Corp	US Equity	Europe Equity
Basic Materials	202	663	171	353	1478	579	698	191	325
Communications	19	14	7	12	12	11	33	5	8
Consumer, Cyclical	68	107	26	31	114	77	136	23	14
Consumer, Non-cyclical	9	22	11	19	20	34	53	9	9
Energy	271	356	242	266	109	289	314	256	291
Financial	1	2	2	3	2	11	4	13	1
Industrial	22	699	44	72	190	94	264	34	132
Technology	2	11	4	7	21	17	12	3	4
Utilities	12	360	207	278	381	1507	711	375	352
Index	26	152	37	77	136	134	209	40	77

Source: Bloomberg, MSCI, JP Morgan, S&P Global, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, US Equities and Europe Equities; JPM CEMBI for Emerging Markets Corporate Bonds. Carbon Intensity and Carbon Footprint data are calculated on Scope 1 and 2 emissions.

This variation, both among asset classes and within them, makes it possible to set the constraints on financed emissions with a wide range, which should help to achieve a meaningful additional reduction in carbon intensity and footprint with minimal impairment of estimated risk-adjusted return. That is indeed what we find, as shown for the Continental European life insurer portfolio in figure 6.

It is also worth noting that this Climate SAA lowers financed emissions despite *raising* the allocation to core fixed income, which is made up of asset classes that have generally higher financed emissions. This result is possible due to the wide variation in financed emissions *within* these asset classes, as well as among them, which, once again, give us abundant opportunity to realize asset-allocation alpha.

FIGURE 6. FINANCED EMISSIONS CAN BE REDUCED BY MORE THAN 50% WITHOUT SUBSTANTIAL IMPAIRMENT OF ESTIMATED RETURN

Effect of *ex-ante* Climate SAA on a Continental European life insurer portfolio, with and without financed emissions constraints

	Standard	Climate	Climate with Carbon Footprint Constraints (CF)	Climate with Carbon Intensity Constraints (CI)	Δ (CF – Climate)	Δ (CI – Climate)
Euro Gov/Agency	20.7%	21.0%	21.3%	20.9%	0.3%	-0.1%
Euro IG Corp	60.4%	61.1%	61.8%	60.8%	0.8%	-0.2%
US IG Corp	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Core Fixed Income	**81.2%**	**82.1%**	**83.1%**	**81.7%**	**1.1%**	**-0.3%**
HY BB&B	5.0%	5.0%	5.0%	5.0%	0.0%	0.0%
EMD	5.0%	4.5%	0.0%	0.0%	-4.5%	-4.5%
Extended Fixed Income	**10.0%**	**9.5%**	**5.0%**	**5.0%**	**-4.5%**	**-4.5%**
US Equity	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Europe Equity	5.9%	5.5%	8.9%	10.3%	3.4%	4.8%
Private Equity	0.5%	0.5%	0.5%	0.5%	0.0%	0.0%
Hedge Funds	0.4%	0.4%	0.4%	0.4%	0.0%	0.0%
Real Estate	2.0%	2.0%	2.0%	2.0%	0.0%	0.0%
Equity & Alternatives	**8.8%**	**8.5%**	**11.9%**	**13.3%**	**3.4%**	**4.8%**
Expected Return	3.59%	3.75%	3.74%	3.73%	-0.01%	-0.02%
Surplus Volatility	4.0%	4.0%	4.0%	4.0%	0.0%	0.0%
Asset Volatility	7.1%	7.1%	7.2%	7.2%	0.1%	0.1%
Asset Duration	9.0	9.0	9.0	9.0	0.0	0.0
Surplus Duration	-0.9	-0.9	-0.9	-0.9	0.0	0.0
Carbon Intensity	170	106	78	72	-28	-34
Carbon Footprint	111	67	52	54	-15	-13
Total SCR	**13.6%**	**13.4%**	**13.7%**	**13.8%**	**0.3%**	**0.4%**

Source: Bloomberg, MSCI, JP Morgan, S&P Global, Cambridge Associates, HFRI, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, US Equities and Europe Equities; JPM EMBI for Emerging Markets Sovereign Debt; JPM CEMBI for Emerging Markets Corporate Bonds; Cambridge Associates Indices for Private Equity; HFRI Indices for Hedge Funds; MSCI and S&P Global Indices for Real Estate. Carbon Intensity and Carbon Footprint data are calculated on Scope 1 and 2 emissions. **Past performance is no guarantee of future results.** Please note that estimated returns data is based on NB's capital markets assumptions and are provided for information purposes only. There is no guarantee that estimated returns will be realized or achieved nor that an investment strategy will be successful, and may be significantly different than shown here. Investors should keep in mind that the securities markets are volatile and unpredictable. There are no guarantees that historical performance of an investment, portfolio, or asset class will have a direct correlation with its future performance. Net returns will be lower.

As we have already seen, a Climate SAA already reduces financed emissions by almost 40%. Adding carbon intensity and carbon footprint as constraints in the Climate SAA reduces them by another 20 – 30%.

The impact on estimated volatility and return is minimal, although there is a small sacrifice in terms of SCR efficiency—this is because the major change in asset allocation is to remove emerging markets debt (which generates high financed emissions but a relatively low SCR) and reallocate most of the proceeds to European equities (which generates low financed emissions despite its relatively high Climate VaR, but has a higher SCR).

Conclusion: Lower Climate Costs, Lower Solvency Costs, Higher Estimated Returns

Investors are increasingly cognizant of the potential impact that climate change, and the measures imposed to mitigate climate change, might have on the value of their portfolios. However, efforts to assess and address these costs and opportunities happen almost exclusively during the bottom-up, issuer-level stages of the investment process. As such, climate-related adjustments to valuations and estimated returns are imposed upon portfolios whose asset-class, region and sector allocations have already been determined.

We believe that integrating climate-related costs into SAA processes—before asset allocation is determined—can "recover" some of the estimated return that gets lost when climate-related adjustments are imposed on existing portfolios. The wide dispersion of climate impact we find between asset classes, regions and sectors provides abundant opportunity to optimize between risk-adjusted estimated return and climate effects.

Moreover, in the context of insurance portfolios, we find that integrating climate-related costs into SAA processes can not only raise estimated return with no additional volatility, but also lower a portfolio's SCR, thereby enhancing solvency capital efficiency.

Finally, we think it is important to underline the flexibility and adaptability of Climate SAA. An investor can introduce or "dial up" the effect of any risk or parameter it chooses by adding it as a constraint to the optimization. As governments, regulators, corporations and investors increasingly adopt Net-Zero and other emissions-reduction targets, the flexibility Climate SAA has to take account of these parameters could become a major advantage.

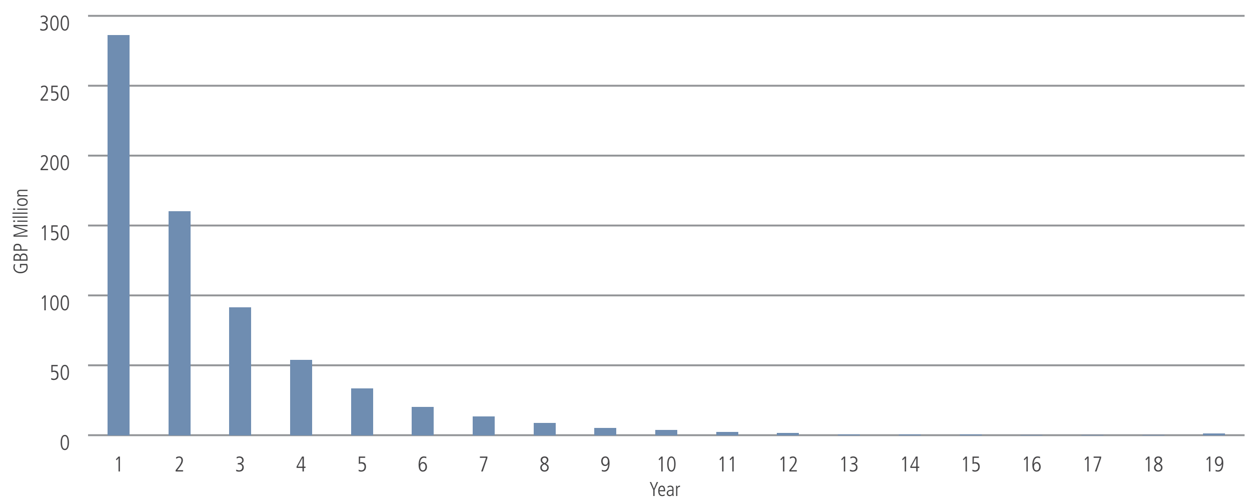
PROFILES OF AN ILLUSTRATIVE UK GENERAL INSURER AND CONTINENTAL EUROPEAN LIFE INSURER

Illustrative UK General Insurer

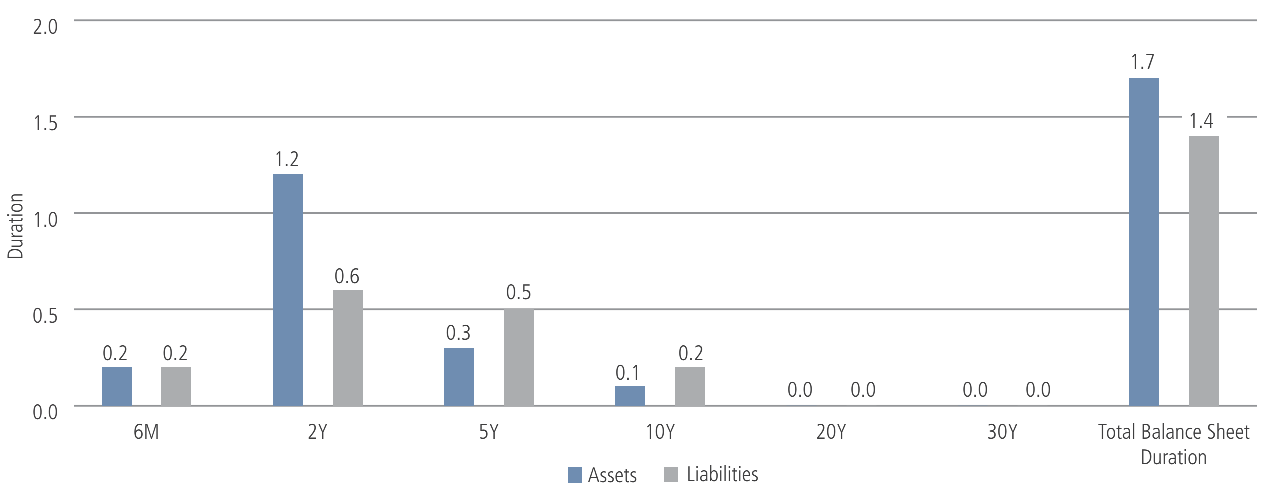
Balance Sheet

	Original		Duration Scaled to Assets	
	Assets	**Liabilities**	**Liabilities**	**Surplus**
Market Value (GBP Million)	1,000	623	623	377
Duration (years)	1.7	2.3	1.4	0.3
DV01 (GBP Million)	17	14	14	3

Illustrative Liability Cash Flows



Key Rate Duration, Assets vs. Liabilities (Years, Scaled to Assets)



Asset Allocation, with Estimated Reduction in Annualized Return from Climate Adjustments

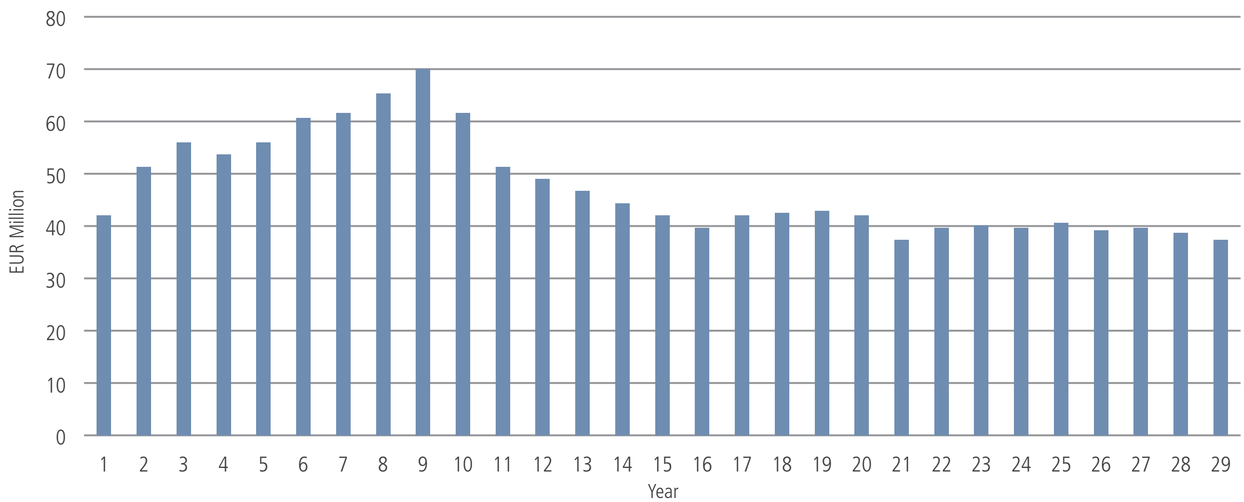
Asset Class	Allocation (%)	Return Reduction (bps)	Portfolio Return Reduction (bps)
Sterling Cash	7	NA	NA
Sterling Gilt 1-3 yrs	13	0	0
Sterling IG Corp 1-3 yrs	23	-12	-3
Euro Treasury 1-3 yrs	6	0	0
Euro IG Corp 1-3 yrs	11	-47	-5
Euro Mortgage Loans	6	NA	NA
US Treasury 1-3 yrs	6	-1	0
US IG Corp 1-3 yrs	11	-14	-2
Sterling HY BB&B 1-3 yrs	2	-56	-1
Euro HY BB&B 1-3 yrs	1	-113	-1
US HY BB&B 1-3 yrs	1	-163	-2
Europe Real Estate	2	NA	NA
UK Equity	5	-77	-4
US Equity	2	-18	0
Global Equity	3	-25	-1
Total	**100**	**NA**	**-19**

Source: Bloomberg, MSCI, JP Morgan, S&P Global, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, and US Equities; MSCI Indices for UK Equity and Global Equity; JPM EMBI for Emerging Markets Sovereign Debt; JPM CEMBI for Emerging Markets Corporate Bonds; MSCI and S&P Global Indices for Real Estate. Carbon Intensity and Carbon Footprint data are calculated on Scope 1 and 2 emissions. **Past performance is no guarantee of future results.** Please note that estimated returns data is based on NB's capital markets assumptions and are provided for information purposes only. There is no guarantee that estimated returns will be realized or achieved nor that an investment strategy will be successful, and may be significantly different than shown here. Investors should keep in mind that the securities markets are volatile and unpredictable. There are no guarantees that historical performance of an investment, portfolio, or asset class will have a direct correlation with its future performance. Net returns will be lower.

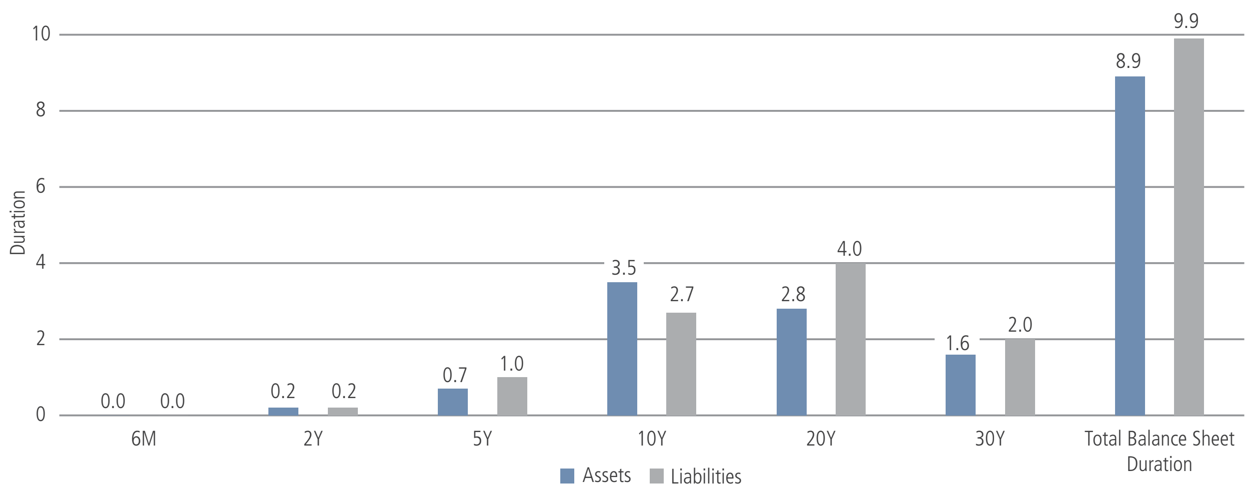
Illustrative Continental European Life Insurer
Balance Sheet

	Original		Duration Scaled to Assets	
	Assets	**Liabilities**	**Liabilities**	**Surplus**
Market Value (EUR Million)	1,200	1,000	1,000	200
Duration (years)	8.9	11.9	9.9	-1.1
Dollar Duration (EUR Million)	106	119	119	-13

Illustrative Liability Cash Flows



Key Rate Duration, Assets vs. Liabilities (Years, Scaled to Assets)



Asset Allocation, with Estimated Reduction in Annualized Return from Climate Costs

Asset Class	Allocation (%)	Return Reduction (bps)	Portfolio Return Reduction (bps)
Euro Cash	3	NA	NA
Euro Gov 1-10 Yr	2	1	0
Euro Gov 10+ Yr	21	3	1
Covered Bonds	12	NA	NA
Euro Corp A/above 1-10 yrs	1	-11	0
Euro Corp A/above 10+ yrs	11	-1	0
Euro Corp BBB 1-10 yrs	2	-66	-2
Euro Corp BBB 10+ yrs	22	-26	-6
Euro Mortgage Loans	9	NA	NA
US Corp A/above 1-10 yrs	0	-1	0
US Corp A/above 10+ yrs	0	-2	0
US Corp BBB 1-10 yrs	0	-21	0
US Corp BBB 10+ yrs	1	-19	0
Euro HY BB&B	3	-89	-3
US HY BB&B	0	-56	0
EM Sovereigns	0	-15	0
EM Corporates	0	-48	0
US Equities	1	-18	0
Europe Equities	7	-55	-4
Private Equity	1	NA	NA
Hedge Funds	0	NA	NA
Europe Real Estate	2	NA	NA
Total	**100**	**NA**	**-14**

Source: Bloomberg, MSCI, JP Morgan, S&P Global, Cambridge Associates, HFRI, Neuberger Berman. Data as of April 2023. Indices used: Bloomberg-Barclays Indices for Government/Agency Debt, Corporate Bonds, US Equities and Europe Equities; JPM EMBI for Emerging Markets Sovereign Debt; JPM CEMBI for Emerging Markets Corporate Bonds; Cambridge Associates Indices for Private Equity; HFRI Indices for Hedge Funds; MSCI and S&P Global Indices for Real Estate. German Government Bonds and Pfandbriefe are used as proxies for Euro Government Bonds and Covered Bonds. Carbon Intensity and Carbon Footprint data are calculated on Scope 1 and 2 emissions. **Past performance is no guarantee of future results.** Please note that estimated returns data is based on NB's capital markets assumptions and are provided for information purposes only. There is no guarantee that estimated returns will be realized or achieved nor that an investment strategy will be successful, and may be significantly different than shown here. Investors should keep in mind that the securities markets are volatile and unpredictable. There are no guarantees that historical performance of an investment, portfolio, or asset class will have a direct correlation with its future performance. Net returns will be lower.

