Impact of climate scenario choices on climate financial risk assessment:

High variance company performance under consistent climate stress test

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Executive summary

1. Widespread heterogeneity in climate scenario providers and trajectories indicate large uncertainty for financial institutions in assessing corporate climate transition scenario pathways.
2. This has significant implications for climate financial stress testing that are premised on climate scenario pathways to meet certain temperature targets and policy ambitions.
3. A consistent, bottom–up, climate financial stress test is applied to a set of 3,419 power companies using different scenario trajectories and provides two main outputs: a measure of net present value change for the power company under a climate transition stress scenario compared to the baseline, and a measure of probability of default change under the stress scenario compared to the baseline.
4. Five scenarios from four different providers are compared under a less ambitious goal of reaching a global average surface temperature increase of below 2°C, and four scenarios under three different providers are compared under a more ambitious goal of reaching a global Net Zero by 2050.
5. Distribution of company–level NPV changes under the stress test show that there are significant differences in company impacts based on the climate scenario. This can lead to significant differences in the assessment of market and credit risk for companies.
6. Analysis of individual power technologies shows that the heterogeneity in company performance is driven by the same disagreeing technology pathways across climate scenario source Integrated Assessment Models for the same climate policy ambition.
7. Renewable technology companies consistently show improvement in NPV under any stress scenario, but there is some disagreement and wide-ranging results on the extent to which coal, gas, and oil companies lose NPV, with some companies under each technology showing positive NPV growth.
8. Hydro and nuclear technology power companies show the greatest uncertainty in performance under stress scenarios showing widespread disagreement in positive or negative performance depending on the climate scenario being used.
9. Results of probability of default change show similarly conflicting results with high variation in a company’s PD, and disagreement in positive or negative change in PD, but overall higher levels of agreement between scenarios compared to NPV change.
10. Further research is needed to address both the uncertainty and assumptions in climate scenario trajectories as they are applied to financial climate risk analysis, and the various approaches that are used to conduct climate financial stress testing.

Acknowledgements

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Impact of climate scenario choices on climate financial risk assessment:

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Abstract

Climate scenarios that forecast potential future pathways of the green transition are increasingly being applied by financial institutions to assess financial risk, including for climate stress testing. There are a variety of climate scenarios that apply different modelling techniques to forecast future economic trajectories. These models often project different trends of key economic indicators and variables, even when the scenario is based on the same temperature target or the same policy ambition. Using a consistent climate stress test applied across eleven different climate scenarios under two different temperature targets and policy ambitions for a global set of power companies, this paper finds significant variation in the impact that each scenario has on the assessment of company valuation, and in the probability of default. First, we demonstrate that climate scenarios have significantly different and varying impacts on power company performance depending on the choice in climate scenario, even when using scenarios with the same policy ambition or temperature target. Second, we find variability and disagreement in positive and negative company performance based on different energy sector technology trajectories within each scenario. Third, variability in company performance by technology is also differentiated based on climate scenario stringency, with more stringent and ambitious scenarios leading to less variability compared to less stringent

and less ambitious ones. Finally, differences and variability in company performance have implications for financial institutions based on the probability of default. Based on these findings, we show that the variation in the probability of default and the company valuation is ultimately related to differences in the assumptions of the transition pathway. This can have significant implications for how financial institutions conduct portfolio selection and climate stress testing.

1. Introduction

The economic transition towards a low–carbon economy introduces opportunities and risks that can have a significant impact on the performance of companies, with larger potential ramifications for financial stability.[1] This transition represents significant challenges for financial institutions that can directly translate to real values, behaviours, planning, and strategy.[2] Central banks have cautioned the potential destabilising effects of climate change risk on financial stability, and policymakers have underscored the potential of climate transition as a source of systemic risk.[3] Such concerns have motivated central banks and regulatory authorities to consider the extent to which climate–related risks might undermine financial stability by implementing transition–based stress testing exercises.[4]

Substantial progress has been made to develop risk frameworks and analytical tools that assess financial losses based on the financial stress associated with a given future climate scenario.[5] Yet, most of these assessments place insufficient attention on the different ways the green transition could unfold, driven by differences in key assumptions inherent in models that underlie climate scenarios.[6] Consequently, the reliance on certain climate scenario trajectories over others may give an inaccurate evaluation of financial risk, and an inherent uncertainty in their trajectories.[7] Assessing the resilience and vulnerability of financial institutions under only a limited number of mitigation pathways that were generated across consistently defined Integrated Assessment Models does not sufficiently capture the wide range of different beliefs and assumptions built into the modelling dynamics of the energy system, the speed of technological progress, and the extent to which socio–economic and climate constraints are reflected.[8]

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[1] Catriona Marshall et al. *Financial markets and climate transition: Opportunities, challenges, and policy implications*. Committee on Financial Markets Report. Paris: Organisation for Economic Co-operation and Development, 2021.

[2] Irene Monasterolo. "Climate change and the financial system". In: *Annual Review of Resource Economics* 12.1 (2020), pp. 299–320.

[3] Stefano Battiston, Yannis Dafermos, and Irene Monasterolo. "Climate risks and financial stability". In: *Journal of Financial Stability* 54.06 (2021), pp. 1–6.

[4] Pierpaolo Grippa, Joachen Schmittmann, and Felix Suntheim. *Climate change and financial risk*. Global Financial Stability Report. International Monetary Fund, 2019.

[5] Patrizia Baudino and Jean-Philippe Svoronos. *Stress-testing banks for climate change: A comparison of practices*. FSI Insights 34. Bank for International Settlements, July 2021.

[6] John Colas et al. *Extending our horizons: Assessing credit risk and opportunity in a changing climate: Outputs of a working group of 16 banks piloting the TCFD recommendations*. Tech. rep. UNEP Finance Initiative and Oliver Wyman, Apr. 2018.

[7] Matteo Gasparini, Moritz Baer, and Matthew C. Ives. "A re-evaluation of the financial risks of the Net Zero transition". In: *Oxford Working Paper* (2023), pp. 1–39.

[8] Moritz Baer et al. "TRISK: A climate stress test for transition risk". In: *Oxford Sustainable Finance Group* (2022), pp. 3–68.

The broad range of methods for evaluating firm value or financial risk from the climate transition, and the data required to do such analysis, has several constraints that make it uncertain for two reasons.

First, uncertainty in the scenario forecasts is due to the lack of information in the underlying modelling behaviour and methods.[9] The application of climate scenario trajectories for stress testing is not easily or transparently conveyed to the financial sector and practitioners. Such variability, without sufficient information on what is driving forecasts, makes it increasingly difficult for practitioners to judge the credibility or application of scenario trends for their own analysis, including for climate stress testing.[10] However, a better understanding of differences between climate transition trajectories that drive the variation in the assessment of firm and financial performance can help practitioners in the application of climate scenarios for evaluating climate risk. While there is an extensive literature on the modelling and design of climate scenarios, how these scenarios are applied to corporate and financial risk and strategy in the green transition has not been widely studied. The choice of modelling techniques in a climate shock scenario is an important consideration in stress test design, however the lack of analysis or transparency in the underlying assumptions and uncertainties makes it hard to gauge the overall materiality of these choices.