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CLIMATE RISK ASSESSMENT OF THE SOVEREIGN BOND PORTFOLIO OF EUROPEAN INSURERS[40]

Stefano Battiston[41], Petr Jakubik[42], Irene Monasterolo[43], Keywan Riahi[44], Bas van Ruijven[44]

ABSTRACT

In the first collaboration between climate economists, climate financial risk modellers and financial regulators, we apply the CLIMAFIN framework described in Battiston at al. (2019) to provide a forward-looking climate transition risk assessment of the sovereign bonds' portfolios of solo insurance companies in Europe. We consider a scenario of a disorderly introduction of climate policies that cannot be fully anticipated and priced in by investors. First, we analyse the shock on the market share and profitability of carbon-intensive and low-carbon activities under climate transition risk scenarios. Second, we define the climate risk management strategy under uncertainty for a risk averse investor that aims to minimise her largest losses. Third, we price the climate policies scenarios in the probability of default of the individual sovereign bonds and in the bonds' climate spread. Finally, we estimate the largest gains/losses on the insurance companies' portfolios conditioned to the climate scenarios. We find that the potential impact of a disorderly transition to low-carbon economy on insurers portfolios of sovereign bonds is moderate in terms of its magnitude. However, it is non-negligible in several scenarios. Thus, it should be regularly monitored and assessed given the importance of sovereign bonds in insurers' investment portfolios.

1. INTRODUCTION

The topic of sustainable finance has gained attention among European insurers and the financial supervisory community alike. This is fuelled by recent initiatives promoted by

40 The authors are grateful to Alan Roncoroni and Alejandra Salazar Romo from the UZH FINEXUS Center for Financial Networks and Sustainability for their support in the pricing model and in the empirical analysis as well as Alessandro Fontana from the European Insurance and Occupational Pensions Authority for the provided data support. In addition, Stefano Battiston acknowledges the support of the Schwyzer-Winiker foundation, while Irene Monasterolo acknowledges the support of the RiskFinPorto ACRP 10th call project. Irene Monasterolo and Stefano Battiston acknowledge the support of the EU FET Innovation Launchpad CLIMEX and of the INSPIRE grant.

41 Dept. of Banking and Finance, FINEXUS Center, University of Zurich (UZH) and Swiss Finance Foundation.

42 European Insurance and Occupational Pensions Authority (EIOPA)

43 Vienna University of Economics and Business (WU) and Boston University (BU)

44 International Institute for Applied Systems Analysis (IIASA)

financial supervisors, central banks and policy makers to align finance to sustainability. For instance, in 2018 several international central banks and financial regulators launched the Central Banks and Financial Regulators' Network for Greening the Financial System (NGSF 2018). In 2019, the European Commission (EC) launched the "Action Plan on Sustainable Finance" to tackle climate related risks and achieve the long-term goal of economic transformation towards a low-carbon economy. These initiatives are aimed to mitigate the potential financial risks stemming from a disorderly low-carbon transition, by supporting the alignment of investments to the climate targets.

Limiting the global temperature increase to 2°C above pre-industrial levels (i.e. consistently with Paris Agreement, UNFCCC 2016) requires the timely and coordinated introduction of climate policies, e.g. a global carbon tax (Stiglitz et al., 2017; IMF, 2019) aimed to drastically decrease the CO_2 emissions produced by the combustion of fossil fuels in the economy.

However, governments are delaying in the introduction of climate policies, leading potentially to a disorderly transition, where the introduction of climate policies is sudden and cannot be fully anticipated and priced in by investors (Battiston et al., 2017). In this context, firms whose revenues depend directly or indirectly on use of fossil fuels energy and electricity could face significant losses (the so-called "carbon stranded assets", Leaton et al. 2012). These losses will affect the value of the financial contracts issued by such firms and cascade onto their investors (Battiston et al., 2017), with implications on price volatility if large and correlated asset classes are involved (Monasterolo et al., 2017), and on firms and countries' financial stability (Battiston and Monasterolo, 2019). In this respect, not only climate related exposures of insurance firms towards the corporate sector but also towards the sovereigns in which those activities take place could be negatively affected. Given the role of the insurance sector in the economy and finance, the exposure of insurance firms to climate-related financial risks deserve to be monitored and assessed.

A main obstacle for insurers to embed climate in their portfolios' risk management strategies is represented by the lack of appropriate methodologies to price forward-looking climate risks and opportunities in the value of individual financial contracts and in the probabilities of default of investors portfolios. The reason is that climate risks are forward-looking (because they refer to future occurrences), characterised by deep uncertainty (thus leading to fat tailed distributions, Weitzman, 2009), non-linearity (Ackerman, 2017), and endogeneity that could give rise to multiple equilibria (Battiston et al., 2017). These characteristics makes the reliance on historical data much less relevant for risk assessment. This means that climate transition risks cannot be priced based on historical market data (e.g. to calculate volatility measures), but require to use the information on future climate policy shocks produced by climate economic models (e.g. Integrated Assessment Models - IAMs), and to introduce climate ambiguity.

Nevertheless, traditional financial pricing models (e.g. Merton, 1974; Black and Scholes, 1973; Black and Cox, 1976; Duffie and Singleton, 1999) are not able by construction to embed the characteristics of climate risks. Indeed, their financial risk assessment is based on past firms' performance (e.g. the computation of volatility measures based on historical data). In addition, they are constrained by conditions of normal distributions, complete markets, and lack of arbitrage (Battiston and Monasterolo, 2019).

Thus, pricing climate in investors' portfolio requires to move from the backward-looking nature of traditional financial risk assessment and of investors' benchmarks to a forward-looking assessment of risk. In this paper, we develop an application of the CLIMA-

FIN framework (Battiston et al., 2019) to calculate the probability of default of sovereign bonds, portfolio's financial risk metrics (e.g. the Climate Spread), and the largest losses/gains on insurers' portfolios conditioned to future climate transition shocks. This analysis represents the first climate-financial risk assessment developed in collaboration between scientists of the climate economic community that informs the Intergovernmental Panel on Climate Change (IPCC), climate financial risk experts and a financial regulatory institution with a mandate to contribute to financial stability.

We build on CLIMAFIN, because it is the first approach to combine forward-looking climate transition risk shocks and associated economic trajectories based on We build on CLIMAFIN because it is the first approach to combine forward-looking climate transition risk scenarios and associated economic trajectories based on climate economic models, with financial pricing models and financial risk metrics. In addition, CLIMAFIN provides a transparent and robust methodology for climate financial risk assessment under deep uncertainty, by considering the characteristics of climate risks and of financial risks.

In this application, we build on the LIMITS[45] database of climate policy scenarios (Kriegler et al., 2013). These models are the reference for scientific community and the IPCC, with climate financial risk metrics and methods that are now a reference in both the academic and practitioners' community, i.e. the Climate Spread, the Climate VaR, climate financial pricing models and financial network-based Climate Stress-tests (Battiston et al., 2017). In the context of potentially destabilizing financial impact of a disorderly climate transition and of unmitigated climate change, transparent and robust methodologies can support financial supervisors' policy decisions to align finance to sustainability and climate targets while preventing financial instability.

This article is organized as follows. Section 2 elaborates on the relevant literature. Section 3 provides a description of the data sample used and the section 4 describes the CLIMAFIN methodology for pricing forward-looking climate transition risks in the value of sovereign bonds and in investors' portfolios. The results of empirical analysis conducted on the portfolios of EU insurance companies are presented in section 5, while section 6 concludes discussing the linkages with the next steps of this research into the Climate Stress-test.

2. LITERATURE REVIEW

Recent research suggest that climate risks (and opportunities) are not properly priced yet in the value of financial contracts and thus, in investor portfolios' risk management strategies. This means that investors might, on the one hand, increase (and trade) their exposure to climate risks, and on the other hand, they might delay the scaling-up of green investments.

The literature has mostly covered corporate debt contracts, only recently the attention has focused on sovereign bonds and equity holdings. Alessi et al. (2019), Zerbib (2019) and Karpf and Mandel (2018) assessed if a green bonds' premium exists in the bond market, but found very different results, based on the type of bonds contract analysed and the "green" definition used. In the catastrophe bonds (CAT) market, Morana and Sbrana

45 See the LIMITS database documentation for more details https://tntcat.iiasa.ac.at/LIMITSDB/static/download/LIMITS_overview_SOM_Study_Protocol_Final.pdf

(2019) found that despite climate-led disasters have steadily increased from year 2000, the "multiple" (i.e. the return per unity of risk) of the CAT bonds has decreased.

Monasterolo and de Angelis analysed the US, EU and global stock market's reaction to the announcement of the Paris Agreement. They found that the overall systematic risk for the low-carbon indices decreases consistently, while stock markets' reaction is mild for most of carbon-intensive indices. Ramelli et al. (2018) and Wagner et al. (2018) analysed the stock market's reaction to the election of Trump as President of the United States, and the appointment of the climate skeptic Scott Pruitt as a head of the US Environmental Protection Agency, and found opposite results, i.e. that investors rewarded companies in high-emissions industries/companies demonstrating more responsible climate strategies.

With regard to sovereign bonds, Crifo et al. (2017) find that high country's Environmental Social Governance (ESG) ratings are associated with low borrowing costs (spread) for short-maturity sovereign bonds in advanced economics. In the contest of low-income countries, Kling et al. (2018) focus on the most climate vulnerable low-income countries (V20) exposed to climate physical risk occurred in the past. They find a slightly higher cost of debt for a few countries, but they also point out the caveats that apply, such as the peculiarity of sovereign bonds' markets in low- income countries and the nature of risks (e.g. geopolitical) to consider in the sovereign valuation.

All these analyses, despite focusing on different types of financial contracts and climate risks analyse climate shocks that occurred in the past, and that could have represented a structural break in the series of prices and performance. In contrast, Battiston and Monasterolo (2019) developed the first approach to price *forward-looking* climate transition risks in the value of individual sovereign bonds, by including the characteristics of climate risks (i.e. uncertainty, non-linearity and endogeneity of risk) in financial valuation. They applied the model to the sovereign bonds of the OECD countries included in the Austrian National Bank (OeNB)'s non-monetary policy portfolio. They found that the (mis)alignment of an economy could already be reflected in the sovereign bonds' spread (i.e. the climate spread) and change the fiscal and financial risk position of a country.

Since financial investors take decisions based on what they can measure, and their decisions do influence (and are influenced by) the benchmark in their respective markets, assessing climate risks in financial contracts is crucial from an investors' risk management perspective, and for financial supervisors whose mandate is about preserving financial stability. To our knowledge, this article is the first study assessing climate-related financial risks stemming from insurance companies' exposures to sovereign bonds.

3. DATA SAMPLE

We utilized Quarterly Solvency II Reporting Template on List of Assets (SII QRT)[46] and Centralized Security Database (CSDB). Solo data of insurers from 31 countries in EU/EEA that reported Solvency II data at the end of 2018 are employed. Our dataset includes all insurers' investments into sovereign bonds (CIC code equal 1). This data is complemented by information on the characteristics of the bonds available from the CSDB. The final dataset contains 1576 insurance companies, 142 bond issuers and 10746 bonds. The total amount of the insurance government portfolio considered is 2.1 trillion EUR. The full description of the data set utilized in this study is provided in the table below.

46 S.06.02 template.

Table A1.1: List of variables utilized

Variable name	Description
Insurance identifier	Unique identifier of solo insurance company (SII QRT)
Home country	Country of authorization of the insurer (SII QRT)
ISIN code	ISIN conde of the sovereign bond (SII QRT)
Issuer's country	Country that issued the bond (SII QRT)
Duration	Residual duration of the bond (SII QRT)
Maturity	Maturity date of the bond (SII QRT)
Term	Difference in years between the date of bond's maturity and the date of bond issuance (SII QRT)
Price	Market value of the bond (SII QRT)
Nominal value	Nominal value of the bond (SII QRT)
Coupon	Coupon of the bond (CSDB)
Coupon type	Type of the bond's coupon (fix, zero coupon) (CSDB)
Coupon frequency	Coupon frequency of the bond (monthly, bi-monthly, quarterly, semi-annually, annually, zero coupon) (CSDB)

Note: All variables refer to 2018Q4.

4. METHODOLOGY

In this section, we introduce the concepts of climate physical and transition risks. Then, we define the climate policy shocks that we analyse in the context of a disorderly low-carbon transition. Finally, we present the CLIMAFIN tool that we apply to price forward-looking climate transition risk in the value of individual sovereign bonds (introducing the climate sovereign spread) under deep uncertainty, and to assess the largest gains/losses on investors' portfolios. CLIMAFIN includes climate scenarios adjusted financial pricing models (for equity holdings, sovereign and corporate bonds, and loans) and climate scenarios conditioned risk metrics (such as the Climate Spread and the Climate VaR). These allow us to embed forward-looking climate risk scenarios in the valuation of counterparty risk, in the probability of default of securities and in the largest losses on investors' portfolios (Battiston et al., 2019).

We opted for CLIMAFIN for two reasons. First, it is the first approach that combines forward-looking climate transition risk shocks and associated economic trajectories based on climate economic models (in this application, the LIMITS IAMs), which are the reference for the scientific community and the IPCC, with climate financial risk metrics and methods that are now a reference in both the academic and practitioners' community (Battiston et al., 2019). Second, CLIMAFIN provides a transparent and robust methodology for climate financial risk assessment under deep uncertainty. Importantly, this represents the first climate-financial risk assessment developed in collaboration between scientists of the climate economic community, climate financial risk experts and a financial regulatory institution with a financial stability mandate.

4.1. CLIMATE CHANGE AND FINANCIAL STABILITY: TRANSITION RISKS

Two main channels of risk transmissions from climate change to finance have been identified and analyzed so far, i.e. climate physical risks and climate transition risks. In our analysis we focus on *climate transition risk* because while climate physical risks are expected to be more visible in the mid to long-term period, triggering potentially irreversible socio-economic and environmental impacts (see IPCC 1.5°C 2018 Allen et al. 2018, Steffen et al. 2018), climate transition risks could happen sooner and be more financially relevant (V. de Gaulhau (2018))[47].

Climate transition risk refers to the economic and financial risk arising from a sudden revaluation of carbon-intensive and low-carbon assets and that cannot be fully anticipated by financial actors. This risk can be driven by (i) *Technological shocks* (e.g. the fast decrease of renewable energy production costs and fast increase in their performance, or the change in minimum technology standards); (ii) *Policy and regulatory shocks* (e.g. the disordered introduction of a global carbon tax IMF, 2019) or a change in prudential regulation such as the introduction of Green Supporting Factors (HLEG, 2018); (iii) the sudden changes in the *climate sentiments* of financial actors (Dunz et al., 2019), as a result of the expectations of market participants about the implementation of the climate policies.

Most important, climate risks differ from the type of risks that investors are used to consider in finance. In particular, the nature of climate risks introduces several conceptual and methodological challenges for traditional economic and financial models, which then need to consider (Monasterolo, 2019):

- *Non-linearity of impacts*. The probability of forward-looking climate shocks can't be inferred from historical data being non-linear and not normally distributed (Ackerman, 2017);
- *Forward-looking nature of risk***.** The impacts of climate change are on the time scale of two decades or longer[1]. However, the time horizon of financial markets is much shorter. Investors' decisions follow a much shorter time horizon (e.g. three months for fund managers) and are based on a market benchmark (performance) that is backward-looking because estimated on past companies' performance.
- *Deep uncertainties* that characterize climate impacts and their costs, due to the nature of the earth system that leads to the presence of tail events (Weitzman 2009), tipping points and domino effects (Steffen et al., 2018), which are associated to large uncertainty (Kriegler et al., 2009). Tipping points mean that the estimates of the costs and benefits of (in)action may vary substantially across climate scenarios with the assumptions on agents' utility function, future productivity growth rate, and intertemporal discount rate (Stern, 2008, Pyndick, 2013).
- *Endogeneity and circularity of climate risk*. The likelihood of achieving the global climate targets depends on the orderly introduction of climate policies, and their anticipation by financial actors in their investment decisions. However, climate policies' uncertainty affects investors' expectations on the financial risk deriving from the very same policies, and thus their investment decision. In turn, the lack of climate aligned investments makes it impossible to achieve the climate policy targets. This generates the possibility of multiple equilibria, a situation where a rational agent cannot identify a preferred investment strategy (Battiston and Monasterolo, 2018).

47 https://www.bis.org/review/r180419b.htm

4.2. THE CLIMAFIN CLIMATE FINANCIAL RISK PRICING MODEL

4.2.1. Climate policy scenarios

We consider the climate policy scenarios developed by the International Scientific Community and reviewed by the IPCC. In particular, we select all the climate policy scenarios aligned to the 2°C target made available from the LIMITS project, which includes six IAMs. We use the LIMITS project database (Kriegler et al., 2013) to compute the trajectories of the shocks in the market shares for several variables, including the output of all the economic activities in primary and secondary energy (e.g. primary energy from fossil fuels, electricity produced by solar panels, etc.) conditioned to climate policies' introduction (i.e. a carbon tax). The two emissions concentration targets chosen under milder and tighter climate policy scenarios (i.e. 500 parts per million (ppm) and 450 ppm) refer to the stabilization concentration of CO_2 at the end of century consistently with the 2°C aligned scenarios, and are associated to two different policy implementation scenarios, i.e. the

Reference Policy (RefPol) and the Strong Policy (StrPol) (IPCC, 2014). RefPol assumes a weak near-term target by 2020 with fragmented countries' action, while StrPol assumes a stringent near-term target by 2020 with fragmented countries' action, to achieve emissions reduction by 2050. The 500 and 450 ppm scenarios are associated to a probability of exceeding the 2°C target by 35-59% and 20-41% respectively (Menishausen et al., 2009). Thus, the choice of specific emissions concentration targets could be considered as a proxy for the stringency of the global emission cap imposed by potential climate treaty. A change in climate policy (i.e. in the value of the carbon tax every 5 years' time step) implies a change in the sectors' macroeconomic trajectory, and thus a change in the market share of primary and secondary energy sources based on their energy technology (fossil/renewable).

4.2.2. Climate policy shocks

In the context of climate transition risks, climate policy shocks are defined as the transition from a business as usual scenario of no climate policy, to a policy scenario characterised by the introduction of a climate policy (e.g. a carbon tax, or a Green Supporting Factor). Climate policy shocks arise from a disorderly transition, i.e. when the introduction of climate-aligned policies is carried out at a schedule that is not predictable by investors. These, in turn, cannot fully anticipate (and price) it in their portfolios' risk management strategies (Battiston et al., 2017; NGSF, 2019). In the current scenario where governments have not coordinated yet to introduce stable climate policies, we might end up in a disorderly transition scenario (Battiston, 2019). The transition entails a jump from one equilibrium state of the economy (e.g. the current state) to another equilibrium state where the composition of the economy and the weight of the economic activities (carbon-intensive, low-carbon) could consistently change.

In a disorderly transition, assets price adjustments would directly or indirectly negatively impact the value of fossil fuels and related assets. The lack of investors' anticipation of the climate policy shock could have relevant and long-lasting consequences for the financial conditions of a private investor and of a sovereign, and eventually it would affect the achievement of the 2°C aligned climate mitigation scenarios. As several recent policy events show (e.g. the US withdrawal from Paris Agreement, the outcome of 2018 Italian elections), the assessment of the future policy shock could be incorrect even on average across market participants, and yet can have severe long-term effects on the financial conditions of a country (Battiston, 2019).

4.2.3. Investors' information set

Here we present the information set that a rational risk averse investor should use to assess financial risk under climate transition scenarios. We consider a risk averse investor that aims to assess the exposure of her portfolio to forward-looking climate transition risk. This information set can accommodate the presence of incomplete information and deep uncertainty (Keynes, 1973; Knight, 1921; Greenwald and Stiglitz, 1986). The information set covers a time-horizons that is relevant both for investment strategies and for the low-carbon transition from 2020 to 2050, and is composed of:

- **Climate policy scenarios** corresponding to Greenhouse Gases (GHG) emission reduction target across regions (B = Business-as-Usual), provided e.g. by the IPCC reports;
- The future **economic trajectories** for carbon-intensive and low-carbon activities, provided by climate economic models (e.g. IAMs);
- A set of forward-looking **Climate Policy Shock Scenarios** intended as a disorderly transition from B (Business as Usual) to P (a given climate policy scenario);
- A set of **Climate Policy Shocks** on the economic output of low-carbon/carbon-intensive activities, on their Gross Value Added (GVA) and on their contribution to the fiscal revenues of the sovereign. The policy shocks are conditioned to transition scenarios and, to a specific climate economic model.

4.2.4. Investors' risk management strategy

The investor's risk management strategy is based on the minimization of the worst-case losses of the portfolio under different forward-looking climate transition scenarios. The definition of the risk management strategy accounts for (i) the investor's specific risk aversion levels, (ii) the counterparty risk adjusted for climate policy shock scenarios (e.g. Probability of Default (PD)), (iii) metrics relevant for financial regulation (e.g. risk measures such as the Climate Spread and VaR). The Climate VaR Management Strategy can be written as:

$$\mathrm{ClimVaRStr} = \min_{\mathrm{Portfolio}}\{\max_{\mathrm{Shock}}\{\mathrm{VaR}(\mathrm{Portfolio}, \mathrm{Adj.PD} \mid \mathrm{Policy\ Shock})\}\}$$

In this context, future asset prices are subject to shocks that depend on the issuer's future economic performance, the risk premia demanded by the market, as well as the implementation of the climate policy and the outcome of the energy transition of individual firms and countries. The investor considers different feasible climate policy scenarios (but has no information on the probability associated) for which she can calculate the impacts (negative or positive) on the market share of carbon-intensive or low-carbon economic activities and firms. The investor is subject to incomplete information on her (and competitors') exposure to risk stemming from a disordered transition from a climate policy scenario to another one, uncertainty on the outcome of the firms and country's energy transition, and no information on the probability distribution. Thus, her risk management strategy is to consider a set of feasible climate transition scenarios that her portfolio should withstand, and then compute the VaR conditional to those scenarios.

4.2.5. Composition of the economy

We consider n countries j whose economy is composed of m economic sectors *S*. Economic activities included in *S* are based on a refined classification of the Climate Policy Relevant Sectors (CPRS Rev 2), which identify the main sectors that are relevant for climate transition risk (fossil-fuel, electricity (from fossil or renewable sources), energy-intensive, transportation (low/high-carbon), buildings), and were originally introduced in Battiston et al. (2017). As a difference from the NACE classification of economic sectors, CPRS Rev 2 capture the energy and electricity technology embedded in the economic activity (e.g. utility|electricity|wind, solar, gas). Firms that compose economic sectors *S* are considered as a portfolio of cash-flows. The classification of countries and regions affected by the climate shock is based on the LIMITS aggregation[48], see Kriegler et al. (2013).

4.2.6. Impact of climate policy shock on economic activities' GVA and profitability

We consider the contribution of issuer *j* to the sector *S* GVA and fiscal assets and how this can be affected by changes in its economic performance, either negatively or positively. We then relate the performance of the economic activity to the change in its market share as a result of a climate transition scenario.

In a disorderly transition, a climate policy shock affects the performance of issuers in sectors *S* via a change in economic activities' market share, cash flows and profitability, eventually affecting the GVA of the sector. The climate policy shock is calculated at the sector, country and regional level. The country's GVA composition is available at NACE 2-digit level from official statistics (e.g. from Eurostat). Negative shocks result from the policy impact on the GVA of sectors based on carbon-intensive (i.e. fossil fuels) technologies, while positive shocks result from the impact on the GVA of sectors based on low-carbon (i.e. renewable energy) technologies.

We assume that a percentage shock on output to a percentage shock on GVA, u_j^{GVA},for each sector *j*,so that:

$$u_j^{GVA}(P) = \frac{GVA_j\,(P) - GVA_j\,(B)}{GVA_j\,(B)} = \sum_S u_{j,s}^{GVA}(P)\; w_{j,s}^{GVA}(B)$$

Where $u_{j,s}^{GVA}(P)$ is the shock on the GVA of sector *S* of the sovereign issuer *j;* $w_{j,s}^{GVA}(B)$ is the share of GVA of sector *S*. We then define the net fiscal assets related to sector *S*, $A_j(S)$,as the difference between accrued fiscal revenues from sector *S* and public investments and subsidies granted by *j* to the same sector. The impact of the market share shock (resulting from the policy shock *P*) on net fiscal assets of sector *S* is thus assumed to imply a change $A_j(S, P, M)$ as follows:

$$\frac{\Delta A_j(S,P,M)}{A_j(S)} = \chi_S\, u_j(S,P,M)$$

Where χ denotes the elasticity of sector *S* profitability with respect to the market share. While the policy shock could affect at the same time several sectors in the economy of the issuer *j*, here we consider the total net effect on the issuer's net fiscal assets as follows:

48 See the LIMITS database documentation for more details https://tntcat.iiasa.ac.at/LIMITSDB/ static/download/LIMITS_overview_SOM_Study_Protocol_Final.pdf

$$\frac{\Delta A_j(P,M)}{A_j} = \sum_s \left(\frac{\Delta A_j(S,P,M)}{A_j(S)} \frac{A_j(S)}{A_j}\right) = \sum_s \chi_s \, u_j(S,P,M) \frac{A_j(S)}{A_j}$$

The elasticity coefficient could be estimated empirically for the specific sectors of the sovereign issuers in the portfolio. However, in our application, the data to carry out this estimation was not available. Thus, for estimating the elasticity we consider a mild and adverse scenario with values equal to equal to 0.2 and 0.5, respectively (see also Battiston and Monasterolo, 2019). This allows us to provide an estimation of the magnitude of the shocks due to a given climate policy scenarios *P*, where the shock is transmitted to the value of the sovereign bond via the change in sectors' market share, GDP and fiscal assets.

4.2.7. Model for sovereign bonds' valuation

We consider a risky (defaultable) bond of a sovereign entity *j*, issued at t_0 with maturity *T*. The value of the sovereign bond at time *T*, with *R* being the Recovery Rate of the bond (i.e. the percentage of notional recovered upon default), and LGD Loss-Given-Default (i.e. the percentage loss) can be written as:

$$v_j(T) = \begin{cases} R_j = (1 - LGD_j) & if\ j\ defaults\ (with\ probability\ Q_j) \\ 1 & else\ (with\ probability\ 1 - Q_j) \end{cases}$$

The unitary price $P_j(t)$ of the sovereign bond at time $t<T$ and $t>t_0$ follows the usual definition of discounted expected value at the maturity,

$\Delta q_j(P) = q_j(P) - q_j(B) = \int_{\eta_{inf}}^{\theta_j(P)} \phi_{(\eta_j)} d\eta_j$, with $\theta_j(P) = \theta_j(B) - \xi_j(P)$

$$P_j = \exp(-r_f(T-t))\ E[v_j(T)] = \exp\left(-r_f(T-t)\right)\ (1 - Q\ LGD),$$

where r_f is the risk-free rate and the expectation is taken under the risk neutral measure. Moreover, the cumulative probability of default *Q*, is related to the annual probability of default as follows: $Q = 1 - (1 - q)^{(T-t)}$.The formula can be used to determine from the market price the value of the annual default probability q, called "q implied", for a given risk free rate and LGD. In the case of a multi-coupon bond, the formula gets more complicated since one has to sum over the expected value of the coupons but the logic remains the same. For each coupon *k*, the coupon amount is assumed to be paid only if *j* does not default before. The determination of the q implied requires then to solve numerically a polynomial equation.

4.2.8. Sovereign default conditions

Following a stream of literature (Gray et al., 2007), we model the payoff of the defaultable sovereign bond as dependent on the ability of the sovereign to repay the debt out of its fiscal revenues accrued until the maturity. Differently from Gray et al. (2007), we do not consider whether debt is issued in local or foreign currency, nor the exchange rate risk.

We can define the sovereign's net fiscal assets at the present time of the valuation and at the maturity respectively as $A_j(t)$ and $A_j(T)$,and the liabilities at the maturity as $L_j(T)$.Thus, the sovereign default conditions read as:

$$A_j(T) = A_j(t)\ (1+\eta_j(T)) < L_j(T)$$

We add a climate policy shock ξ_j on *j*'s net fiscal assets (as a "jump" up or down), assuming that the idiosyncratic shock η_j and policy shock ξ_j are independent. The new sovereign default condition reads as:

$$A_j(T) = A_j(t)\ (1+\eta_j(T) + \xi_j(P)) < L_j(T) \Leftrightarrow \eta_j(T) < \theta_j(P)$$
$$= L_j(T)/A_j(t) - 1 - \xi_j(T,P)$$

where $\theta_j(P)$ is the default threshold under scenario *P*, $\xi_j(P)$ is the climate policy shock from *B* to *P* (can be positive or negative) that shifts the idiosyncratic shock η_j, with $\xi_j(P)$>1, possibly correlated across *j*.

4.2.9. Sovereign default probability

We can define the Probability of Default (PD) $q_j(P)$ of issuer *j* under Climate Policy Scenario *P as:*

$$q_j(P) = \mathcal{P}\ (\eta_j < \theta_j(P)) = \int_{\eta_{inf}}^{\theta_j(P)} \phi_{(P)}(\eta_j) d\eta_j$$

where $\phi_{(P)}(\eta_j)$ is the probability distribution of idiosyncratic shock η_j, η_{inf} is the lower bound of distribution support.

In principle, frequent small productivity shocks across time and firms occur in a similar way, with or without the climate policy shock. We introduce now a proposition of the PD adjustment Δq conditioned to the climate policy shock, which shifts the probability distribution of the small productivity shocks and thus the default probability of issuer *j*:

$$\Delta q_j(P) = q_j(P) - q_j(B) = \int_{\eta_{inf}}^{\theta_j(P)} \phi_{(\eta_j)} d\eta_j, \text{ with } \theta_j(P) = \theta_j(B) - \xi_j(P)$$

Thus, assuming that the climate policy shock on fiscal asset is proportional to shock on GVA of low-carbon and carbon-intensive sectors i.e. $\xi_j = \chi_j u_{j,s}^{GVA}$ (*P*), with elasticity the adjustment $\Delta q_j(P)$, the default probability of sovereign *j* under Climate Policy Shock Scenario:

- Increases with GVA shock magnitude $|u_{j,s}^{GVA}(P)|$ if $u_{j,s}^{GVA}(P)<0$, and decreases vice versa;

Is proportional to the GVA shocks on the CPRS (in the limit of small Climate Policy Shocks).

5. EMPIRICAL RESULTS

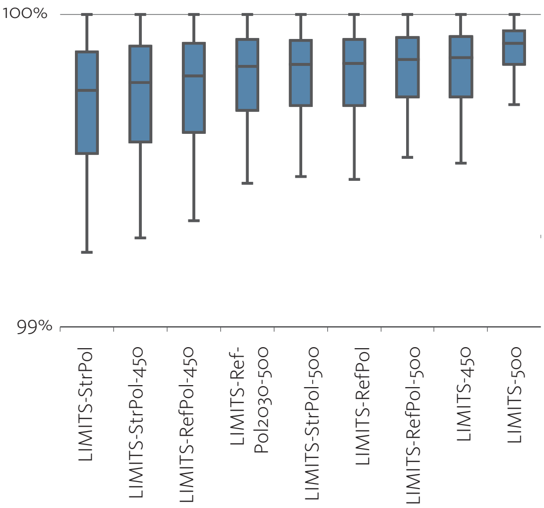
Overall, we consider the combination of two market conditions scenarios with climate policy scenarios described in Section 4. The market condition scenarios are reflected in the different values of loss-given-default LGD and elasticity.In the mild scenario, LGD = 0.2 and = 0.2. In the adverse scenario, LGD = 0.4 and = 0.5.

For each scenario combination and IAM, we compute the shock on the value of each bond in the holdings' dataset. The description of the scenarios considered in this exercise are provided in the Appendix. We then compute the resulting aggregate shocks on the value of the portfolio of each European insurance company ("solo"). We define as *portfolio impact* of the climate policy shock the ratio of the value of the portfolio after the shock over the initial value before the shock. In a series of boxplots, we study the distribution of the values of the portfolio impact of climate policy shocks under varying levels of aggregation. The difference between the median impact and 100% is considered as the *median shock* on the portfolio values.

Notice that three dimensions drive the magnitude of portfolio impact. First, for each sovereign bond negative shocks (e.g. on primary energy fossil sector) can be possibly compensated by positive shocks (e.g. on secondary energy electricity based on renewable sources). Second, in a portfolio of sovereign bonds issued by several countries, negative aggregate shocks from a less climate-aligned sovereign can be possibly compensated by positive shocks from another more climate-aligned sovereign (see also Appendix Table A1.3). Third, in some of the figures the results from several models or several scenarios are pooled together in one distribution. These three dimensions concur to limit the magnitude of the median value of the portfolio impact in the following charts. Further, recall that in this application of the CLIMAFIN framework, we do not consider the macro-economic reverberations of a shock on a given sector. Therefore, the results are to be considered as conservative.

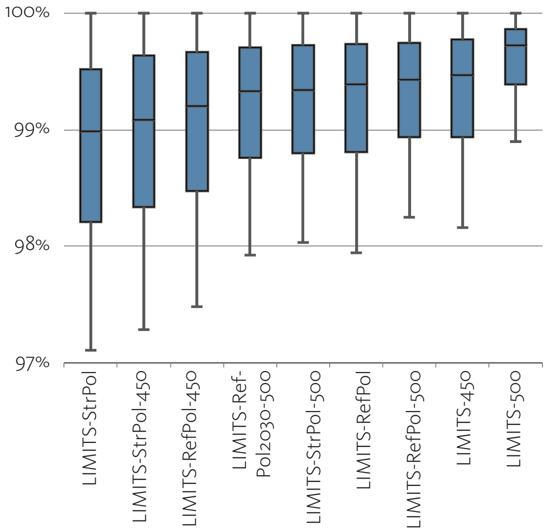
Chart A1.1-2 show the box plots of the portfolio impact distribution across insurance holders and IAMs, for selected climate policy scenarios. Chart A1.1 and A1.2 refer, respectively, to the mild and adverse scenario on market conditions. In the mild scenario, the first quartile of the distribution varies between 99.6% and 99.8%. In the adverse scenario, the same quantity varies between 98.2% and 99.4%. The median shock in the adverse scenario is about 3 times larger than in the mild scenario.

Figure A1.1: Distribution of impact on sovereign holdings of European insurers across climate policy shock scenarios, under the ***mild*** scenario on market conditions.



Source: EIOPA and own calculations

Figure A1.2: Distribution of impact on sovereign holdings of European insurers across climate policy shock scenarios, under the ***adverse*** scenario on market conditions.

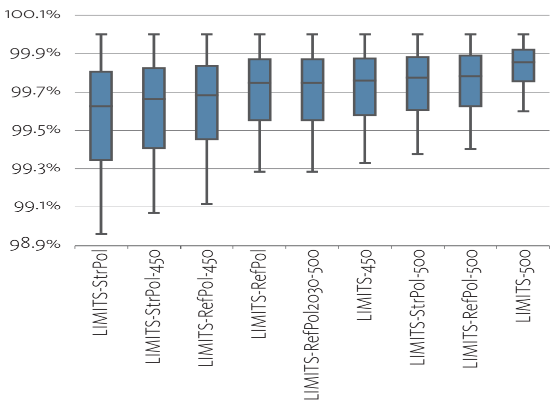


Source: EIOPA and own calculations

Note: Y-axis corresponds to the percentage of the original value of government portfolios (e.g. 100% expresses 0% impact, 97% corresponds to drop of 3%). The description of scenarios is provided in Appendix.

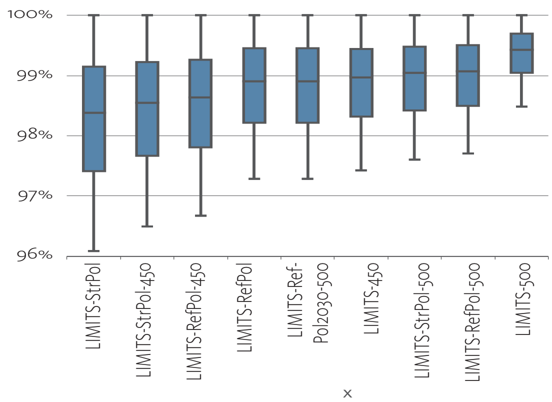
Chart A1.3-4 show the box plots of the portfolio impact distribution across holders, estimated by the model MESSAGE (Krey et al. 2016; Fricko et al. 2017), for selected climate policy scenarios. Chart A1.3 and A1.4 refer, respectively, to the mild and adverse scenario on market conditions. In the mild scenario, the first quartile of the distribution varies between 99.3% and 99.8%. In the adverse scenario, the same quantity varies between 97.4% and 99.0%. The median shock in the adverse scenario is again about three times larger than in the mild scenario.