Second, the design of a climate stress testing exercise has become an uncertain endeavour for banks and supervisory institutions, since there is not yet a well–established methodology or consensus on conducting such testing.[11] There are several potential reasons for this, including the wide and varying set of variables of interest that are either explicitly modelled or implicitly assumed in a forward–looking stress test exercise. For example, the level and stringency of carbon taxes and renewable subsidies which needs to be projected into the future for determining transition risks are generally unknown, and hence are either derived from within a model using various techniques, or exogenously imposed on the model, based on the primary factors of interest for the user.[12]Similarly, interactions between large systems such as climate change and the macroeconomy are difficult to specifically apply to transmission channels to derive the effects of high physical climate risk on GDP growth.[13] Prevalence of additional risks such as social, economic, and political factors further confound the problem.[14] These types of interactions and the mechanisms by which they are compounded in the real

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[9] Mark M. Dekker et al. “Spread in climate policy scenarios unravelled”. In: *Nature* 624.7991 (2023), pp. 309–316.

[10] Kevin Tang and Francesca Pianosi. *An input-output sensitivity analysis of climate-economy integrated assessment models*. Report. Centre for Greening Finance and Investment, 2024.

[11] Banking Supervision. *Good practices for climate stress testing*. Report. European Central Bank, 2022.

[12] Nicholas Stern. “The structure of economic modelling of the potential impacts of climate change: Grafting gross underestimation of risk onto already narrow science models”. In: *Journal of Economic Literature* 51.3 (2013), pp. 838–859.

[13] Emanuele Campiglio et al. “Climate change challenges for central banks and financial regulators”. In: *Nature Climate Change* 08.06 (2018), pp. 462–468.

[14] Jakob Thoma. “How climate stress-tests may underestimate financial losses from physical climate risks by a factor of 2-3x”. Report. 1in1000, Theia Finance Labs, 2024.

economy and the financial system are not well–established, but have been modelled in a variety of ways based on different sets of assumptions from process–based climate–economy Integrated Assessment Models (IAMs). These IAMs can draw from the same input data and the same assumptions about the future, but since the model environment within which climate and economic interactions are designed are different, this can lead to a wide range of future projections that are key for assessing climate financial risk.

Several methodologies have been developed for climate stress testing to assess climate–related risks to the financial system. Prominent methodologies include network–based climate stress testing that examines how climate policies affect different sectors in the real economy with indirect effects on financial sectors.[15] Market–based climate stress tests have investigated the immediate expected impacts on bank equity values from changes in climate risk along a range of horizons.[16] The TRISK framework assesses both market risk in the form of valuation, and credit risk in the form of probability of default.[17] A network approach to the hierarchy of financial dependencies looks at how various climate policies create risk that are propagated through the financial system.[18]Financial risk is also endogenous and can become amplified when there are overlapping portfolios when two different financial institutions invest in common assets, creating a measure of systemic risk.[19] Other papers have reviewed such climate stress test methodologies used by central banks and researchers.[20]

The objective of this study is to investigate the impact of the choice of climate scenario inputs on climate financial risk assessment, and to determine whether the commonly used scenarios generate significant variability in financial risk depending on the underlying scenario assumptions and the Integrated Assessment Model. For this purpose, we compare several climate scenarios with the same overall temperature target of Below 2°C from four different scenario providers – the Network for Greening the Financial System (NGFS), the International Energy Agency (IEA), the Inevitable Policy Response (IPR) and the Institute For New Economic Thinking (INET) at the University of Oxford – into one comprehensive and consistent ‘TRISK’ climate transition stress testing framework, developed and maintained by the 1in1000 initiative.[21] This allows for the compilation of several TRISK output metrics across a wide set of companies, according to various IAMs, and several different narrative pathways. Results

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[15] Stefano Battiston et al. “Leveraging the network: A stress test framework based on DebtRank”. In: *Statistics and Risk Modelling* 33.3 (2016), pp. 117–138; Andrew G. Haldane and Robert M. May. “Systemic risk in banking ecosystems”. In: *Nature* 469.7330 (Apr. 2011), pp. 351–355.

[16] Jung Hee Noh and Heejin Park. “Greenhouse gas emissions and stock market volatility: An empirical analysis of OECD countries”. In: *International Journal of Climate Change Strategies and Management* 15.01 (2023), pp. 58–80.

[17] Baer et al., “TRISK: A climate stress test for transition risk”, op. cit.

[18] Stefano Battiston et al. “A climate stress-test of the financial system”. In: *Nature Climate Change* 7 (2017), pp. 283– 290.

[19] Sebastian Poledna et al. “Quantification of systemic risk from overlapping portfolios in the financial system”. In: *Journal of Financial Stability* 52.100808 (Feb. 2021).

[20] Fanny Cartellier. “Climate stress testing: An answer to the challenge of assessing climate-related risks to the financial system?” In: *SSRN* (Aug. 2022).

[21] Baer et al., “TRISK: A climate stress test for transition risk”, op. cit.

show four main findings. First, on average, when applying a consistent stress test, various scenarios under the same temperature target or policy ambition produces significantly different results across power companies. Second, variability in company performance for a climate stress scenario depends upon the type of technology for the power company. Third, findings indicate that the more stringent the climate policy ambition, the less variability in risk between scenarios. Finally, variability in company performance is similarly represented in financial risk in terms of impacts on probability of default. Overall, we find that financial institutions and regulators need to consider a broader set of models and scenarios in stress testing research, and that applications of climate scenarios should consider bulk stress testing exercises as ranges rather than as a particular discrete set of values.

2. Data and methods

2.1. Data

Conducting climate stress testing requires a set of forward–looking projections of the potential trends and changes in the economy that shape the economic transition. As previously discussed, Integrated Assessment Models develop large systems of climate and economic interactions to estimate forecasts of trends of key variables that are used as inputs into climate stress testing exercises. Since IAMs estimate climate–economy interactions in different ways, they will result in different forecast trends, even if they are designed under the same parameters, such as the temperature target or policy ambition. IAMs take the intended temperature target, policy ambition, and level of coordination in a given year based on an assumed narrative of the future to produce forecast trends of key strategic variables to the climate transition.

The most ambitious narratives assume global coordination to reach a Net Zero emissions target by 2050. In contrast, the least ambitious narratives assume no further changes to countries' climate policies or international cooperation, thus allowing for continued emissions and temperature rises. Alternatively, there are several narratives that are premised on varying levels of coordination between countries, temperature targets, and policy objectives. As each of these narrative pathways for how the climate transition will unfold are applied to each IAM, they will produce different trends for how key variables and factors to the transition will reach that target. Each projected trend of key transition variables produced by a model under a specified narrative pathway produces a scenario of the future. As a projection of the future, there is a wide margin of error, hence any scenario resulting from a particular narrative pathway–IAM combination should only be seen as a representative trend, rather than the discrete forecast.