Figure A1.3: Distribution of impact on sovereign holdings of European insurers estimated by the model MESSAGE across climate policy shock scenarios, under the ***mild*** scenario on market conditions.



Source: EIOPA and own calculations

Figure A1.4: Distribution of impact on sovereign holdings of European insurers estimated by the model MESSAGE across climate policy shock scenarios, under the ***adverse*** scenario on market conditions.

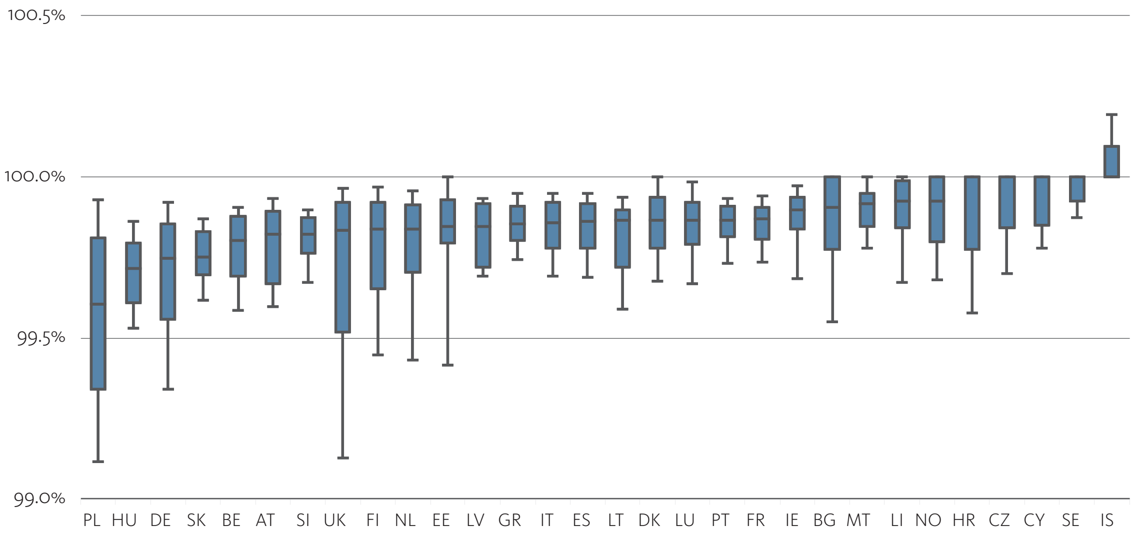


Source: EIOPA and own calculations

Note: Y-axis corresponds to the percentage of the original value of government portfolios (e.g. 100% expresses 0% impact, 97% corresponds to drop of 3%). The description of scenarios is provided in Appendix.

Chart A1.5-6 shows the box plots of the portfolio impact distribution across holders, conditioned to the country of the insurance holder, for a given selected climate policy scenario, and estimated across all the models in the LIMITS database (Kriegler et al. 2013). Chart A1.5 refers to the climate policy scenario RefPol500 and the mild market condition scenario. Chart A1.6 refers to the climate policy scenario StrPol450 and the adverse market condition scenario. In the mild scenario, the first quartile of the distribution varies between 99.3% and 100.0%. In the adverse scenario, thefirst quartile varies between 96.2% and 99.5%. The median shock in the adverse scenario is about 5 times larger than in the mild scenario. Note that we have excluded countries for which the number of observations did not allow to draw the box plot (i.e. Romania in A1.5, Romania and Iceland in A1.6).

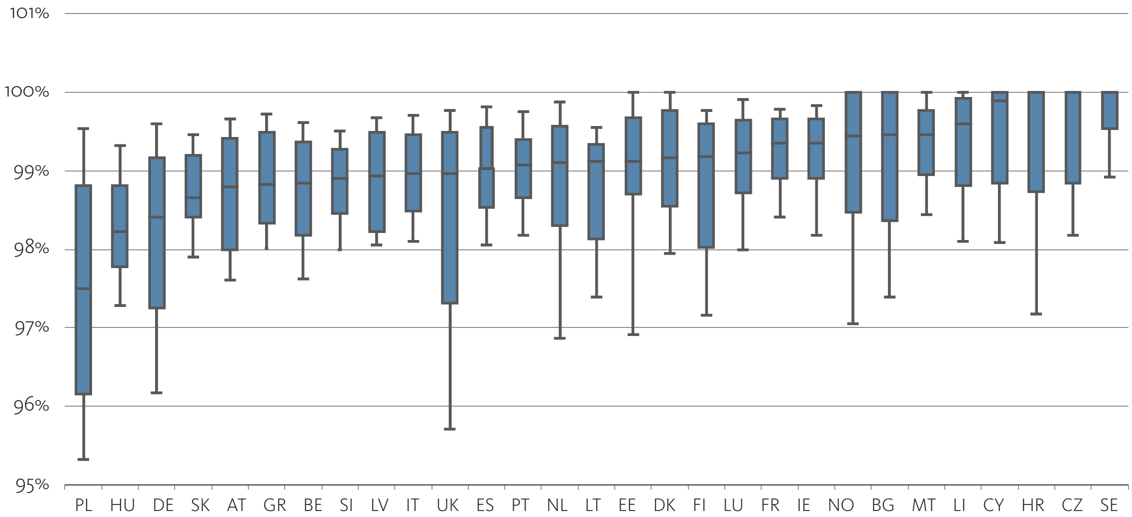
Figure A1.5: Distribution of impact on sovereign holdings of European insurers conditioned to the country of the holder, across climate policy shock scenarios and under the ***mild*** scenario on market conditions.



Source: EIOPA and own calculations

Note: Y-axis corresponds to the percentage of the original value of government portfolios (e.g. 100% expresses 0% impact, 97% corresponds to drop of 3%). The description of the scenarios is provided in Appendix.

Figure A1.6: Distribution of impact on sovereign holdings of European insurers conditioned to the country of the holder, across climate policy shock scenarios and under the ***adverse*** scenario on market conditions.



Source: EIOPA and own calculations
Note: Y-axis corresponds to the percentage of the original value of government portfolios (e.g. 100% expresses 0% impact, 97% corresponds to drop of 3%). The description of the scenarios is provided in Appendix.

The results of this analysis should be considered as conservative for the following reasons. First, since global GHG emissions are still increasing (WMO 2019) and countries are not aligning their policies to their climate pledges, stricter climate policies might be introduced. Second, the IAMs' policy scenarios that we considered were defined before the Paris Agreement. Thus, tighter policy scenarios are likely to be needed to achieve the 2°C target. Further, it must be noticed that the energy technology shocks (both on fossil and renewable energy sources) vary considerably across the IAMs used, for the same regions and countries considered. Finally, we should consider investors' sentiments, i.e. the expectations about changes in (even few decimal points) in GVA and GDP growth could impact sovereign bonds' yields.

6. CONCLUSION

In this analysis, we have developed the first climate transition risk assessment of the sovereign bonds' portfolios of solo insurance companies in Europe under deep uncertainty. This is the result of the first collaboration between, climate economics modellers, climate financial risk scholars and researchers from a public authority with a mandate to contribute to financial stability. We opted for the CLIMAFIN framework by Battiston et al. (2019) because it is the first and transparent approach that combines 1) forward-looking climate transition risk shocks obtained from climate economic models that are the reference for scientific community and the IPCC (in this context, the LIMITS IAMs) with; 2) climate financial risk metrics and methods that are now a reference in both the academic and practitioners' community (Battiston et al., 2017). In particular, the CLIMAFIN approach allows to embed forward-looking climate transition risk scenarios (i.e. a disorderly introduction of climate policies that cannot be fully anticipated and priced in by insurers) in the valuation of counterparty risk, in the probability of default of individual sovereign bonds and largest losses on investors' portfolios (Battiston et al., 2019).

In this application, we have considered a simple financial pricing model for zero and multi-coupon sovereign bonds adjusted for climate policy shock scenarios. This allows to compute an adjusted value of bonds' portfolios in order to assess how future climate transition risk could affect the probability of default of individual sovereign bonds, the financial solvability of the sovereign and the performance of European insurers who are exposed to those bonds. The analysis uses the solo data of insurers from 31 countries in EU/EEA that reported Solvency II data at the end of 2018, including all insurers' investments into sovereign bonds, complemented by information on the characteristics of the bonds available from the CSDB.

Our results show that the potential impact of a disorderly low carbon transition on insurers portfolios of sovereign bonds is moderate in terms of its magnitude. However, it is non-negligible in several feasible scenarios. Overall, it emerges that the climate policy transition path chosen, and the role of fossil fuels and renewable energy technologies in the sovereign's GVA and fiscal revenues, can considerably affect the fiscal and financial risk position of a country, via the change in the probability of default (PD) and in the value of the sovereign bonds and the Climate Spread. In general, countries that have already started to align their economy to the low-carbon transition (and thus where renewable energy technologies play a larger role on its GVA and fiscal revenues) face a decrease in the PD and in the Climate Spread, and thus better refinancing conditions. In contrast, countries whose GVA is carbon intensive would face an increase in the PD and in the Climate Spread.

This, in turn, could have relevant implications for the financial risk profile of the insurers who own sovereign bonds of countries that are misaligned to the low-carbon transition and the climate targets. Thus, it would be in the interest of insurers' supervisors to extend this climate financial risk pricing exercise (ideally in a climate stress-test exercise, see e.g. Battiston et al., 2017) for financial risk monitoring and assessment purposes.

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APPENDIX

CLIMATE POLICIES SCENARIOS LIMITS.

In this exercise we consider the scenarios elaborated by the international scientific consortium LIMITS. This is a database of economic trajectories that are consistent with 10 climate transition scenarios. The main features of climate mitigation are the following:

- The level of ambition in emission reduction in the near-term (2020):
  - reference policy 'weak' corresponds to unconditional Copenhagen Pledges; more 'stringent' based on conditional Copenhagen Pledges.
- The level of ambition in emission reduction in the long-term (2100):
  - either no target or concentrations targets of 450 and 500 ppm CO2-eq, corresponding to high chances of achieving 2°C
- The level of international cooperation until 2020 and 2030:
  - no cooperation, fragmented action, coordinated action.

Table A1.2: LIMITS scenarios' characteristics.

Scenario class	Scenario name	Scenario type	Level of ambition (near term)	Level of ambition (long term)	Level of international cooperation
No policy	Base	Baseline	None	N/A	None
Fragmented action	RefPol	Reference	Weak	2100	None
	StrPol	Reference	Stringent	2100	None
Immediate action	450	Benchmark	None	N/A	450 ppm
	500	Benchmark	None	N/A	500 ppm
Delayed Policy	RefPol-450	Climate Policy	Weak	2020	450 ppm
Delayed Policy	StrPol-450	Climate Policy	Stringent	2020	500 ppm
Delayed Policy	RefPol-500	Climate Policy	Weak	2020	500 ppm
Delayed Policy	StrPol-500	Climate Policy	Stringent	2020	500 ppm
Delayed Action	RefPol2030-500	Climate Policy	Weak	2030	501 ppm

Source: Table based on: E. Kriegler, M. Tavoni, T. Aboumahboub, G. Luderer, K. Calvin, G. De Maere, V. Krey, K. Riahi, H. Rosler, M. Schaeffer, D. van Vuuren (2013): Climate Change Economics 4(4), doi: 10.1142/S2010007813400083.

We consider the trajectories computed under 6 Integrated Assessment Models (AIM-Enduse, GCAM, IMAGE, MESSAGE, REMIND, and WITCH). More information is available at: https://tntcat.iiasa.ac.at/LIMITSDB/dsd?Action=htmlpage&page=about#tutorial

CLIMATE POLICIES SCENARIO LIMITS REDPOL-450 MILD COMPUTED WITH THE IAM MESSAGE

The following table provides simple average of results of shock for the scenario LIMITS RedPol-450 mild computed with the IAM MESSAGE aggregated by bond issuers and their residual maturities. The sovereigns that were not sufficiently represented across different residual maturities were excluded from the table. As sovereign bonds that are held by insurers in their investment portfolios could have different parameters, the obtained results were smoothed out using estimated linear trends. In this way the results could be generated even for residual maturities that were not available in our data sample. The following table could be used as an illustrative example how to integrate forward-looking climate transition in a bottom up insurance stress test. The climate shocks could be then combined with other shocks, e.g. market shocks prescribed in the given stress test scenario.

Table A1.3: Average impact of scenario LIMITS RedPol-450 mild computed by IAM MESSAGE for different sovereigns and residual maturities

	1	2	3	4	5	6	7	8	9	10	15	20
Austria	-0.31%	-0.33%	-0.35%	-0.37%	-0.38%	-0.40%	-0.42%	-0.44%	-0.46%	-0.48%	-0.57%	-0.66%
Belgium	-0.24%	-0.27%	-0.29%	-0.31%	-0.34%	-0.36%	-0.38%	-0.41%	-0.43%	-0.45%	-0.57%	-0.68%
Denmark	-0.07%	-0.10%	-0.13%	-0.16%	-0.19%	-0.22%	-0.25%	-0.29%	-0.32%	-0.35%	-0.50%	-0.65%
Finland	-0.07%	-0.11%	-0.15%	-0.19%	-0.23%	-0.27%	-0.31%	-0.35%	-0.39%	-0.42%	-0.62%	-0.82%
France	-0.32%	-0.34%	-0.37%	-0.39%	-0.42%	-0.45%	-0.47%	-0.50%	-0.52%	-0.55%	-0.67%	-0.80%
Germany	-0.12%	-0.19%	-0.25%	-0.31%	-0.38%	-0.44%	-0.50%	-0.56%	-0.63%	-0.69%	-1.00%	-1.32%
Greece	-0.26%	-0.27%	-0.27%	-0.28%	-0.28%	-0.29%	-0.30%	-0.30%	-0.31%	-0.31%	-0.34%	-0.37%
Iceland	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Ireland	-0.01%	-0.07%	-0.13%	-0.18%	-0.24%	-0.30%	-0.36%	-0.42%	-0.48%	-0.54%	-0.83%	-1.12%
Italy	-0.22%	-0.2.3%	-0.25%	-0.26%	-0.27%	-0.29%	-0.30%	-0.31%	-0.33%	-0.34%	-0.40%	-0.47%
Luxembourg	-0.02%	-0.04%	-0.07%	-0.09%	-0.12%	-0.14%	-0.16%	-0.19%	-0.21%	-0.24%	-0.36%	-0.48%
Netherlands	-0.10%	-0.20%	-0.30%	-0.40%	-0.50%	-0.60%	-0.70%	-0.80%	-0.90%	-1.00%	-1.49%	-1.99%
Norway	-0.01%	-0.01%	-0.02%	-0.02%	-0.02%	-0.03%	-0.03%	-0.04%	-0.04%	-0.04%	-0.06%	-0.08%
Poland	-0.74%	-0.73%	-0.72%	-0.71%	-0.70%	-0.69%	-0.68%	-0.67%	-0.66%	-0.65%	-0.60%	-0.54%
Spain	-0.18%	-0.21%	-0.25%	-0.28%	-0.32%	-0.35%	-0.39%	-0.42%	-0.46%	-0.49%	-0.67%	-0.84%
Sweden	-0.02%	-0.02%	-0.02%	-0.01%	-0.01%	-0.01%	-0.01%	0.00%	0.00%	-0.01%	0.00%	0.01%
United Kingdom	-0.33%	-0.28%	-0.23%	-0.18%	-0.12%	-0.40%	-0.44%	-0.47%	-0.50%	-0.53%	-0.69%	-0.85%
Switzerland	-0.24%	-0.28%	-0.31%	-0.34%	-0.37%	-0.07%	-0.02%	0.00%	0.00%	0.14%	0.40%	0.66%
United States	-0.13%	-0.13%	-0.14%	-0.14%	-0.15%	-0.16%	-0.16%	-0.17%	-0.18%	-0.18%	-0.22%	-0.25%

Source: EIOPA and own calculations
Note: The columns represent residual maturities. The obtained results were smoothed out cross residual maturities using estimated linear trends.

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Climate value at risk and expected shortfall for Bitcoin market

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ABSTRACT

The economic risk of the carbon footprint of the Bitcoin network remains unexplored. We develop the real-time artificial price for the carbon footprint of the Bitcoin network and thereby extend the climate value at risk (VaR) into the climate expected shortfall (ES) by employing both parametric and semiparametric models. On the basis of the best-fitted climate VaR and ES estimations, we find that the 95th percentiles (upper bound) of the climate VaR and ES are 8.04 and 10.37 billion euros, respectively, and the 99th percentiles (upper bound) of climate VaR and ES are 11.33 and 14.15 billion euros, respectively. Moreover, given the climate VaR and ES estimations on the basis of similar carbon footprint, the negative environmental externality of the Bitcoin network based on the current carbon price is not sufficient to reflect the environmental cost. Overall, our research provides new insight into the linkage between the Bitcoin network and the environment, which will provide meaningful information for both investors and policymakers.

1. Introduction

The climate value at risk (VaR) is a risk measure for estimating the amount of loss due to climate change within a firm, portfolio, or financial market within a specific investment horizon. The pioneering work of Dietz et al. (2016) quantifies the climate VaR of global financial assets by calculating the present value of losses in global financial assets under different climate change scenarios. When the discounted cash flow model of corporate finance is adopted, the 99th percentile climate VaR is 24.2 trillion USD without cutting carbon emission and 13.2 trillion USD when limiting climate change to under 2 °C. Although Dietz et al. (2016) provide the intuitive landscape of the climate VaR in the financial market, the climate VaR highly depends on assumptions and parameter settings.

Introduced by Nakamoto (2008), the Bitcoin network is becoming a new infrastructure of the financial system as a private, decentralized, and secure digital asset in the blockchain network. Bitcoin is not only challenging the dominance of the traditional payment system but is also highly sought after as an alternative financial investment. Currently, the market cap of Bitcoin is 158 billion USD, with a daily trading volume of 44 billion USD on February 28, 2020. However, Bitcoin is carbon intensive and consumes enormous computational and electric power, with an annual carbon footprint of approximately 36,937 kilotons; this is comparable to the annual carbon footprint of New Zealand (Stoll et al., 2019). In addition, the 2019 annual aviation allowances cap of carbon emission for the EU Emissions Trading System (EU ETS) was approximately 35,173 kilotons. Thus, the annual carbon footprint of the Bitcoin network is almost similar to that of the European aviation industry. In this paper, we extend the climate VaR to the climate

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expected shortfall (ES) by employing the real-time artificial carbon price to evaluate the economic cost of the carbon intensity of the Bitcoin network.

To understand the economic cost of the Bitcoin network's impact on the environment, we develop the artificial carbon price of the Bitcoin network by using the Cambridge Bitcoin Electricity Consumption Index (CBECI), the weighted average carbon intensity of the Bitcoin network (CIBN), and the price of the EU ETS carbon emission allowance (EUA). First, we use CBECI to measure the real-time electricity consumption of the Bitcoin network. Second, following the study conducted by Stoll et al. (2019), we employ the weighted average carbon intensity of the Bitcoin network to calculate real-time carbon emission as the product of CBECI and CIBN. Third, we calculate the real-time carbon market cap by multiplying the real-time carbon emission by the price of carbon emission allowance. Finally, we obtain the unit real-time carbon price of Bitcoin (UCB) by dividing the real-time carbon market cap by the real-time number of bitcoins. Therefore, the UCB acts as a direct real-time estimate of the environmental cost of the Bitcoin network.

Furthermore, the environmental cost of the Bitcoin network has been estimated in the previous literatures. For example, Mora et al. (2018) and Foteinis (2018) suggest that the Bitcoin network alone is capable of pushing global warming to beyond $+2\ ^{\circ}C$. However, Masanet et al. (2019) argue against the projections of Mora et al. and demonstrate that the projections of Bitcoin CO_2 should be lower after errors in adoption scenarios are corrected. Köhler and Pizzol (2019) estimate the environmental impact of Bitcoin mining and reveal that the carbon footprint of Bitcoin mining was 17.29 $MtCO_2$ in 2018. The findings demonstrate that the energy consumption and environmental footprint produced per bitcoin mined is expected to decrease as the hashrate increases. Nevertheless, Krause and Tolaymat (2018) argue that the carbon cost is still a major concern considering that the network hashrate and energy consumption for cryptocurrency mining will continue to increase. However, these studies consider only the energy consumption or carbon footprint of the Bitcoin network; they do not measure economic losses incurred under extreme climate change conditions. To fill this gap, we estimate the climate VaR of the Bitcoin market to measure the external economic cost of its carbon footprint.

In practice, Morgan Stanley Capital International has already provided climate VaR solutions for various financial products. In academia, by estimating climate beta, Dietz et al. (2018) provide additional evidence of a positive relationship between climate damages (beta) and consumption risk in the economy. Monasterolo and De Angelis (2020) demonstrate that stock market investors began to demonstrate a preference for low-carbon investments after the Paris Agreement. As a new infrastructure of the financial market, the Bitcoin investment should appeal to the low-carbon preference of investors. Given the increasing importance of the Bitcoin network in the financial system and the critical environmental concerns it raises, understanding the climate VaR and ES of the Bitcoin market is crucial. Thus, our study extends the literature by developing real-time estimates of climate VaR and ES for the Bitcoin market under extreme climate change conditions.

Moreover, similar to the VaR, the ES is an extreme risk measure recommend by the Basel III to be used instead of VaR and has been internationally adopted by investors, risk managers, and banking supervisors and regulators. In the current study, climate ES measures the weighted average of the "extreme" loss due to climate change beyond the climate VaR cutoff point. Our UCB may exhibit some extreme price movements; therefore, understanding the climate ES may enable more accurate estimation and forecasting of climate change risk, especially in cases of extreme risk. Moreover, because we employ the real-time data of UCB, the climate ES can be estimated on the basis of the distribution of the climate VaR. In contrast to Dietz et al. (2016), we employ an accurate model for distribution and conditional volatilities to estimate the dynamic climate VaR and ES. Thus, our study extends the literature by developing real-time estimates of climate VaR and ES for the Bitcoin market under extreme climate change conditions.

Methodically, three types of approaches are applied to estimate the VaR and ES: parametric, nonparametric, and semiparametric approaches. The generalized autoregressive conditional heteroscedastic (GARCH) model (Bollerslev, 1986) as the cornerstone of the parametric models in VaR and ES measurements, has been widely extended by incorporating various types of distributions (e.g., Ardia et al., 2018; Aloui and Mabrouk, 2010; Lyu et al., 2017; Tolikas, 2014). However, the accuracy of VaR and ES estimations depends on the best-fitted distribution, which varies with the type of financial assets. Usually, three types of distributions function well—normal distribution, Student's or skewed Student's *t* distribution (SKT), and empirical distribution. Therefore, we consider all three of these distributions in our estimations of the climate VaR and ES.

By contrast, the nonparametric approach relaxes the assumptions on distribution and parameter settings. Engle and Manganelli (2004a) estimate the VaR directly on the basis of quantiles, which is referred to as nonparametric conditional autoregressive VaR (CAViaR) estimates. By incorporating the asymmetric Laplace (AL) distribution into CAViaR, Chen et al. (2012) extend the CAViaR model to a semiparametric nonlinear model; however, this extended model still fails to estimate the ES directly. Taylor (2017) provides the first evidence that dynamic VaR and ES measures can be estimated jointly by incorporating a time-varying density scale into an AL distribution. Fissler and Ziegel (2016) further extend the AL log-likelihood function to a family of joint loss functions, providing consistent VaR and ES estimations. Through a semiparametric approach combining the Fissler–Ziegel (FZ) loss function with the generalized autoregressive score (GAS) framework, Patton et al. (2019) develop new dynamic VaR and ES models.

The semiparametric approach provides better estimation and forecasting for dynamic VaR and ES. The UCB exhibits properties of not only financial data (EUA), such as nonstationary, fat-tail, and heteroscedasticity (Lyu et al., 2017; Yuan and Yang, 2020), but also economic data (CBECI), such as serial correlation, seasonality, and cyclicity (Krause and Tolaymat, 2018; Li et al., 2019); this makes the parametric models insufficient for describing the complexity of UCB's properties. To obtain accurate climate VaR and ES estimations, we also use three semiparametric models proposed by Patton et al. (2019): GARCH-FZ, DCS, and hybrid models. Through a comparison of the average forecast loss of parametric and semiparametric models and their goodness-of-fit, our study not only estimates the climate VaR and ES in the Bitcoin market but also examines the goodness-of-fit of parametric and semiparametric models in forecasting the climate VaR and ES.

Our findings reveal that the semiparametric models may not always work best on climate VaR and ES estimation and forecasting, especially for the 99th percentile. Specifically, for upper bound and best-guess estimates of UCB, GARCH-FZ and GARCH-EDF models are suitable for the 95th and 99th percentile climate VaR and ES, respectively. For the lower bound estimate of UCB, the GARCH-SKT model is suitable for both percentiles. Overall, we find increasing climate VaR and ES since 2014 and a notable surge in 2019. Specifically, the 95th percentile climate VaR is 8.04 billion euros, which is similar given the same carbon footprint. Moreover, we find that the lower bound and best-guess climate VaR and ES are farther from the actual economic value of carbon emissions of the Bitcoin network compared with the estimation based on the study by Dietz et al. (2016). However, the 99th percentile climate VaR did not provide the same results, which is 11.33 billion euros—less than half of that estimated by Dietz et al. (2016).

Our paper makes the following three contributions to the literature. First, our study provides a direct bridge between the environment and the Bitcoin network by quantifying the climate VaR and ES, thus helping us to understand the economic cost of the environmental externality of the Bitcoin network. In contrast to other studies, our analysis provides various data-based estimates of the climate VaR and ES across different stress scenarios, thus improving the analysis robustness. Second, we provide real-time dynamic climate VaR and ES estimates to understand the dynamic environmental cost of the Bitcoin network since 2014, which will help investors and policymakers in developing a real-time alarm system to evaluate the environmental impact of the Bitcoin network. Third, we propose the climate ES to measure the economic value of the environmental cost of the Bitcoin network under extreme conditions, which further helps us to capture the negative externality of the Bitcoin network under extreme conditions. Additionally, to enhance the comprehensiveness of our analysis, we examine the suitability of recent semiparametric models for estimating the dynamic climate VaR and ES. This paper is the first to describe the dynamic climate VaR and ES of the Bitcoin market from both financial and environmental perspectives.

The remainder of the paper proceeds as follows. Section 2 describes the methods applied, including parametric and semiparametric models, to forecasting the VaR and ES, along with its estimation methodology. Section 3 presents the descriptive statistics of data and the preliminary analysis. Section 4 summarizes the in-sample estimates and out-of-sample forecasts of the climate VaR and ES along with measurement comparison and robustness evaluation. Section 5 presents conclusions and a discussion of policy implications and future research directions.

2. Methodology

2.1. Parametric models

In this section, we follow the standard GARCH(1,1) model (Bollerslev, 1986) to describe the volatility of the returns series (r_t) of artificial carbon prices. The mean equation and conditional volatility functions are as follows:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t \eta_t \tag{1}$$

$$\sigma_t^2 = \omega + \gamma \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2}$$

where μ and σ_t denote the mean and conditional volatility, respectively, of the GARCH model, and η_t denotes the standardized residual following the three proposed distributions: normal distribution, SKT (Hansen, 1994), and empirical distribution:

$$\eta_t \ iidN(0,1), \quad \eta_t \ iidSkewt(0,1,\theta,\vartheta). \tag{3}$$

These distributions have been widely used in the literature (Aloui and Mabrouk, 2010; Lyu et al., 2017). When the skewness parameter ϑ of SKT equals zero, it returns to the standard Student's distribution. Therefore, we refer to these three types of parametric models (normal distribution, SKT, and empirical distribution) as GARCH-N, GARCH-SKT, and GARCH-EDF, respectively. In particular, even though the empirical distribution function is estimated using a nonparametric approach, we estimate the GARCH model parametrically. We still consider GARCH-EDF as a parametric model. However, the empirical distribution function has been proven to be the best model for the ES (Engle and Manganelli, 2004b), which is another reason to include it in our analysis. Therefore, we consider these three types of distributions as the benchmarks for comparison with semiparametric models.

2.2. Semiparametric models

Following the studies of Patton et al. (2019), we consider three types of semiparametric models to estimate the dynamic volatility of the returns series. The first is the GAS one-factor model, also referred to as the DCS model (Thiele, 2019), which is defined as follows:

$$\kappa_t = \omega + \beta \kappa_{t-1} + \gamma s_{t-1}, \quad s_t = H_t \eta_t = \left[E_{t-1}\left(-\frac{\partial^2 \ln L_t}{\partial \kappa_t^2}\right)\right]^{-1} \frac{\partial \ln L_t}{\partial \kappa_t} \tag{4}$$

where H_t denotes the rescale term of the innovations and the log-likelihood $\ln L_t$ is time dependent.

The second model incorporates the FZ loss minimization to estimate the GARCH model without considering the mean-reverting process and is referred to as the GARCH-FZ model. Following the study of Francq and Zakoïan (2015), the GARCH (1,1) model in Section 2.1 can be rewritten as:

$$\sigma_t^2 = \omega + \gamma r_{t-1}^2 + \beta \sigma_{t-1}^2, \quad r_t = \sigma_t \eta_t \tag{5}$$

Similarly, the conditional volatility parameter $\sigma_t$follows the GARCH process.

The third model is a hybrid of the DCS and GARCH-FZ models, specified as follows:

$$\kappa_t = \omega + \beta\kappa_{t-1} + \gamma s_{t-1} + + \delta \log|r_{t-1}|, r_t = \exp\{\kappa_t\}\eta_t \tag{6}$$

where the log-volatility κ_t is the latent variable. The log absolute return is employed to ensure the linear evolution of κ_t.

2.3. VaR and ES

Following the standard definitions of the VaR and ES, we can specify the VaR and ES as risk measures for a given time horizon as follows:

$$VaR_t^\alpha = F_t^{-1}(\alpha), \quad ES_t^\alpha = E(r_t|(r_t \le VaR_t^\alpha), F_{t-1}), \quad r_t|F_{t-1}\ F_t \tag{7}$$

where the left-tailed quantile α is set as 0.05. The conditional distribution F_t is based on the r_t. For the parametric models, we specified the VaR (v_t) and ES (e_t) as

$$v_t = \mu + a\sigma_t, \quad e_t = \mu + b\sigma_t \tag{8}$$

where $b < a < 0$, $b\ = E(\eta_t|\eta_t \le a)$, and $a\ = F_{\eta_t}^{-1}(\alpha)$. Similarly, for the GARCH-FZ model, v_t and e_t are driven by the volatilityσ_t given the mean equation $r_t = \sigma_t\eta_t$:

$$v_t = a\sigma_t, \quad e_t = b\sigma_t \tag{9}$$

For both DCS and hybrid models, the VaR and ES are driven by the latent variable of log-volatility κ_t:

$$v_t = a\exp\{\kappa_t\}, \quad e_t = b\exp\{\kappa_t\} \tag{10}$$

By incorporating the FZ loss function into the evolution equation of κ_t, we can rewrite Eq. (4) as follows:

$$s_t \equiv \frac{1}{e_{t-1}}\left(\frac{1}{\alpha}1\{r_{t-1} \le v_{t-1}\}r_{t-1} - e_{t-1}\right) \tag{11}$$

where v_t denotes $\mathrm{VaR_t}$, and e_t denotes $\mathrm{ES_t}$. As suggested by Creal et al. (2013) and Patton et al. (2019), v_t and e_t can be identified by the FZ loss function, whereas the parameters ω, β, and γ in Eqs. (4) and (6) are governed by the GAS process:

$$\kappa_t = \omega + \beta\kappa_{t-1} + \gamma\frac{1}{e_{t-1}}\left(\frac{1}{\alpha}1\{R_{t-1} \le \phi_{t-1}\}R_{t-1} - e_{t-1}\right) \tag{12}$$

where the FZ loss function only identifies ϕ_t and e_t, whereas the generalized autoregressive process determines the parameters ω, β, and γ. For simple identification, we set ω to zero.

2.4. Estimation methodology

We construct the FZ loss functions to minimize the expected loss of the scoring functions G_1 and G_2 to derive the climate VaR and ES:

$$(VaR_t, ES_t) = \underset{(v,e)}{argmin}\mathbb{E}_{t-1}[L_{FZ}(r, v, e; \alpha, G_1, G_2)]. \tag{13}$$

where the true VaR and ES are represented by the information set, $\mathrm{X}_{t-1} \in \mathscr{F}_{t-1}$. Hereby, the elicitability problem of the ES measure is addressed by the scoring function to provides the true VaR and ES. Therefore, we can reconstruct Eq. (12) as follows:

$$(VaR_t, ES_t) = \underset{(\boldsymbol{\theta})}{argmin}\mathbb{E}_{t-1}[L_{FZ}(r_t, v(\mathrm{X}_{t-1};\boldsymbol{\theta}), e(\mathrm{X}_{t-1};\boldsymbol{\theta}); \alpha)] \tag{14}$$

The parameters $\boldsymbol{\theta}$ can be accurately estimated using asymptotic theory for (non-) linear models (Patton et al., 2019). Moreover, because the semiparametric VaR and ES estimates do not depend on the assumptions of distribution and regularity conditions, it is possible to compare semiparametric VaR and ES estimates with parametric VaR and ES estimates.

3. Data and preliminary analysis

To estimate the externality or environmental cost of the Bitcoin network, we first must capture the carbon footprint of Bitcoin. We employ the CBECI to measure how much electricity is consumed by the Bitcoin network. Second, as suggested by Stoll et al. (2019), the weighted average CIBN is estimated at 480–500 g CO_2 per kWh. For simplicity, we consider the weighted average CIBN to be 500 g CO_2 per kWh. Therefore, we can estimate the annualized carbon intensity of the Bitcoin network by multiplying the CBECI by the CIBN. Finally, to evaluate the economic value of the externality or environmental cost of the Bitcoin network, we employ the daily spot price of carbon emission allowance in the EU ETS. We retrieve the daily closing price of carbon emission allowance from Datastream. Therefore, the total annualized carbon market cap or externality of the Bitcoin network can be estimated by multiplying these three

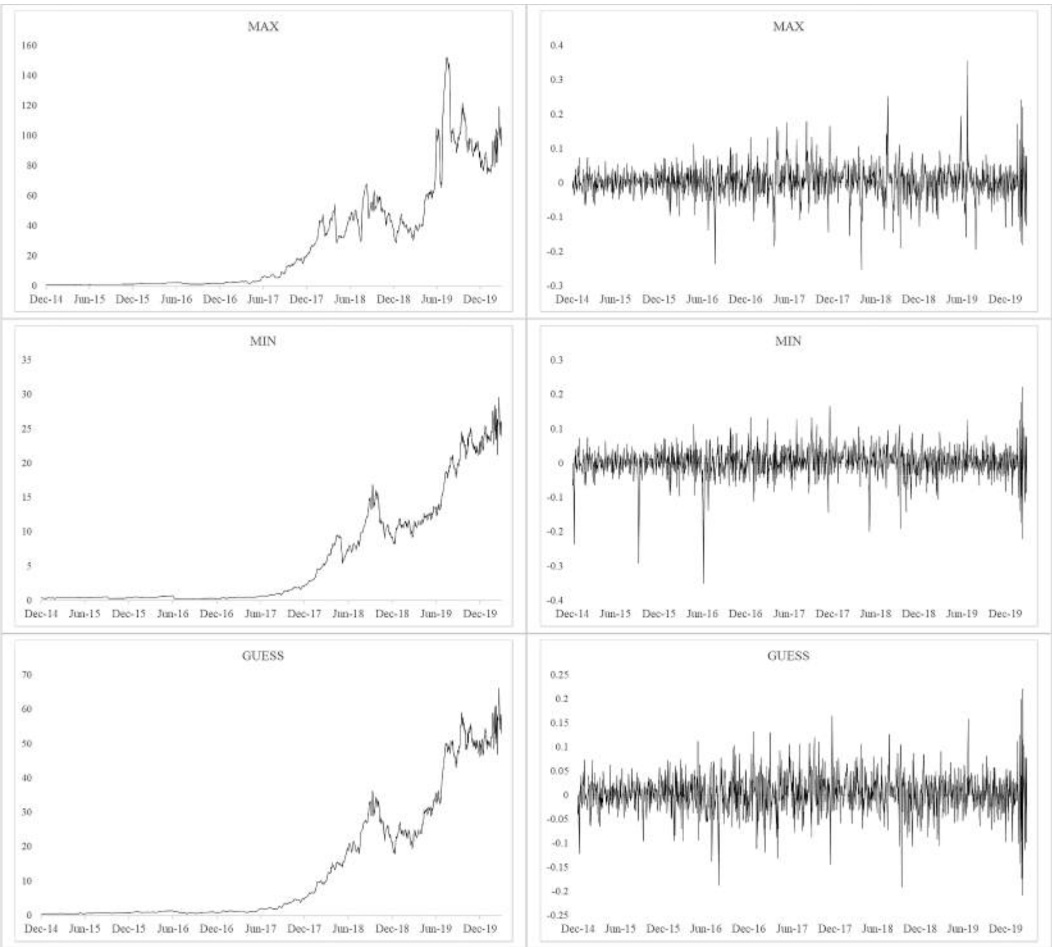

Fig. 1. The plots of upper bound, lower bound, and guess artificial carbon price and its returns for the Bitcoin network. The unit is Euro per one unit of Bitcoin. The sample period is from December 2, 2014 to February 28, 2020.