The NGFS scenarios provide four narrative pathways derived from three IAMs, each of which provides scenarios that provide a wide range of policy and technological dimensions.[22] In contrast, the IEA uses a single model, the World Energy model (WEM), but has three narrative pathways to model key variables for the energy sector.[23] However, not all scenarios are produced from an integrated assessment model environment. Key transition variables can also be produced from other modelling techniques, including general or partial equilibrium models, such as those used by IPR or Oxford.[24] Despite the variety of modelling techniques and narrative pathways available from different scenario providers, they can broadly be categorised according to narrative pathway of the policy ambition or temperature target. Table 1 shows the different narrative pathways used by each of the IAMs included in our analysis, and which pathways and temperature targets offer the widest basis of comparison between IAMs based on the most common narrative developed.

IAM	Net Zero 2050	Below 2°C	Divergent Net Zero	Delayed Transition
GCAM	X	X	X	X
REMIND	X	X	X	X
MESSAGEix	X	X	X	X
IEA	X	X		
IPR	X	X		
Oxford		X		

Table 1: *Climate–economy models according to different narrative pathways*

This paper utilises three types of data inputs to develop a unique climate stress test measure of credit and market risk for each individual company in the dataset, which includes a wide set of 3,419 power companies. The first data inputs are the climate–economy scenarios, which project alternate trends of key variables affecting the economy and the financial system including production for key sectors, potential carbon tax prices, and projections on the evolution of technological change in power generation. The stress test estimates market and credit risk for companies based on the difference between the company's performance under a baseline scenario compared to the shock scenario, where the shock scenario is the trend provided from the same model but different narrative pathway. The baseline scenario for the

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[22] Thomas Allen et al. *NGFS Climate Scenarios for Central Banks and Supervisors*. Tech. rep. Network for Greening the Financial System Macrofinancial Workstream, June 2021.

[23] International Energy Agency Secretariat. *World Energy Outlook 2023*. Tech. rep. International Energy Agency, 2023.

[24] *Inevitable Policy Response forecast policy scenarios 2023*. Tech. rep. Berlin, Germany: Inevitable Policy Response, 2023; Rupert Way et al. "Empirically grounded technology forecasts and the energy transition". In: *Joule* 6.9 (2022), pp. 2057–2082.

NGFS Models i.e., GCAM, REMIND, and MESSAGEix, is Nationally Determined Contributions (NDC). Under the NDC pathway, future trends of key transition variables are projected based on a future world in which the only restrictions to high–emitting sectors, the amount of carbon emissions, and the level of global coordination is simply based on what countries have agreed to commit to, without further adjustments or increases.

For other models, the baseline scenario against which the shock scenario is compared is also derived from the model under a similar narrative pathway as nationally determined contributions. The baseline scenario for the International Energy Agency – World Energy Outlook (IEA–WEO) uses the WEO Stated Policy Scenario (STEPS). For the Oxford–INET model it is a combination of Oxford baseline scenario variables with some elements complemented from the IEA–STEPS. Due to a lack of baseline scenario assumptions provided by Inevitable Policy Response (IPR) scenario, the IEA WEO–STEPS scenario is adapted from the baseline reference for IPR–NZE, the IPR– B2DS scenarios, and the IPR–FPS. To ensure consistency in the application of different scenarios and the different baseline and shock scenarios, this analysis uses global scenarios and thus does not fully capture regional decarbonisation pathways.

For this analysis, we have chosen the B2DS ('below 2°Celsius global warming from pre-industrial level') as the main reference ambition (shock) scenario for all assessed models.[25] The below 2°C target has been recognised as a crucial threshold by the Paris Climate Agreement (UN, 2023) and is considered as a desirable and a plausible scenario. Further, it is broadly aligned with the 'Middle of the road' Shared Socio-Economic Pathway (SSP2)[26] defined by the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2022) and forecasted to be most 'likely climate outcome' by the Inevitable Policy Response's (IPR) latest forecast of global climate policies (IPR, 2023).[27] While the 2–degree target is the most likely scenario and may prevent the most threatening natural and economic impact, scientific and political consensus has considered limiting warming to 1.5 degrees Celsius as more desirable. This is reflected in the Net Zero ambition, for example, IEA's Net Zero scenario (NZE) presents a roadmap for the energy sector to transition to a Net Zero energy system by 2050 with a 50 percent chance of limiting the global temperature rise to 1.5°C without a temperature overshoot.

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[25] The ambition scenarios for these models are NGFS B2DS, IEA Sustainable Development Scenario (SDS), IPR Forecast Policy Scenario (FPS) and Oxford INET Fast Transition Scenario (FTS), which have a similar level of ambition below 2 Degree C.

[26] The SSPs are socio–economic scenario assumptions about expected economic, societal, and demographic conditions and driving forces. They have been defined and updated by IPCC, in the 6th Assessment Report, published in February 2022 (IPCC, 2022).

[27] The Inevitable Policy Response's (IPR) forecast is informed by live tracking of over 300 climate policies over the past two years, as well as input from over 100 climate policy experts across 12 countries, concludes that the world will likely achieve the Paris Agreement goal of limiting temperature increase to 'well below 2°C' (IPR, 2023).

While some scenario providers and their models may provide data for a longer horizon (i.e., until the year 2100), all scenario horizons considered in this assessment have been limited to the year 2050. This is for two reasons. Firstly, this allows better comparability across a varied set of scenario horizons considered. Second, the TRISK framework estimates the climate financial impacts from a transition risk technology shock that is set to occur before the year 2050 for all assessed scenarios and models, since beyond 2050 the discount rate becomes marginal.

The second type of data inputs includes highly granular company business unit production data for 3,419 companies, including information on production activity, such as business unit production plans, and ownership structure, provided by Asset Impact Physical Assets Matched with Securities (PAMS) dataset.[28] The key aspect of the asset-based production data is that it is forward-looking which includes information both on the company's production capacity today and the production plans going forward by 5 years. This allows company-specific assessments on market risk and credit risk based on asset-level production shocks, and differences in carbon pricing policies between countries based on the asset location.

The companies in this analysis are a sample of the universe of production companies that can be provided by Asset Impact PAMS database but are limited in two ways. First, we only cover companies that operate in the Power sector. Second, we only cover companies which exhibit variability for the initial 5-year production forecast period. Companies with constant production forecasts in a specific technology show largely similar percentage NPV changes when transitioning from a baseline to a stress scenario. The reason behind this is that they adhere to a consistent growth trajectory in baseline and target pathways, dictated by their chosen technology in the power sector. While absolute difference between the companies might be significant, the relative change between baseline and target pathways remains the same for these companies. Therefore, to identify results apart from the clusters that can be generated by the constant production mechanism, in this paper, we have limited the sample data to cover only companies with variable production forecasts.

The third type of data inputs are the company-level information on company finances and financial risk profiles- provided by Refinitiv Eikon. This includes data on market capitalisation, asset volatility, structural leverage ratio, and net profit margin. The financial data is available only for publicly listed companies and for companies that are not publicly listed and tracked on Refinitiv Eikon. The missing data entries are completed using average values of those variables of companies in the same sector and country.

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[28] *Understanding climate impacts with asset-based data*. White paper. Paris, France: Asset Impact, 2023.

2.2. Methodology

The data inputs are connected through a set of transmission channels, which propagates the climate–adjusted economic impact to the asset value of firms and subsequently translates the impacts into financial market and credit risk. **The model framework is composed of the following three main methodological 'layers':** 1) construction of company–level climate financial scenario pathways, 2) calculation of the real economic impact assets and firms, and 3) climate adjusted impact on financial institutions. The difference in financial market risk i.e., transition related changes in the net present valuation (NPV), and credit risk i.e., transition related changes in the probability of default (PD) – across a set of global energy firms in the power sector using the TRISK model for each of the models and scenarios included in Table 1 is estimated through the transmission channels illustrated in Figure 1.

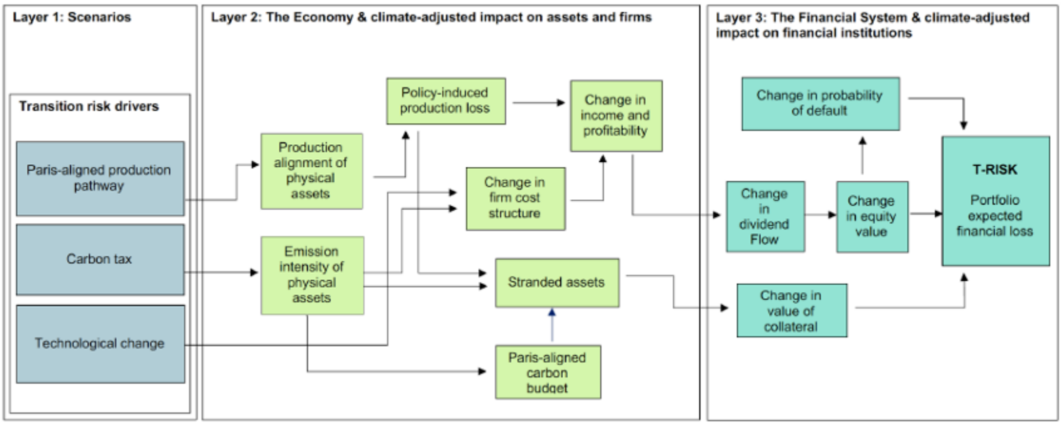

Fig. 1: *Representation of the key model layers, stylised overview of the climate stress testing framework and its transmission channels*

The first layer of the TRISK framework translates input climate financial scenarios into sector–level decarbonisation pathways, and subsequently into technology–level changes to individual company production capacity. The level of each company's decarbonisation effort is determined by the alignment of the company with a decarbonisation pathway (using the forward–looking production plans) and the respective market share of that company within a particular production sector. Three types of decarbonisation production pathways are constructed: (i) baseline, (ii) climate target, and (iii) climate transition shock pathway. The baseline production pathway describes a state of 'business as usual' wherein the production pathway reflects no climate ambition beyond what is assumed in the company's forward-looking production plans. The climate target pathway projects a sustainable mode of production, as it already has been on a path of climate transition presently as well as in the future as determined by the input climate scenarios. The key decarbonisation pathway of interest is the climate transition shock scenario which accounts for the technology and asset-level production migration from the baseline pathway towards the target pathway in a defined policy ‘shock year’ which is 2030 in our analysis.

The second layer interacts with the company’s decarbonisation pathways with real economic projections on costs, price, and general economic developments, as well as company’s financial risk profile. The shock scenario pathway determines the firm cost structure and production mix across technologies and business units (e.g., electricity produced from solar power plants or coal-fired power plants) and impacts their income and profitability. Production trajectories are taken from climate scenarios as shocks to the TRISK framework, and are treated in two different ways for carbon–intensive and low carbon technologies. For high carbon technologies, trajectories are based on the growth rates implied for each technology over time, as given in each climate scenario. In contrast, for low carbon technologies, the trajectories are derived from the technology’s relative share in relation to the total sectoral production over time. This allows for a better estimation of the build–out of companies that operate multiple technologies within the power sector, as well as for those planning production expansions in the coming years but with no production realised in the starting year. Company–level impacts are translated into profit and cashflow projections based on technology–specific production shocks, and subsequently via discounted cash flow models into asset and equity valuation changes.[29]

In the third layer, the model estimates the market and credit risk of companies. In this case, company market risk is assessed based on the change in the net present value (NPV) of a company derived from the baseline scenario. The latter is essentially the value of a company according to the gradual policy changes according to the nationally determined contributions (NDCs) of the country in which the company is located. This is compared to the adverse shock test scenario, which determines the value of the company according to various climate scenario trajectories that involve more stringent reductions in emissions and higher rates of carbon pricing than the current policies or the projected NDCs. The difference in the valuation change under the baseline scenario and the shock test scenario is the measure of transition market risk. Building on the company-level changes in valuation under the shock scenario calculated via a discounted dividend flow model, the changes in company-level asset valuation impacts enter a time-horizon adjusted Merton credit risk framework to estimate the impact on firm-level probability of default (PD). The company PDs are calculated both for the baseline

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[29] Simon Dietz et al. “‘Climate value at risk’ of global financial assets”. In: *Nature Climate Change* 6 (Apr. 2016), pp. 676–781.

and the shock scenarios, with the main output being the difference between these scenarios – which is the additional impact on company–level PD as a result of climate transition shock.

The 1in1000 TRISK engine holds all of the separate asset and financial datasets used as inputs into the TRISK model and computes the key metrics of transition risk. To isolate the effect of the different scenario pathways on the financial market risk and credit risk we keep all other TRISK model assumptions constant. This study follows the work by Gasparini et al. (2022), which provides an overview of the qualitative and quantitative differences across these scenarios and may be referred to for better interpretability of our results.[30] By applying a consistent TRISK model to a variable set of climate scenarios and pathways, we observe the extent to which uncertainty in climate scenarios has implications in the assessment of corporate and financial transition risk.

In order to compare differences in climate risk depending on the selection of a particular climate scenario or pathway, this paper integrates a variety of models according to the same temperature target and policy ambition across the different scenario providers according to Table 1. We show the difference in financial market risk based on the transition related changes in the net present value and credit risk transition related changes in the probability of default for a set of global energy firms. It is expected that there may be some differences in the transition risk performance of firms based on the different models, however not necessarily that this should significantly affect the performance of individual companies or differ from one scenario to another for the power sector overall, given that the same temperature target and policy pathway is being input to a consistently applied climate financial stress test.