Table 1
The descriptive statistics of upper bound, lower bound, and guess artificial carbon returns (%).

	UBD	LBD	GUS
Mean	0.374	0.287	0.339
Median	0.401	0.421	0.387
Maximum	35.508	22.129	22.129
Minimum	−25.350	−35.111	−20.842
Std. Dev.	4.638	4.228	3.970
Skewness	0.176	−1.129	−0.134
Kurtosis	9.471	11.792	6.392
Jarque-Bera	2395.713***	4700.526***	660.461***
LB (20)	0	0	0
Observations	1369	1369	1369

Notes: Jarque-Bera denotes the *p*-value from Jarque-Bera test. LB(20) denotes the Ljung–Box autocorrelation test of returns with a lag length of 20, in which the *p*-value is provided. UBD, LBD and GUS denotes upper bound, lower bound, and guess acritical carbon returns, respectively.

values. We estimate the UCB by dividing the daily number of bitcoins (NUM). Accordingly, we have:

$$UCB = CBECI \times CIBN \times EUA/NUM \tag{15}$$

The sample period is from December 1, 2014, to February 28, 2020. The starting point is based on the time at which the CBECI first became available. The plots provide upper bound (UBD), lower bound (LBD), and best-guess (GUS) estimates of artificial carbon price (left side) and its returns (right side) for the Bitcoin network. The unit is euros per unit of Bitcoin. Therefore, the returns of UCB for

Table 2
The estimations of parametric and semi-parametric models for upper bound artificial carbon returns.

	GARCH	GARCH-FZ	DCS	Hybrid
μ	0.847 (0.213)***			
ω	0.040 (0.006) ***			0.000 (0.000) ***
γ	0.035 (0.039) ***	0.080 (0.012)***	0.014 (0.001)***	0.009 (0.003) ***
β	0.963 (0.257) ***	0.862 (0.017)***	0.941 (0.009)***	0.942 (0.009)***
θ	6.247 (1.025) ***			
ϑ	−0.037 (0.095)			
a		−1.114 (0.351)***	−4.615 (2.239)**	−4.604 (6.618)
b		−1.601 (0.457) **	−6.802 (3.351)**	−6.717 (9.973)
AVL		1.987	1.944	1.943
LB^2 (20)	0.207	0.211	0.295	0.231

Notes: $LB^2(20)$ denotes the Ljung–Box autocorrelation test of squared standardized residuals with a lag length of 20, in which the *p*-value is provided. AVL denotes the average loss.
** denotes the significant at the 5% level.
*** denotes the significant at the 1% level.

Table 3
The estimations of parametric and semi-parametric models for lower bound artificial carbon returns.

	GARCH	GARCH-FZ	DCS	Hybrid
μ	−0.0135 (0.019)			
ω	5.172 (1.134) ***			0.000 (0.064)
γ	0.093 (0.021) ***	0.290 (0.361)	0.036 (0.001) ***	0.036 (0.007)***
β	0.829 (0.103) ***	0.629 (0.176) ***	0.782 (0.089) ***	0.775 (0.088) ***
ν	5.251 (0.895) ***			
λ	−0.077 (0.091)			
a		−1.528 (1.575)	−5.676 (4.797)	−5.681 (3.315)
b		−2.106 (2.139)	−7.986 (7.670)	−8.041 (5.378)
AVL		2.113	2.074	2.073
LB^2 (20)	0.582	0.175	0.102	0.107

Notes: *LL* denotes the log likelihood. $LB^2(20)$ denotes the Ljung–Box autocorrelation test of squared standardized residuals with a lag length of 20, in which the *p*-value is provided. AVL denotes the average loss.
*** denotes the significant at the 1% level.

these estimates are calculated as:

$$r_{i,t} = log\left(\frac{UCB_{i,t}}{UCB_{i,t-1}}\right), i \in \{UBD, LBD, GUS\} \tag{16}$$

We plot the carbon price for each bitcoin in Fig. 1. Because the CBECI provides upper bound, lower bound, and best-guess electricity consumption, we have included upper bound, lower bound, and best-guess artificial carbon prices, respectively. Fig. 1 (left side) displays a significant surge of carbon price, mainly due to a sharp increase in the marginal mining cost of Bitcoin (Li et al., 2019) along with a surge in carbon price (Yuan and Yang, 2020), which also implies an increase in the CIBN. From the results of a marginal cost analysis, Hayes (2019) indicates that the market price of Bitcoin is supported by the marginal cost of production, except for the bubble period from the fall of 2017 to early 2018. Overall, the externality of the Bitcoin network is increasing with time. Fig. 1 (right side) also illustrates the log-returns of the carbon price for these three estimates of the Bitcoin network. Clearly, all these returns demonstrate the volatility clustering process. Furthermore, we report the descriptive statistics of prices and their returns in Table 1. In particular, the returns series begins in December 2, 2014, because the initial value serves as the basis for calculating returns.

The mean returns for upper bound, lower bound, and best-guess carbon price are 0.374%, 0.287%, and 0.339%, respectively (Table 1), which are consistent with the initial settings. However, when the standard deviations are considered, the lower bound carbon returns are higher than the best-guess carbon returns. Moreover, the skewness and kurtosis of the lower bound carbon return are highest among these threes, which indicates that extreme returns are more likely to occur. The negative skewness also suggests a greater tendency for extreme positive returns in the lower bound and best-guess carbon prices. Along with the Jarque–Bera test and the Ljung–Box autocorrelation test, all properties of the returns series suggest nonnormal, fat-tail, and heteroscedastic distribution. Thus, with the adoption of the GARCH and DCS models to estimate the volatilities of the return series, our analysis can provide more robust results for estimating the climate VaR and ES.

Table 4
The estimations of parametric and semi-parametric models for guess artificial carbon returns.

	GARCH	GARCH-FZ	DCS	Hybrid
μ	0.129 (0.022) ***			
ω	6.690 (1.623) ***			0.000 (0.010)
γ	0.027 (0.016)	0.016 (0.018)	0.007 (0.008)	0.025(0.017)
β	0.970 (0.103) ***	0.945 (0.079) ***	0.961 (0.060) ***	0.963 (0.035) ***
ν	6.689 (1.235) ***			
λ	−0.074 (0.084)			
a		−2.579 (1.599) **	−5.18 (22.448)	−3.705 (18.678)
b		−3.760 (1.591) ***	−8.034 (31.990)	−5.522 (28.599)
AVL		2.032	2.058	2.041
LB^2 (20)	0.215	0.575	0.412	0.200

Notes: *LL* denotes the log likelihood. $LB^2(20)$ denotes the Ljung–Box autocorrelation test of squared standardized residuals with a lag length of 20, in which the *p*-value is provided. AVL denotes the average loss.
** denotes the significant at the 5% level.
*** denotes the significant at the 1% level.

Table 5
Out-of-sample average losses and goodness-of-fit tests (alpha = 0.05).

	UBD			LBD			GUS		
	AVL	VaR	ES	AVL	VaR	ES	AVL	VaR	ES
GARCH-N	2.528	0.730	0.512	2.223	0.000	0.002	2.189	0.597	0.963
GARCH-SKT	2.511	0.856	0.539	**2.210**	0.978	0.003	2.184	0.572	0.785
GARCH-EDF	2.512	0.684	0.404	2.211	0.872	0.001	2.187	0.171	0.640
GARCH-FZ	**2.509**	0.690	0.404	2.240	0.000	0.001	**2.181**	0.308	0.661
DCS	2.607	0.004	0.001	2.227	0.008	0.000	2.189	0.047	0.153
Hybrid	2.612	0.004	0.001	2.227	0.000	0.000	2.213	0.186	0.455

Notes: The left panel of this table presents the average losses, using the FZ0 loss function, for estimated carbon and lower bound carbon return series, over the out-of-sample period from March 1, 2017 to February 28, 2020, for six different forecasting models. The lowest average loss (AVL) in each column is highlighted in bold. The goodness of fit tests in this table present *p*-values of the VaR and ES forecasts, respectively.

4. Empirical results

4.1. Parametric and semi-parametric estimations

For this analysis, we use the sample period from December 2, 2014, to February 28, 2017, for in-sample estimations for the distribution of both parametric and semiparametric models. Therefore, our out-of-sample period is from March 1, 2017, to February 28, 2020, with 783 observations. Table 2 presents the in-sample estimations of parametric and semiparametric models for upper bound carbon return. The first column presents the estimation of the parametric GARCH model. The estimated β parameter is 0.963, implying a high persistence of the GARCH processes. However, we do not identify a significant skewness in the standardized residual because the skewness parameter ϑ is insignificant and has a negative value.

The following three columns provide the estimations of semiparametric models. The empirical results for the GARCH-FZ, DCS, and hybrid models are presented in the first, second, and third columns, respectively. Specifically, we construct the hybrid model by incorporating a GARCH-type forcing variable (σ) with a value significantly higher than 0.85 into an augmented DCS model. Thus, the GARCH process is essential in modeling the return under the semiparametric models. Moreover, the persistence parameter β is significant with a value close to 1, implying similar persistence to that of the GARCH model. Similarly, the latent log-volatility variable is significant, with a value close to 1, suggesting similar persistence to that of the DCS model.

Tables 3 and 4 report the parameter estimations for lower bound and best-guess carbon returns. The parameter estimations of best-guess carbon returns exhibit a degree and significance similar to those of upper bound carbon returns. By contrast, the parameter estimations of lower bound carbon returns have a considerably lower degree of β, especially for the semiparametric models. From an evaluation of the average loss in the semiparametric models, we discover that the hybrid models are slightly better than the other two models in estimating upper bound and lower bound carbon returns, whereas the GARCH-FZ model is slightly better than the other two models in estimating best-guess carbon returns. Moreover, in the last column, we provide the results of the Ljung–Box autocorrelation test of squared standardized residuals, which suggest that our models are capable of addressing heteroscedasticity.

4.2. Performance evaluations

In this section, we employ out-of-sample VaR and ES forecasts to validate the fitness between the parametric and semiparametric models. For simplicity, we discuss only the results for which $\alpha = 0.05$. As mentioned, we choose the best-fitted model to measure the

Table 6
Diebold-Mariano t-statistics on average out-of-sample loss differences (alpha = 0.05).

	GHN	GHT	GHE	GHF	FZF	HYR
Panel A: UBD						
GARCH-N		2.560	2.945	−1.248	2.067	−1.306
GARCH-SKT	−2.560		−0.346	−1.478	0.383	−1.530
GARCH-EDF	−2.945	0.346		−1.510	0.440	−1.564
GARCH-FZ	−2.067	−0.383	−0.440		−1.486	−1.537
DCS	1.248	1.478	1.510	1.486		−4.034
Hybrid	1.306	1.530	1.564	4.034	1.537	
Panel B: LBD						
GARCH-N		1.312	1.660	−0.099	−1.726	−0.088
GARCH-SKT	−1.312		−0.067	−0.454	−2.728	−0.442
GARCH-EDF	−1.660	0.067		−0.458	−2.959	−0.446
GARCH-FZ	1.726	2.728	2.959		0.303	0.311
DCS	0.099	0.454	0.458	−0.303		0.369
Hybrid	0.088	0.442	0.446	−0.369	−0.311	
Panel C: GUS						
GARCH-N		0.623	0.269	0.028	0.443	−0.699
GARCH-SKT	−0.623		−0.295	−0.236	0.154	−0.717
GARCH-EDF	−0.269	0.295		−0.116	0.360	−0.797
GARCH-FZ	−0.443	−0.154	−0.360		−0.334	−0.711
DCS	−0.028	0.236	0.116	0.334		−0.880
Hybrid	0.699	0.717	0.797	0.880	0.711	

Notes: This table presents t-statistics from Diebold-Mariano tests comparing the average losses, using the FZ0 loss function, over the out-of-sample period from January March 1, 2017 to February 28, 2020, for six different forecasting models. A positive value indicates that the row model has higher average loss than the column model. Values greater than 1.96 in absolute value indicate that the average loss different is significantly different from zero at the 95% confidence level. Values along the main diagonal are all identically zero and are omitted for interpretability.

VaR and ES for the bitcoin network. Specifically, by using the normal distribution, SKT, and empirical distribution based on the estimated standardized residuals, we run the VaR and ES forecasts based on the parametric dynamic models. The semiparametric dynamic VaR and ES forecasts are given by the DCS, GARCH-FZ, and hybrid models.

Table 5 shows the average loss of the model, with the lowest values presented in bold. The first-choice models for the VaR and ES forecasts are the parametric GARCH-FZ model for upper bound and best-guess carbon returns and the GARCH-SKT model for lower bound carbon returns. As Christoffersen (1998) and Engle and Manganelli (2004a) demonstrate, we employ the dynamic quantile test by Engle and Manganelli (2004a) to select the best-fitted models in our study. Therefore, to evaluate VaR and ES forecasts, we provide the *p*-value of the goodness-of-fit test according to the average loss in Table 5. However, for the lower bound ES, all models fail the goodness-of-fit test.

To confirm our results, we present Diebold–Mariano (DM) *t* statistics for the loss difference of the upper bound, lower bound, and best-guess VaR and ES by using the "row model minus column model" calculation presented in Table 6. The negative values suggest the outperformance of the column models. The DM *t* statistics confirm the results provided in Table 5. Even though the value is nonsignificant in most cases, the GARCH-FZ and GARCH-SKT models slightly outperform all competing models for the corresponding VaR and ES forecasts.

Finally, we provide the fitted 5% daily VaR and ES in Fig. 2 by selecting the best-performing models—the semiparametric GARCH-FZ model for upper bound and best-guess carbon returns and parametric GARCH-SKT model for lower bound carbon returns. The lower bound VaR and ES are more volatile than the other twos, with more extreme values (Fig. 2). Because the parametric GARCH-SKT model incorporates the mean-reverting process in the mean equation, no trend is observed in volatility and cyclicity. By contrast, the mean equation in the GARCH-FZ model does not include a constant, and the upper bound and best-guess VaR and ES exhibit clear trends of upward volatility and cyclicity over time. In this sense, the semiparametric model captures not only the volatility clustering in the EUA (Zhu et al., 2014) but also the cyclicity in electricity consumption (Li et al., 2019). However, we also observe significantly different patterns of the VaR and ES for the different types of models. Therefore, individually considering the upper bound, lower bound, and best-guess CBECI can fully and dynamically capture the range of the VaR and ES.

4.3. Climate VaR and ES

After identifying the VaR and ES forecasts with the best fit, we further incorporate the economic loss caused by the Bitcoin network to calculate the climate VaR and ES. The artificial carbon price on the Bitcoin network generates a negative externality for the environment and should be negative along with its market cap. Therefore, our estimated VaR and ES should be added back to the negative market cap of carbon intensity in the Bitcoin network. Because we use annual electricity consumption to estimate the Bitcoin network's carbon footprint, we transform the real-time VaR and ES to annual estimates by multiplying them by the square root of 252. Fig. 3 illustrates the dynamic annualized 95th percentile climate VaR and ES of the Bitcoin network. Obviously, the absolute values of the climate VaR and ES have increased considerably since Bitcoin was first introduced, reaching their peaks on July 8, 2019, for the

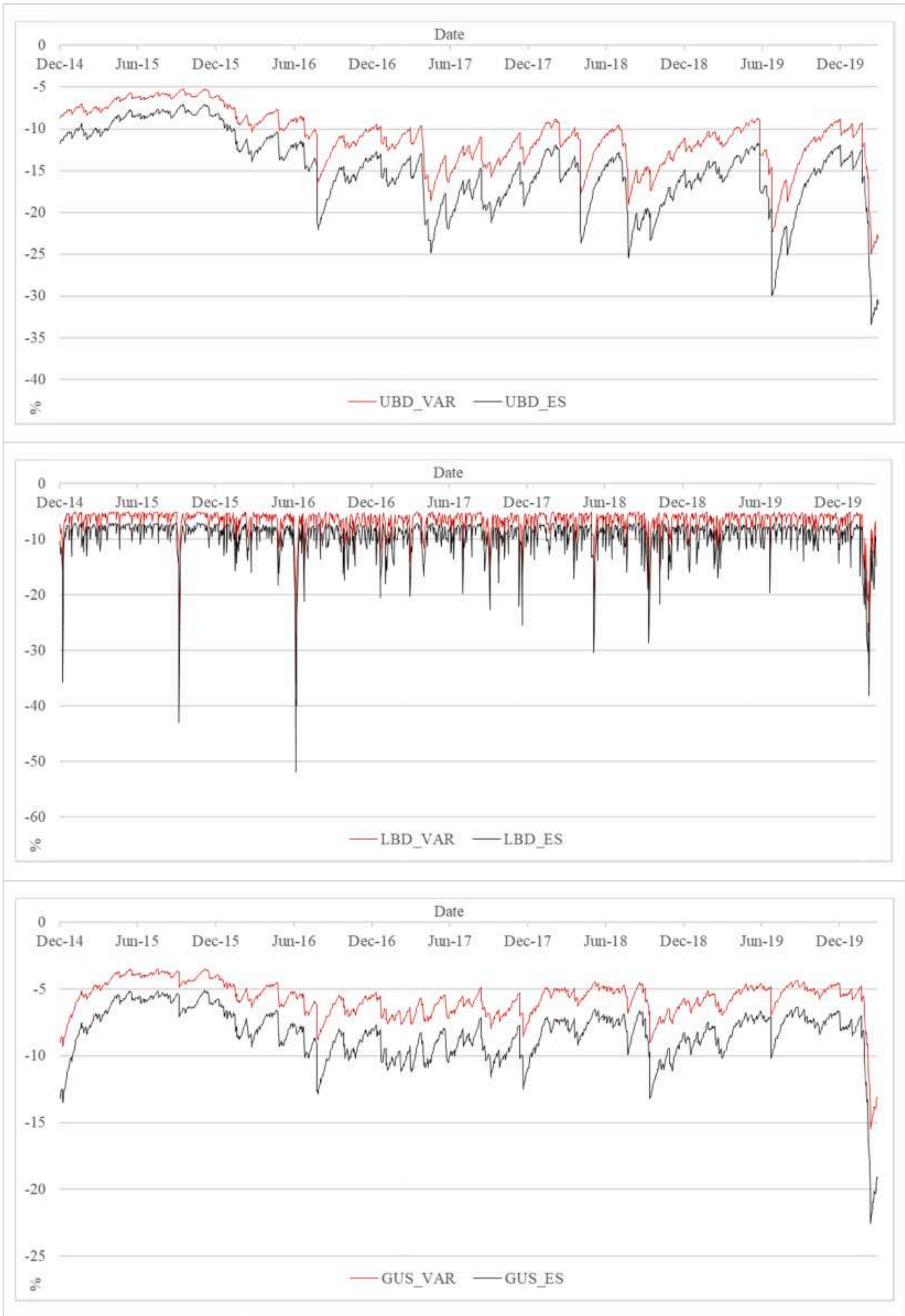

Fig. 2. The plots of 5th percentile VaR and ES for upper bound (up), lower bound (middle), and guess (bottom) artificial carbon returns. Red line denotes VaR and black line denotes ES. The sample period is from December 2, 2014 to February 28, 2020. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