3. Results: Impact on valuations

3.1. Differences in distributions of NPV changes

3.11. Below 2°C pathway

Applying the TRISK climate stress test model using different future trajectories provided by scenarios from Table 1 produces two outputs. First, is the impact of the climate stress scenario on companies in terms of the effect on a company's net present value. The second output is how changes in net present value from the company translate into financial portfolio losses in terms of probability of default. This paper looks at each output of the TRISK model separately, beginning with the impacts of each shock scenario on company's projected net present value.

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[30] Gasparini, Baer, and Ives, "A re-evaluation of the financial risks of the Net Zero transition", op. cit.

Scenario providers develop trajectories for how the global economy will transition to reach specified global temperature targets based on specific policy ambitions, and broad assumptions of how smooth or rough that transition will be for countries, economies, and sectors. The scenarios analysed and their providers have been broadly categorised according to the temperature target, policy ambition and coordination, and technological evolution. Although it is expected that trajectories should vary between scenario providers, the extent to which they vary, and the impact that such variability has for assessment of climate risk has not been observed.[31] By applying the TRISK methodology to each of the climate scenarios using the same narrative pathways, implications of the variability in climate scenarios is observed from variability in the impact of the scenario on company NPV change.

At first glance, the distribution of most companies' impacts shows similar shapes across IAMs for either pathway. Figure 2 shows the shape of the distribution of the impacts on NPV for all power companies in the dataset, based on either the Below 2°C or Net Zero 2050 narrative pathways. Company impacts under REMIND show the highest central density, while GCAM and MESSAGEix show similar shapes. Overall, most companies show a slight improvement with a positive NPV change under the stress scenario represented by the density of companies on the positive side of the distribution. The high peak of positive distribution in company performance is due to the large number of renewable power companies that are included in the dataset. These companies are generally smaller than other technology types of power companies, as defined by their smaller market cap. Conversely, for both pathways, there is also a second, smaller peak density of companies that show a negative NPV change under the stress scenario, which is for the fewer number, but higher market cap power companies including thermal energy companies. Furthermore, bilateral scenario spearman correlations of NPV as shown in Table 2 indicate that they are well correlated.

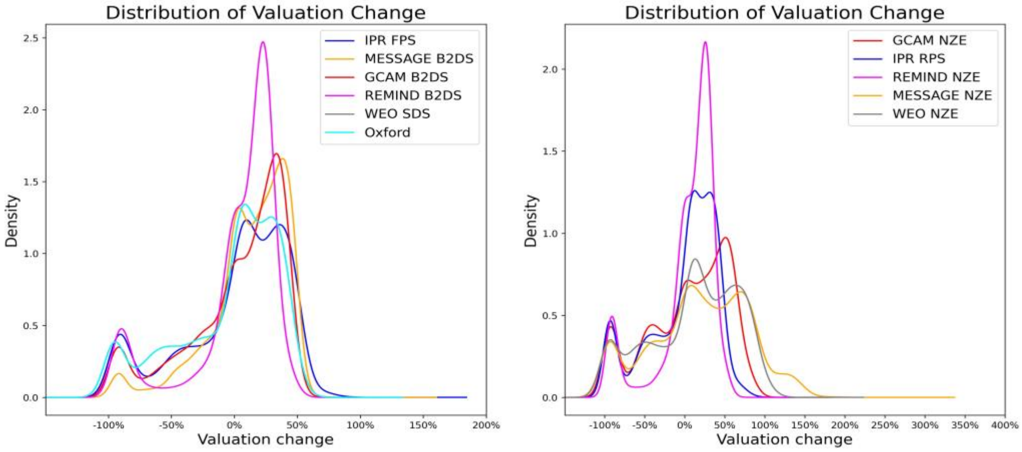

Fig. 2: *Distribution of NPV changes on power companies based on different scenario providers under the Below 2°C and Net Zero 2050 narrative pathways.*

However, in–depth statistical tests show significant differences even within the same narrative pathway, with some exceptions. Although Figure 2 shows a similar distribution of NPV change for power companies under both pathways, this is more formally analysed according to the Wilcoxon signed–rank test. Considering the shape of the distributions of NPV changes for companies under each IAM scenario in Figure 2, the distributions require a non–parametric test of the TRISK set of NPV change values, matched according to each power company. Taking the distribution of NPV changes for each of the IAMs under the same pathway of either reaching Net Zero by 2050, or achieving below 2°C, the Wilcoxon test determines the significance of the differences in NPV change between matched companies under each IAM. The differences between matched pairs on company NPV change is ranked according to the magnitude of difference across all company NPV change bilateral scenario pairs in table 2.

The analysis determines the extent to which the magnitude of difference in company NPV change under two different shock scenarios represents a significant difference in the median NPV change between the two scenarios. Across all power companies, the test illustrates whether a stress test for power companies under different shock scenarios represents a significant difference in aggregate NPV changes, or if the shock scenarios represent similar NPV impacts because they still align to the pathway of either reaching Net Zero 2050 or Below 2°C. Although it is expected that different scenario providers show some degree of difference in trajectory for the same temperature target or policy ambition, how these differences in trajectories are further propagated through subsequent financial risk measures, or the extent to which it would be expected, has not been established. While there is an expectation of some variability in company performance under different climate scenario pathways, whether the choice of one scenario over another should lead to significantly different results in company performance under the same pathway would represent a significant representation of risk for the company and the financial institution. Since trends on key economic transition variables are used as inputs by financial institutions to estimate future risk, understanding the magnitude of difference between shock scenarios under the same narrative pathway is an important consideration for the application of scenarios.

Table 2 shows the results of the Wilcoxon test for the absolute value difference measured in US dollars between bilateral pairs of climate scenarios NPV change under the TRISK framework, as well as whether or not differences in company impacts on shock scenarios are significant. From the table, the magnitude of difference in company valuation represents a high range in NPV changes under each of the shock scenarios, with the minimum absolute value difference in company performance representing over 4 million USD, and the greatest absolute value difference representing nearly 8 million USD. These findings indicate that for a company's assessment of climate transition risk, using the narrative pathway of meeting the Below 2°C target, the estimated in NPV change will range from a median gain or loss of USD 4 million to 8 million, depending on the selection of a scenario. However, these values only represent the difference in median value of change, but represent a much wider range for individual companies, given the significant differences in distributions of NPV change.

Additionally, as a measure of comparison to the Wilcoxon test, the paired t–test is also included. Since the shape of the distributions in Figure 2 indicate some evidence of normal central tendency, the paired t–test results are used as a normalised parametric comparison measure, according to the standard deviation of difference in the number of pairs. Both tests – the Wilcoxon and the t–test – are measures of the variations of differences in distributions in NPV change for companies according to the shock scenario, with larger values for either test indicating a larger average difference in distribution.[31] Next, the correlation in NPV change for the set of power companies between two scenarios is also included. The table shows results of the bilateral scenario comparison under the 'Below 2°C' narrative pathway. From the table, in nearly all cases, the TRISK results show that a company's NPV change under one scenario significantly differs from another, since nearly all t–test results show a significant difference in the distributions of NPV change when compared to any other under the same narrative pathway, based on the p–value. Differences in distribution are further confirmed under both Wilcoxon and standard t–test. **The only bilateral pair of scenarios that do not show a significant difference in company NPV under the 'Below 2°C' pathway are between the NGFS– GCAM scenario, and the IPR scenario**, indicating that the choice of either scenario for the stress test will lead to similar results in company performance.

Shock scenario A	Shock scenario B	Wilcoxon	t–test	Wil. p–value	Correlation
Oxford–fast	WEO SDS	7706611	34.432	1.84E-116	0.9228
NGFS MESSAGE	WEO SDS	7218272	19.16	1.90E-64	0.9565
NGFS MESSAGE	NGFS REMIND	6954966	12.575	1.03E-43	0.9185
IPR FPS	WEO SDS	6500447	5.773	9.51E-16	0.9307
NGFS GCAM	WEO SDS	6441419	7.065	1.15E-13	0.9625
NGFS GCAM	NGFS REMIND	6213285	0.046	1.97E-06	0.9267
NGFS REMIND	WEO SDS	6205468	7.287	5.35E-06	0.9399
IPR FPS	NGFS REMIND	6093202	0.999	1.51E-03	0.9243
IPR FPS	NGFS GCAM	5901780	1.006	4.21E-01	0.9405
IPR FPS	NGFS MESSAGE	5152400	12.35	4.97E-17	0.8945

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[31] The Wilcoxon test provides a difference in distributions measured in changes in USD. Since the t–test uses normalised values, they can broadly be categorised as anything above 20 as being high, between 10 and 20 as medium, and anything below 10 as being low.

NGFS GCAM	NGFS MESSAGE	4975324	11.933	1.24E-25	0.9620
NGFS MESSAGE	Oxford–fast	4519909	27.474	5.04E-58	0.9291
IPR FPS	Oxford–fast	4180702	31.754	1.15E-91	0.9318
NGFS REMIND	Oxford–fast	4170348	31.827	6.51E-92	0.8667
NGFS GCAM	Oxford–fast	4161006	31.596	4.45E-93	0.9421

Table 2: *Difference in distributions of TRISK results on NPV change based on shock scenario for Below 2°C pathway*

The Oxford scenario shows the highest magnitude of disagreement according to Wilcoxon, the greatest magnitude difference for t–test, and some of the lowest correlations compared to all other scenarios.[32] These findings are expected considering that the 'Oxford–fast' trajectories in the TRISK framework are not modelled in a general or partial climate– energy–economy equilibrium environment within an integrated assessment model like the other scenarios, but instead are based on time–series probabilistic forecasting methods of key energy technologies. The trajectories from the 'Oxford–fast' scenario are projected only on technology cost conditions, which are subsequently forecast onto deployment, rather than projecting both deployment and cost conditions onto policies in a larger integrated framework. Hence, modelling only the cost conditions, the relationship between technology costs and the rate of deployment is premised on the assumption of the experience curve or learning rate. In the 'Oxford–fast' scenario, the experience or learning rate is modelled on the basis of Wright's law.[33] The modelling of technologies based on Wright's law therefore imposes a set of assumptions on the shape of the learning curve, and subsequently the rate of deployment and technology costs. This modelling subsequently represents key differences in the climate risk variables, which suggests the wide magnitude of difference in NPV change when forecast variables are input into TRISK.

However, MESSAGEix also shows a high disagreement despite supposedly similar underlying assumptions. Given the difference in model framework of the Oxford scenario compared to others, the high and significant magnitude difference may be expected, especially considering the shape of the distribution of NPV changes from Figure 3. However, perhaps unexpectedly is that the magnitude of difference is second highest for the MESSAGEix scenarios, since it is similarly built within a general equilibrium environment of an integrated assessment model, and parameters are set in the same way as the REMIND or GCAM IAMs, since they all were provided by NGFS. As one of the three NGFS scenarios used in the TRISK

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[32] Gasparini, Baer, and Ives, "A re-evaluation of the financial risks of the Net Zero transition", op. cit.

[33] Wright's law has been widely applied in energy system models. The Oxford model extends Wright's law to provide an estimate of the probability distribution of future technology costs, thus providing an estimate of forecast uncertainty.

analysis, findings from Table 2 showing the MESSAGEix results with such a wide magnitude of difference relative to both other NGFS scenarios as well as other non–NGFS scenario providers is indicative of the significant impact that the choice of scenario can have on the assessment of climate risk for financial institutions.

Despite significant differences in distribution of company impacts from shock scenarios overall, bilateral scenario spearman correlations of NPV show that they are still highly correlated.[34] Although scenario pairs in Table 2 have been ranked according to the Wilcoxon test, across all scenario pairs, correlation coefficients are similar magnitudes, despite the difference in rankings according to overall distribution. This suggests that despite differences in the overall distribution company NPV change, individual pairwise company performance is still similar between two companies, based on the high correlations. This is further observed based on the linear relationship of NPV change between pairwise shock scenarios in Figure 3.

At company level, this disagreement could mean opposite impacts, depending on the scenario choice. This is further observed from the linear relationship of NPV change between pairwise shock scenarios in Figure 3. Figure 3 illustrates the bilateral relationship in a company's NPV change based on two different shock scenarios. The bilateral pair of scenarios are shown as a scatter plot of the relative change in company NPV from the TRISK model under the two scenarios, where the 45-degree line represents agreement in the company NPV change between the two scenarios. The Figure is separated into coloured quadrants to highlight the direction of the difference in NPV change for companies based on the scenario. The blue and red quadrants indicate agreement between scenarios where companies are shown to either improve in positive NPV change under both scenarios in the blue quadrant or