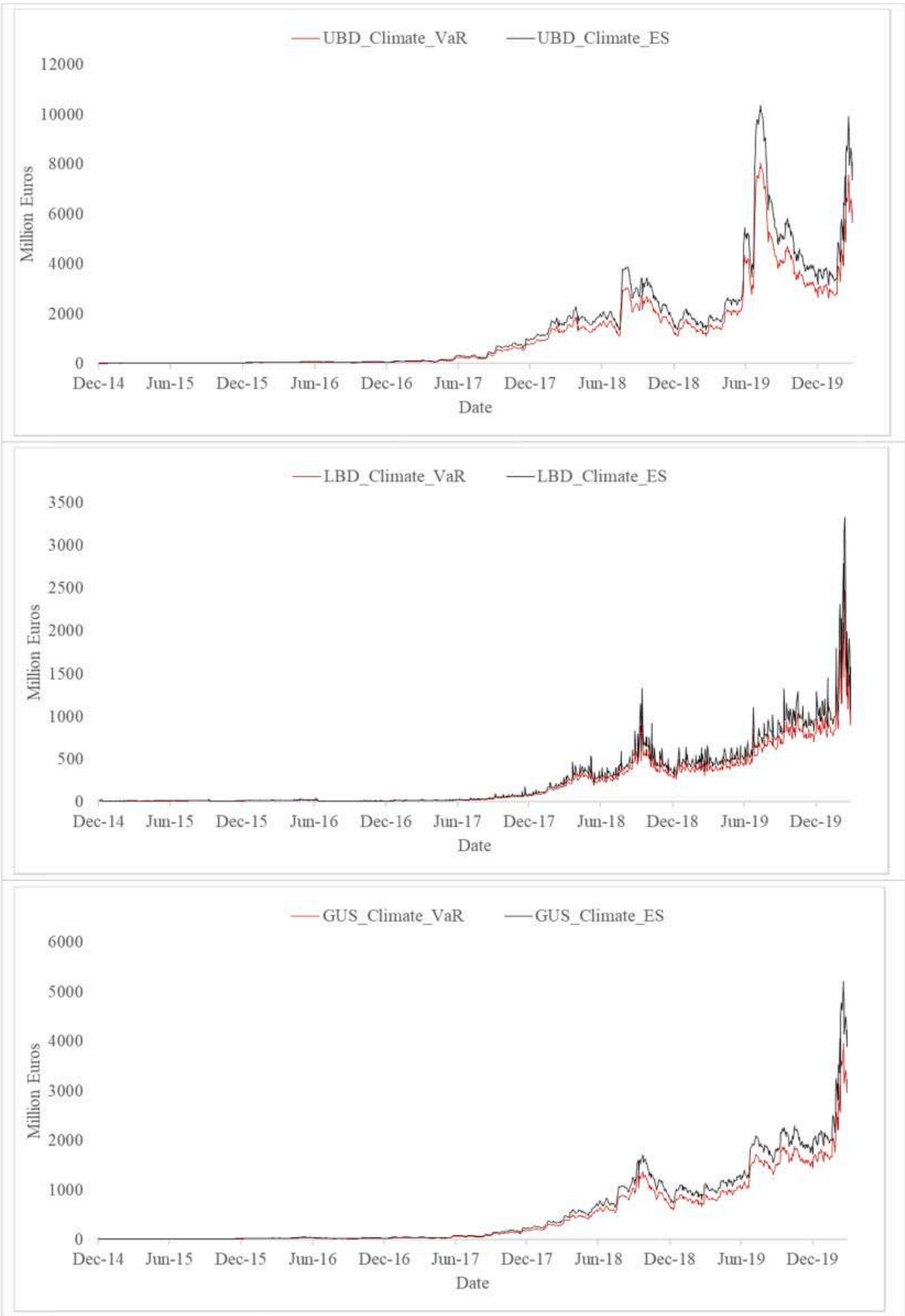

Fig. 3. The plots of 95th percentile climate VaR and ES for upper bound (up), lower bound (middle), and guess (bottom) artificial carbon market. Red line denotes VaR and black line denotes ES. The sample period is from December 2, 2014 to February 28, 2020. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
The descriptive statistics of 95th percentile climate VaR and ES.

	UBD_ VaR	UBD _ ES	LBD_ VaR	LBD_ ES	GUS_ VaR	GUS_ ES
Mean	1156.420	1443.510	226.805	275.961	470.880	576.048
Median	252.382	315.513	27.498	32.828	66.009	81.673
Minimum	12.036	14.024	5.035	5.959	11.051	13.304
Maximum	8042.863	10372.540	2468.769	3332.980	3953.783	5212.581
Current	6191.163	8091.634	1258.126	1586.598	3222.931	4221.154
Std. Dev.	1591.986	2019.150	320.376	398.181	652.510	810.862
Skewness	1.850	1.956	2.021	2.275	1.762	1.947
Kurtosis	6.584	7.159	8.818	11.076	6.632	8.005
Observations	1369	1369	1369	1369	1369	1369

Notes: The unit is million euros. The sample period is from December 2, 2014 to Feb 28, 2020.

upper bound, February 13, 2020, for the lower bound, and February 19, 2020, for the best-guess. Even though the values of the annualized climate VaR and ES change, they tend to increase with time.

Table 7 reports the descriptive statistics of the 95th percentile climate VaR and ES. The historical average climate VaR ranges from 226.805 to 1156.420 million euros, with the best-guess value of 470.880 million euros. The historical average climate ES ranges from 275.961 to 1443.510 million euros, with the best-guess value of 576.048 million euros. Moreover, the upper bound loss of the climate VaR and ES may be approximately 8.04 and 10.37 billion euros. The estimated best-guess values of the climate VaR and ES prior to our analysis may have been 3.222 and 4.221 billion euros, respectively. All these values of the climate VaR and ES assume the carbon emission allowance to be correctly priced. However, many studies suggest that it is often underpriced (Hájek et al., 2019; Palao and Pardo, 2012), implying that the climate VaR and ES on the Bitcoin market are much higher. For comparison, the carbon footprint of the Bitcoin network is similar to the GDP of New Zealand (206 billion USD or 170 billion euros) in 2018. Following the calculation method employed by Dietz et al. (2016), the 95th percentile climate VaR of New Zealand is approximately 8.1 billion euros, which is similar to the upper bound value of the 95th percentile climate VaR and ES of the Bitcoin market. For accurate climate VaR and ES forecasts, the upper bound electricity consumption should be employed as an indicator of the carbon footprint of the Bitcoin network. However, its value is at least double the estimated best-guess value of the 95th percentile climate VaR and ES.

Following the same procedures, we estimate the 99th percentile climate VaR and ES of the Bitcoin market. Specifically, only parametric models are selected as the models with the best fit, namely the GARCH-EDF model for upper bound and best-guess carbon returns and the GARCH-SKT model for lower bound carbon returns. The dynamics of the 99th and 95th percentile climate VaR and ES are similar (Fig. 4). Similarly, we observe a sharp increase in the climate VaR and ES of the Bitcoin network after 2017 due to the increase in the price of not only the carbon allowance but also Bitcoin. Hayes (2019) provides evidence that the cost of Bitcoin mining is highly consistent with its market price. Because of the limited supply of bitcoins, the energy consumption and computation power required to obtain additional bitcoins increase sharply (Krause and Tolaymat, 2018). Specifically, as the hashrate increases due to the increasing participation of miners and increasing difficulty of computations, obtaining an additional bitcoin increases the negative environmental externality. Although the current price of Bitcoin has already surpassed US$10,000, it is associated with a considerably high climate change risk.

Furthermore, we analyze the descriptive statistics of 99th percentile climate VaR and ES (Table 8). The historical average climate VaR ranges from 296.864 to 1603.137 million euros (best-guess value, 664.238 million euros). The historical average climate ES ranges from 296.864 to 1960.730 million euros (best-guess value, 807.011 million euros). The upper bound loss of the climate VaR and ES may be approximately 11.33 and 14.15 billion euros. The estimated best-guess values of climate VaR and ES may have been 8.8 and 11.08 billion euros, respectively. Compared with the 99th percentile climate VaR of New Zealand, which is 28.66 billion euros, the climate VaR of the Bitcoin market is much lower. Therefore, according to the results of the current analysis, our climate VaR and ES may be underestimated. In other words, the negative environmental externality of the Bitcoin network based on the current carbon price is not sufficient to reflect the environmental cost (Hong et al, 2019). Carbon tax on the Bitcoin network and other cryptocurrency blockchains may be an effective method for hindering global warming (Hájek et al., 2019; Zhou et al., 2018)

Overall, unlike traditional financial products, Bitcoin is a blockchain-based product. Hence, Bitcoin mining and trading can be conducted anywhere with an internet connection and sufficient hardware and electrical power, all of which cause considerable energy consumption and environmental impact. With the increasing marginal cost of Bitcoin mining, the negative environmental externality also increases. As revealed in our analysis, the climate VaR and ES has reached a historical high around 2020, indicating the urgency of recognizing the environmental impact of Bitcoin. Moreover, from the low-carbon investment perspective, Bitcoin may not be a suitable consideration for investors.

5. Conclusion

In this study, to explore the negative environmental externality of the Bitcoin network, we develop an artificial carbon footprint of the Bitcoin network by employing CBECI along with the weighted average CIBN estimated by Stoll et al. (2019). Furthermore, we employ the price of carbon emission allowance in EU EST and evaluate the economic value of this externality by estimating the climate VaR and ES. To make our results more robust, following Patton et al. (2019), we compare the parametric and semiparametric models to forecast the climate VaR and ES. Overall, we discover that the semiparametric models always perform well in forecasting the climate

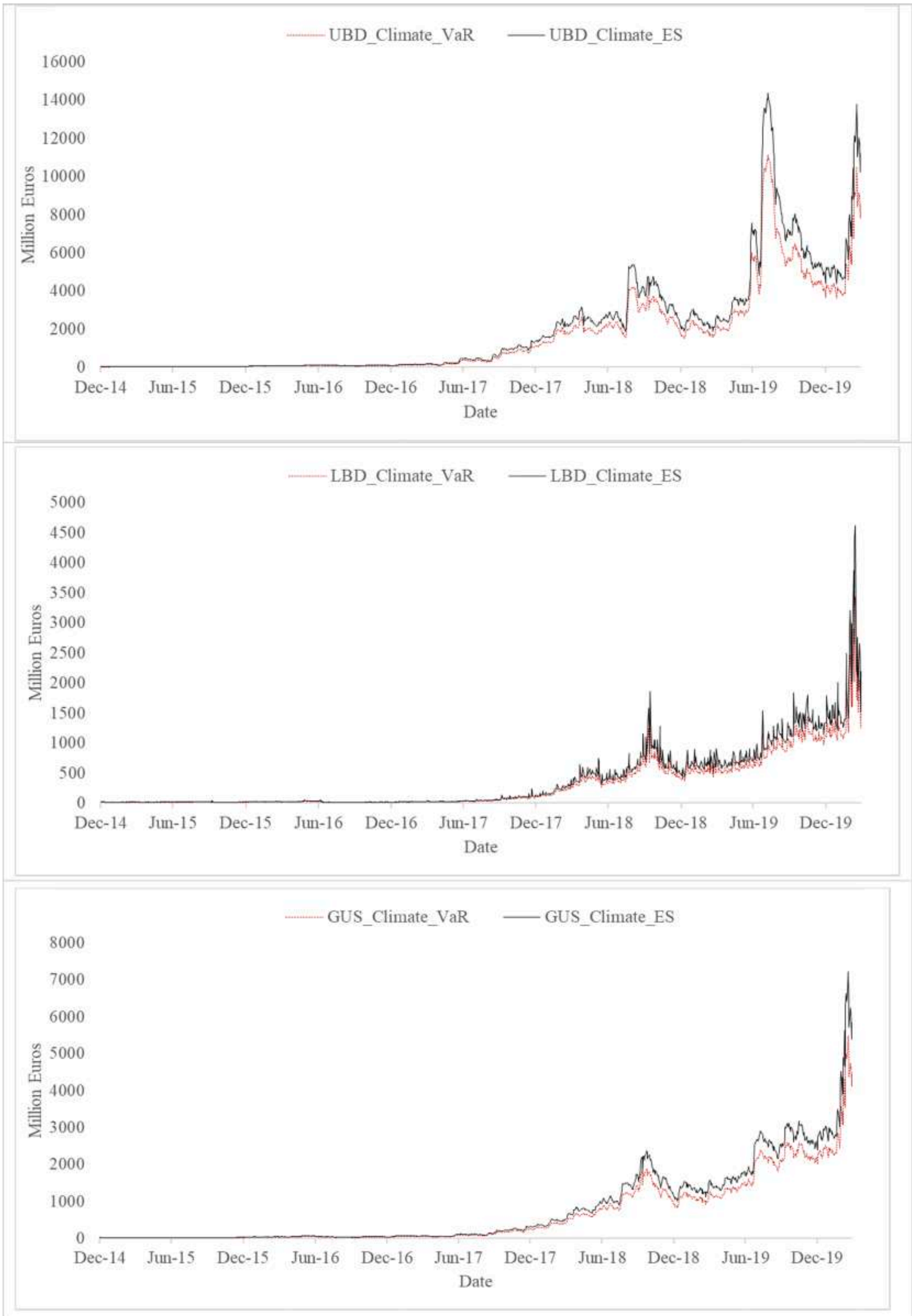

Fig. 4. The plots of 99th percentile climate VaR and ES for upper bound (up), lower bound (middle), and guess (bottom) artificial carbon market. Red line denotes VaR and black line denotes ES. The sample period is from December 2, 2014 to February 28, 2020. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 8
The descriptive statistics of 99th percentile climate VaR and ES.

	UBD_ VaR	UBD_ ES	LBD_ VaR	LBD_ ES	GUS_ VaR	GUS_ ES
Mean	1603.137	1960.730	296.864	296.864	664.238	807.011
Median	349.817	429.452	35.123	35.123	95.637	117.141
Minimum	17.715	20.936	6.352	6.352	14.937	17.942
Maximum	11331.090	14154.010	3700.482	3700.482	5472.823	6951.226
Current	8799.976	11087.533	1726.279	1726.279	4668.196	5923.366
Std. Dev.	2225.151	2750.322	431.472	431.472	911.116	1115.892
Skewness	1.899	1.967	2.362	2.362	1.716	1.820
Kurtosis	6.833	7.205	11.895	11.895	6.430	7.201
Observations	1369	1369	1369	1369	1369	1369

Notes: The unit is million euros. The sample period is from December 2, 2014 to Feb 28, 2020.

VaR and ES of the Bitcoin market, especially for the 99th percentile climate VaR and ES.

From a comparison of estimations made using our best-fitted models based on the findings of Dietz et al. (2016), we determine the 95th percentile climate VaR and ES to be 8.04 and 10.37 billion euros, which is quiet similar to the 95th percentile climate VaR of a country's GDP, such as that of New Zealand, with a similar carbon footprint. By contrast, the best-guess and lower bound 95th percentile climate VaR and ES remain unable to capture the real economic value of carbon emissions. The 99th percentile climate VaR and ES values are still much lower than the 99th percentile climate VaR of New Zealand's GDP. Overall, regardless of whether parametric or semiparametric models are used, estimates of the climate VaR and ES are still far from the real economic cost of carbon emissions in the Bitcoin network. Still, our analysis provides new insight into the economic relationship between the Bitcoin network and environmental concerns and highlights the critical negative environmental externality of the Bitcoin network.

Our results have at least two policy implications. From an environmental perspective, carbon tax should be levied on Bitcoin mining as well as on each transaction on the blockchain. Moreover, the EU EST should improve the efficiency of pricing the carbon emission allowance to hinder global warming by incorporating the cryptocurrency industry. Therefore, a broader carbon tax system should be implemented to penalize the negative environmental impact of carbon-intensive industries, such as the cryptocurrency industry. A tax refund system incorporating the EU EST should also be developed. Accordingly, the carbon emission allowance can be an exchangeable or exit mechanism for the carbon tax

From a financial perspective, derivatives should be developed to hedge environmental risk, and the coverage of some weather derivatives should be extended to include the cryptocurrency market. Further integration of the carbon and cryptocurrency markets through the development of carbon-linked derivatives is necessary. Importantly, the idea of low-carbon investments should be promoted. Accurate values of the climate VaR and ES along with a more efficient and accurate methodology for estimating and forecasting the VaR and ES remain unattained and should be investigated in future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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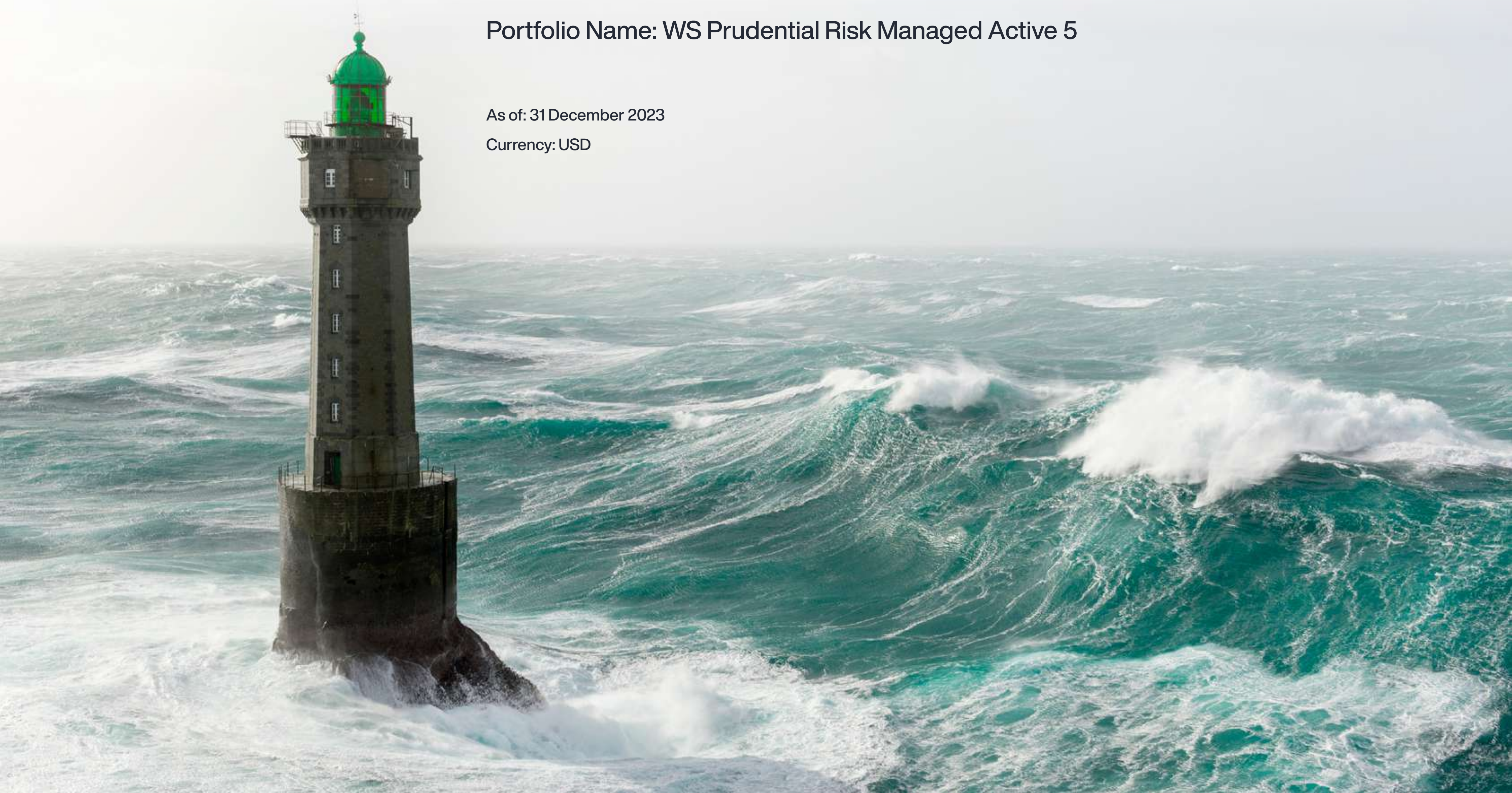
Climate Risk Report