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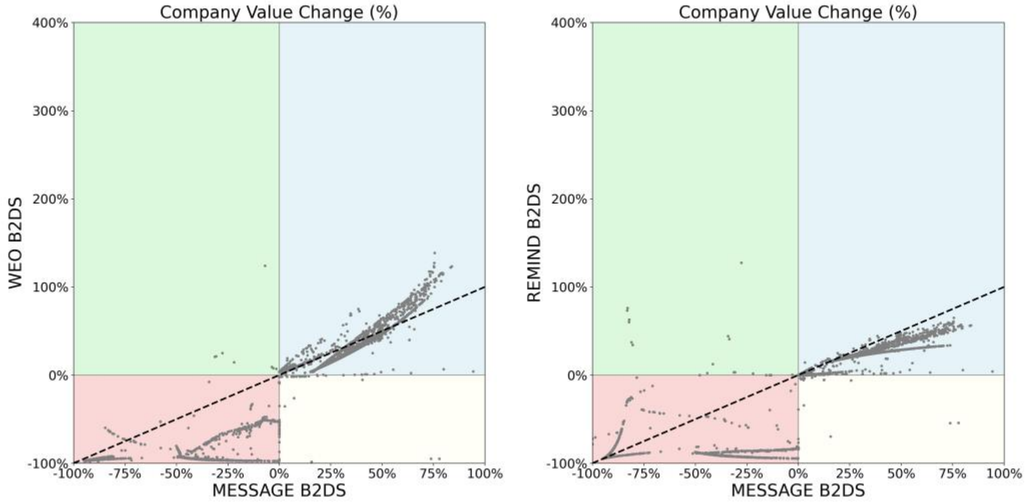
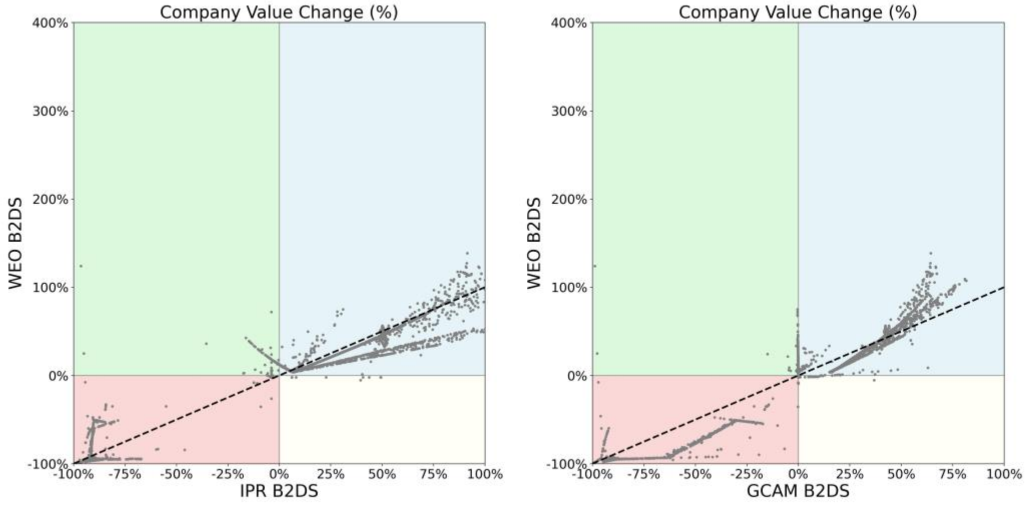
[34] Spearman rank correlation is used over Pearson because Pearson assumes a normal distribution, while Spearman does not. Additionally, given the wide range of companies and the spread of outliers, Spearman is more robust to those outliers.



(a) Message – WEO

(b) Message – Remind



(c) IPR – WEO

(d) GCAM – WEO

Fig. 3: *Distribution of company NPV change by bilateral scenario pairs for the Below 2°C pathway*

lose with negative NPV change under both scenarios in the red quadrant. Importantly, are the green and yellow quadrants where companies show disagreement in NPV change with one scenario indicating a positive NPV change, and the other showing a negative change. From the Figure, there are several companies that fall into the green and yellow quadrants indicating disagreement in company performance based on the shock scenario. This suggests a high risk to companies for assessing resilience to transition risk since they show opposite performance under stress. Differences in the positive or negative NPV change for companies, along with the overall magnitude of difference between scenarios demonstrate wide ranging implications and highly variable evaluation of risk when using climate scenarios.

3.1.2. Net Zero 2050 pathway

To compare results from different pathways, Table 3 shows the NPV change to companies by a set of scenarios provided under the Net Zero 2050 pathway, with differences in scenario pair distributions ranked by the magnitude Wilcoxon test. As previously illustrated from Table 1, there are less scenarios that are broadly aligned with the Net Zero 2050 pathway, so the comparative sample of scenarios is smaller.

Despite the smaller sample, comparisons in the distribution of NPV change under the Net Zero 2050 pathway show some interesting findings. First, all scenarios represent significantly different distributions of NPV change, indicating that the selection of specific climate scenario being applied to a stress test is a significant determinant in the assessment of company risk and impact, regardless of the broad agreement in the temperature target or policy pathway. Second, the range in the absolute value difference in magnitude of valuation is similar under Net Zero 2050 as below 2°C, with the largest difference near 7 million USD, and the smallest 4.5 million USD. Under both pathways, this represents significant differences in corporate NPV change. Third, the ranking of scenarios according to the magnitude difference in distribution according to the Wilcoxon test is consistent with Table 2 for the Below 2°C pathway, where the scenarios representing the largest differences are MESSAGEix and REMIND.[35]

Although MESSAGEix and REMIND feature prominently at the top of the table by average difference in distribution of NPV changes, there is wide disagreement amongst all NGFS–provided scenarios, with GCAM also showing a high degree of differences between each other according to the rankings based on the Wilcoxon test. This demonstrates high variability in corporate risk based not only on the pathway, but also within the same scenario provider, since the IAM parameters for all NGFS scenarios would be the same, as they are designed around the specific assumptions of the same narrative pathway of either Below 2°C or Net Zero 2050. That the three IAMs used by NGFS show such wide-ranging differences in the distribution of NPV change based on Net Zero 2050 indicates significant differences arise from the IAMs themselves, and less so based on the particular parameters used by the scenario provider. Therefore, selection of a climate scenario for the purposes of financial risk assessment needs to consider not only the narrative pathway of the economic transition, but also the scenario

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[35] The ‘Oxford–fast’ scenario does not feature in Table 3 because that is not the broad narrative pathway, and hence is not included in comparisons of other Net Zero 2050 scenarios.

provider, the particular set of assumptions and parameters taken by the provider, and the type of modelling used in developing trajectories.

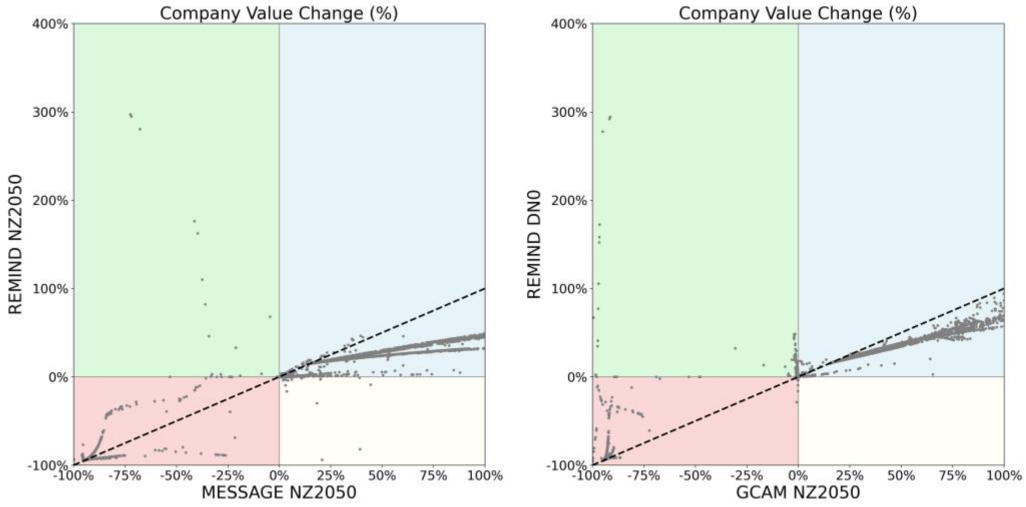
Shock scenario A	Shock scenario B	Wilcoxon	t–test	Wil. p–value	Correlation
NGFS MESSAGE	NGFS REMIND	6848205	12.427	3.77E-36	0.9194
NGFS GCAM	NGFS REMIND	6255199	1.025	1.36E-07	0.9264
NGFS MESSAGE	WEO	6244842	5.769	5.40E-07	0.8601
IPR RPS	NGFS REMIND	5602660	5.301	0.004	0.9282
NGFS GCAM	WEO	5399288	4.646	8.36E-08	0.9116
IPR RPS	NGFS GCAM	5162882	5.528	1.47E-16	0.9564
NGFS REMIND	WEO	5129039	6.159	4.94E-18	0.9365
NGFS GCAM	NGFS MESSAGE	4987461	10.433	5.91E-25	0.9313
IPR RPS	WEO	4881874	10.138	4.04E-32	0.8923
IPR RPS	NGFS MESSAGE	4612709	15.914	6.64E-51	0.9441