Portfolio Name: WS Prudential Risk Managed Active 5

As of: 31 December 2023

Currency: USD



Carbon Emissions Dashboard

Carbon Footprint		Portfolio	Coverage
Allocation Base	EVIC		
Financed Carbon Emissions tons CO2e / USD M invested Investor Allocation: **EVIC**	Scope 1+2	103.4	19.2%
	Scope 3 – upstream	92.3	19.2%
	Scope 3 – downstream	320.9	19.2%
Total Financed Carbon Emissions tons CO2e Investor Allocation: **EVIC**	Scope 1+2	17,812.5	19.2%
	Scope 3 – upstream	15,905.2	19.2%
	Scope 3 – downstream	55,275.4	19.2%
Financed Carbon Intensity tons CO2e / USD M sales Investor Allocation: **EVIC**	Scope 1+2	320.6	19.2%
	Scope 3 – upstream	286.1	19.2%
	Scope 3 – downstream	994.8	19.2%

Weighted Average Carbon Intensity		Portfolio	Coverage
Corporate constituents tons CO2e / USD M sales	Scope 1+2	273.1	20.1%
	Scope 3 – upstream	254.7	20.1%
	Scope 3 – downstream	575.7	20.1%
Sovereign constituents tons CO2e / USD M GDP Nominal	GHG intensity	744.1	1.8%

Fossil Fuel Exposure	Portfolio
Potential emissions from fossil fuel reserves (tCO2e / USD M invested)	5,567.5
Fossil Fuel Based Revenue Exposure	0.9%
Thermal coal exposure (Any tie)	1.5%
Oil & Gas exposure (Any tie)	3.2%
Exposure to Power Generation	
Thermal Coal (apportioned fuel mix, % of generation)	31.4%
Green and Fossil Fuel Based Revenue Coverage	21.1%

MSCI Low Carbon Transition Risk Assessment	Portfolio
Exposure to companies classified as:	
Low Carbon Solutions	0.3%
Low Carbon Transition Risk	5.1%
Low Carbon Transition Risk Coverage	20.0%

Transition Opportunities	Portfolio
Green Revenue Exposure	2.1%
Exposure to Power Generation	
Renewables (apportioned fuel mix, % of generation)	13.5%

Companies' Transition Plans	Portfolio
Companies with GHG emission reduction targets	17.1%
Companies with targets across all scopes	9.8%
Companies with SBTi approved targets	6.6%
Companies with top quartile carbon management score	7.5%

Carbon Emissions: Sectoral Footprint

Financed Carbon Emission (S1+S2) by Sector

	Portfolio
Materials	964.5
Utilities	430.0
Energy	212.6
Industrials	50.3
Consumer Staples	42.7
Communication Services	28.9
Consumer Discretionary	19.2
Financials	14.2
Health Care	11.9
Information Technology	11.2
Real Estate	4.7
Total	**103.8**

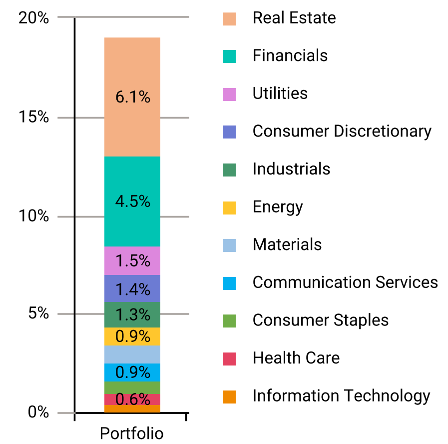
The sector table shows the comparison of the portfolio sector emissions (Scope 1 + Scope 2) to those of the benchmark. The key denotes the magnitude of the emissions in each sector with green denoting lower emissions, and red denoting higher emissions in that sector.

Sectoral Contribution to Financed Carbon Emissions (S1+S2)

	Portfolio
Communication Services	1.3%
Consumer Discretionary	1.3%
Consumer Staples	1.4%
Energy	10.1%
Financials	3.2%
Health Care	0.3%
Industrials	3.2%
Information Technology	0.2%
Materials	45.0%
Real Estate	1.5%
Utilities	32.4%

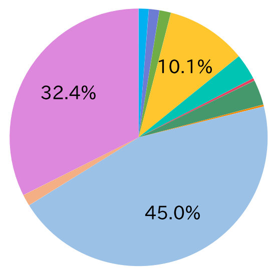
Sector Weight to Financed Carbon Emissions (S1+S2)

Market Cap Weight



The column chart shows the composition by sector of the portfolio and benchmarks by market capitalization to financed carbon emissions. This highlights that dominant sectors, in terms of emissions, tend to be Energy, Utilities, and Materials.

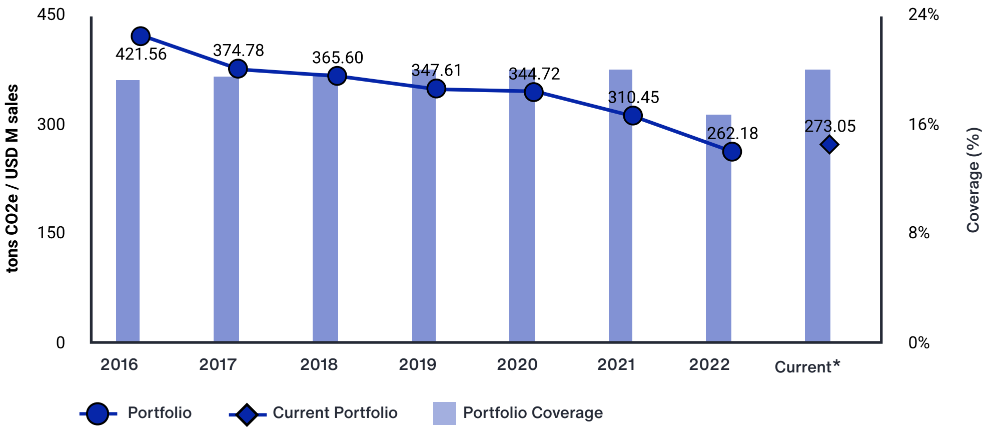
Contribution to Financed Carbon Emissions



The pie chart shows the composition by each sector's contribution to financed carbon emissions. This highlights that dominant sectors, in terms of emissions, tend to be Energy, Utilities, and Materials.

Carbon Emission: Trends and Profile

Weighted Average Carbon Intensity of Current Holdings Over Time



* Current refers to the selected analysis date and provides additional context to the analysis. For example, the figure shown could either be in the past at a specific point in time, or the present date if not specified.

Change across 5 years = -25.3% **Change since baseline NZ year of 2019 = -21.4%**

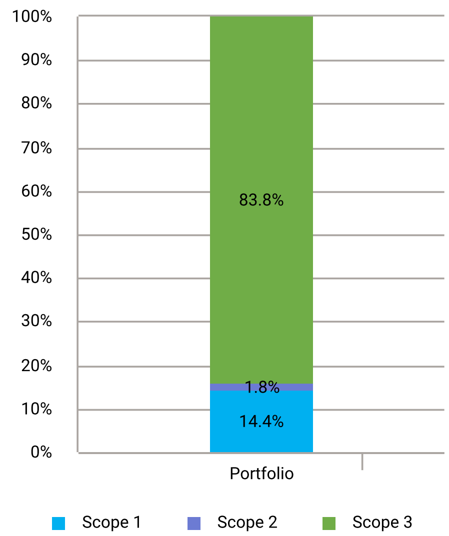
The chart above shows change over time of the weighted average carbon intensity (WACI) of the portfolio constituents and weights at the date of analysis. This analysis is intended to provide an understanding of how the companies in the portfolio have decarbonised over time, as investors increasingly monitor decarbonisation to support climate commitments such as net zero.

The portfolio WACI is illustrated with blue circles. Please note that the analysis does not take into account changes in constituents over this time period.

Portfolio coverage of this metric is also provided which provides contextual information. For example, a lower WACI figure may be related to lower coverage of that metric in a certain year. There can be lower coverage due to companies' reporting cycles and take time in different regions around the world.

Also provided is a % change of the WACI over a 5-year period and a % change compared to the commonly used net zero baseline year of 2019 for further monitoring and reporting.

Contribution of Emissions by Scope



The chart above illustrates the emissions profile of the portfolio denoting the share between Scopes 1, 2, and 3 emissions. Please note Scope 3 here utilises a combination of estimated and reported emissions data.

Climate Scenario Analysis

Climate Value at Risk

Selected Scenario : 1.5°C NGFS Orderly

	1.5°C NGFS Orderly	1.5° REMIND NGFS Orderly	1.5° REMIND NGFS Disorderly	2° REMIND NGFS Orderly	3° REMIND NGFS NDC
	Portfolio	Portfolio	Portfolio	Portfolio	Portfolio
Policy Climate Var (Scope 1,2,3)	-9.3%	-9.3%	-13.7%	-3.7%	-3.0%
Technology Opportunities Climate VaR	0.6%	0.6%	1.2%	0.2%	0.1%
Physical Climate VaR Aggressive	-5.2%	-5.2%	-5.2%	-6.6%	-8.9%
Aggregated Climate VaR	**-13.9%**	**-13.9%**	**-17.7%**	**-10.1%**	**-11.9%**

Physical Climate Value at Risk Detail

Selected Scenario : Aggressive

Chronic Risks (0.5° global grid)

Extreme Heat	Extreme Cold	Wind Gusts	Heavy Snowfall	Heavy Precipitation
-0.7%	0.0%	0.0%	0.0%	-0.1%

Acute Risk (high res)

Tropical Cyclones	Coastal Flooding	Fluvial Flooding	River Low Flow	Wildfires
-0.2%	-4.3%	-0.2%	-6.3%	0.0%

Aggregate Physical Climate VaR

-5.2%

Climate VaR Portfolio Coverage Summary

	Portfolio
Policy Climate VaR (Scope 1,2,3)	18.7%
Technology Opportunities Climate VaR	15.7%
Physical Climate VaR	17.9%

Top 10 Physical Risk Climate VaR Companies

Security	Physical Risk Climate VaR Contribution	Primary Physical Risk Hazard
SUN HUNG KAI PROPERTIES LIMITED	-0.66%	Coastal Flooding
NEW CHINA LIFE INSURANCE COMPANY LTD.	-0.44%	Coastal Flooding
Link Real Estate Investment Trust	-0.27%	Coastal Flooding
WHARF REAL ESTATE INVESTMENT COMPANY LIMITED	-0.22%	Coastal Flooding
SEGRO PUBLIC LIMITED COMPANY	-0.13%	Coastal Flooding
Mitsui Fudosan Co., Ltd.	-0.09%	Coastal Flooding
CK ASSET HOLDINGS LIMITED	-0.09%	Coastal Flooding
Sino Land Company Limited	-0.09%	Coastal Flooding
SEMPRA	-0.06%	Coastal Flooding
Mitsubishi Estate Company, Limited	-0.06%	Coastal Flooding

The table provides information on the most exposed companies to physical risk exposure in the portfolio such as extreme weather events in the selected physical risk scenario. However, physical risks can be both positive and negative and be expressed in both positive and negative values. MSCI currently models ten hazards including extreme heat and cold, coastal and river flooding, wildfires as well as wind gusts and precipitation. Physical changes can be event-driven ('acute') or longer-term in nature ('chronic').

Climate Value at Risk

Top 10 Aggregated Climate VaR Risk Contributors

Security	Aggregated Policy Risk Climate VaR	Technology Opportunities Climate VaR	Physical Risk Climate VaR	Aggregated Climate VaR	Weight (%)	Climate VaR Risk Contribution
SUN HUNG KAI PROPERTIES LIMITED	-1.98%	0.20%	-100.00%	-100.00%	0.12%	-0.12%
SASOL LIMITED	-100.00%	0.21%	-7.44%	-100.00%	0.11%	-0.11%
EXXARO RESOURCES LIMITED	-100.00%	0.80%	-2.15%	-100.00%	0.10%	-0.10%
NEW CHINA LIFE INSURANCE COMPANY LTD.	-6.36%	0.00%	-30.64%	-37.00%	0.26%	-0.10%
GLENCORE PLC	-61.18%	0.00%	-4.25%	-65.43%	0.11%	-0.07%
SAPPI LIMITED	-100.00%	0.00%	-7.69%	-100.00%	0.05%	-0.05%
Link Real Estate Investment Trust	-0.50%	0.02%	-44.73%	-45.20%	0.11%	-0.05%
DUKE ENERGY CORPORATION	-64.79%	1.56%	-1.63%	-64.86%	0.07%	-0.05%
THE SOUTHERN COMPANY	-63.65%	2.34%	-1.22%	-62.53%	0.07%	-0.05%
CHENIERE ENERGY, INC.	-100.00%	0.00%	-1.25%	-100.00%	0.04%	-0.04%

The table provides an overview of the companies with the highest negative Aggregated Climate VaR contribution in the portfolio. The position weight of each individual security in the portfolio is multiplied by the Aggregated Climate VaR to establish the Climate VaR risk contribution of the portfolio. Aggregated Climate VaR in this chart is the sum of Policy Risk from Direct GHG Emissions (Scope 1) Climate VaR, Technology Opportunities Climate VaR and Physical Climate VaR for the selected scenario.

Climate VaR numbers are calculated at the security level, i.e. 2 securities associated with the same issuer could have different Climate VaR.

Climate Value at Risk

Portfolio Level Sovereign Climate VaR Results

	Portfolio
1p5C NGFS Orderly	-1.21%
1p5C NGFS Disorderly	0.69%
2C NGFS Orderly	0.43%
2C NGFS Disorderly	0.07%
3C NGFS Current Policies	0.95%
3C NGFS	0.08%
Coverage	0.59%

Portfolio Weights of Largest Contributor Countries by Time-to-maturity

Country/Duration	Total
Brazil	**18.32%**
Mexico	**14.84%**
Indonesia	**14.75%**
Poland	**9.30%**
Romania	**7.89%**
South Africa	**7.64%**
Hungary	**6.90%**
Japan	**6.52%**
Singapore	**6.43%**
Germany	**4.29%**
Total	**96.87%**

Total includes all other country buckets not listed in the above list.

Coverage here denotes total portfolio coverage across all asset classes, not only the sovereign portion of the portfolio. The coverage metrics presented in this report are computed in the context of the entire long-only side of the portfolio – no weight adjustments are performed for the respective scopes of corporate or sovereign exposures.

Understanding Sovereign Climate VaR

Sovereign Bond Climate VaR is designed to provide a forward-looking and return-based valuation assessment to measure climate related risks in a sovereign bond investment portfolio. The fully quantitative model offers insights into how climate change could affect sovereign bond valuations through the use of a stress testing framework.
It estimates the change in the sovereign yield curve when market expectations move from a climate-agnostic baseline expectation to any other climate scenario. Yield curve changes are then used to stress test the value of local-currency sovereign bonds.
The model produces two types of outputs: the potential impact of climate change and economic decarbonization on implied yield curves and sovereign bond valuations.

Implied Temperature Rise

MSCI Implied Temperature Rise Company Analysis

Aggregated Implied Temperature Rise

Portfolio: 2.7°C

Implied Temperature Rise: Companies with Highest Temperature Alignment

Company Name	Weight	Implied Temperature Rise
SASOL LIMITED	0.1%	10.0°C
EXXARO RESOURCES LIMITED	0.1%	10.0°C
KfW	0.1%	10.0°C
CELANESE US HOLDINGS LLC	0.0%	10.0°C
NTPC LIMITED	0.0%	10.0°C
LINDE PUBLIC LIMITED COMPANY	0.0%	10.0°C
THE TATA POWER COMPANY LIMITED	0.0%	10.0°C
OCCIDENTAL PETROLEUM CORPORATION	0.0%	10.0°C
MARRIOTT INTERNATIONAL, INC.	0.0%	10.0°C
Carnival Corporation	0.0%	10.0°C

Implied Temperature Rise: Companies with Lowest Temperature Alignment

Company Name	Weight	Implied Temperature Rise
BRITISH AMERICAN TOBACCO P.L.C.	0.2%	1.3°C
BIG YELLOW GROUP PLC	0.1%	1.3°C
NATIONAL GRID PLC	0.0%	1.3°C
ANGLOGOLD ASHANTI PLC	0.0%	1.3°C
Eversource Energy	0.0%	1.3°C
PACIFIC GAS AND ELECTRIC COMPANY	0.0%	1.3°C
NOVO NORDISK A/S	0.0%	1.3°C
CONSOLIDATED EDISON, INC.	0.0%	1.3°C
EDISON INTERNATIONAL	0.0%	1.3°C
Hannover Rueck SE	0.0%	1.3°C

Implied Temperature Rise

The Implied Temperature Rise (ITR) metric provides an indication of how well public companies align with global temperature goals. Expressed in degrees Celsius, it is an intuitive, forward-looking that shows how a company aligns with the ambitions of the Paris Agreement – which is to keep a global temperature rise this century well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5°C. The portfolio-level Implied Temperature Rise compares the sum of “owned” projected GHG emissions against the sum of “owned” carbon budgets for the underlying fund holdings. The portfolio's total estimated carbon budget over- / undershoot is then converted to a degree of temperature rise (°C) using the TCRE. The allocation base used to define ownership is Enterprise Value including Cash (EVIC) in order to enable the analysis of equity and corporate bond portfolios.