Table 3: *Difference in distributions of TRISK results on NPV change based on shock scenario for Net Zero 2050 pathway*

The results from Table 3 broadly demonstrate that the choice in scenario and pathway represent significant differences in evaluating climate transition risk across the set of global power companies. Differences in the distribution of NPV changes show that conducting a stress test based on a climate stress scenario can vary significantly based on the choice in scenario used, even when they are premised on the same pathway. However, while analysis of the distribution of NPV change represent a significant difference in magnitude of impact in aggregate, the positive or negative direction of the difference for individual companies from one scenario to another has not been observed from analysis of the overall distribution of NPV changes by company.

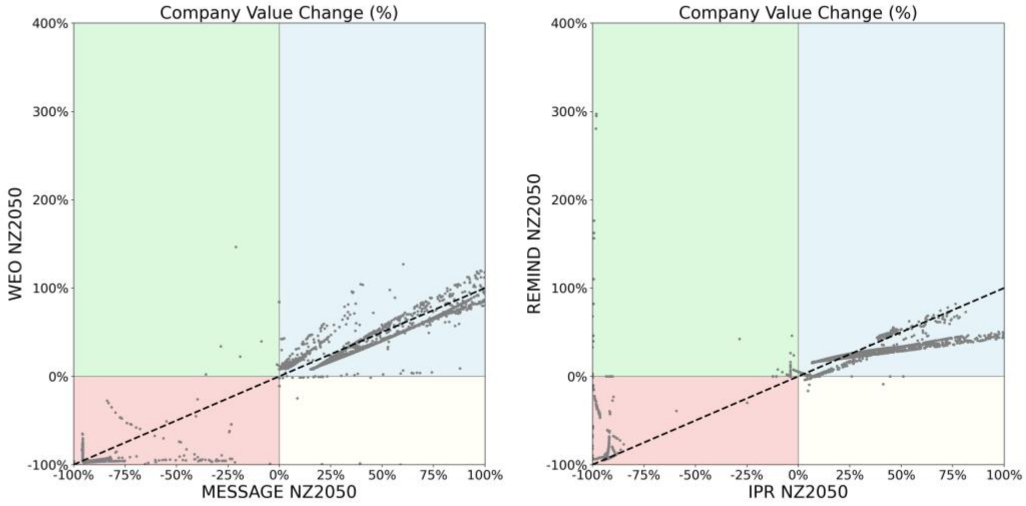
Despite results showing that the distribution of NPV change significantly differs based on each scenario, the bilateral pairwise extent of that difference measured according to correlation is not very high. Across all bilateral scenario pairs in Table 3, company NPV changes are highly correlated, indicating broad agreement in company performance under different scenarios. However, this does not account for outliers or disagreement in company performance between two scenarios, which could still be widely present despite high correlations. Figure 4 plots the relationship in company performance between two Net Zero 2050 scenarios according to the top four highest magnitude differences between scenarios distributions in Table 3. Evidence from Figure 4 shows that despite high correlations between scenarios, significant differences in the distribution of company NPV changes are observed in the relationship between scenarios. First, across all plots, there is a wide distribution in company performance, even when scenarios agree in positive or negative NPV change in the blue and red quadrants.

Second, similar to results from scenarios under the Below 2°C pathway, there are several cases where scenarios disagree in company performance in the green and yellow quadrants. Observations from Figure 4 illustrate that despite high overall correlations between scenario pairs, significant differences in the distribution of NPV change between two scenarios can lead to wide ranging variation in NPV change for individual companies. This can have significant implications for how companies and financial institutions assess risk based on the scenario and pathway they use.



(a) Message – Remind

(b) GCAM – Remind



(c) Message – WEO

(d) IPR – Remind

Fig. 4: *Distribution of company NPV change by bilateral scenario pairs for Net Zero 2050 pathway*

Results in sections 4.1 and 4.1.2 have looked at the overall distribution of NPV changes for a global set of power companies, showing significant differences in the distribution of impacts on companies based on the scenario that is input to the TRISK model, even when scenarios are mapped to the same narrative pathway. While most scenarios show broad agreement in the impact of shock scenarios on companies in terms of positive or negative change in NPV, the range in NPV change between two scenarios can represent significantly different values, and hence difficulty in assessing risk. This can be particularly problematic for companies when one scenario shows an improvement in NPV, and another scenario shows that company losing value. This occurs for a significant share of global power companies in the dataset across all scenarios under either pathway, and is therefore not a particularly outlying case of individual companies, but rather systemic to the choice of scenario.

3.2. Variability in NPV changes: Assessment of company performance from a technology focused analysis

3.2.1. Below 2°C pathway

While analysis has looked at the overall distribution of NPV effects according to each scenario across the full set of global power companies, how these differences are translated or represented for individual power companies has significant implications for financial institutions in the assessment of transition risk. Previous analysis has looked at differences in NPV effects of climate shock scenarios according to the overall distribution of impacts based on each scenario and pathway. In this section, analysis looks at how these differences in distribution of NPV impacts the variability and uncertainty in the assessment of transition risk according to each company.

From the list of scenarios under each pathway in Table 1, for each scenario in each pathway, the impact of the shock scenario is generated for each company's NPV. The results of the NPV change for each scenario and company are aggregated into two different measures to observe the dispersion and variability of a scenario's assessment of a company's transition risk. First, a simple measure of dispersion of NPV effects per company is taken as the range of the percentage change in NPV between the baseline scenario and the shock scenario for each company, or the difference between the largest percentage change in NPV minus the smallest percentage change in NPV across all scenarios within a specified pathway. However, while the range in percentage change values may be a good indicator of dispersion, it does not account for the presence of outliers in potentially skewing this dispersion, which could be the result of one outlying scenario's impact on the assessment of a company's performance, as suggested from the magnitude of difference in distributions of NPV changes observed in sections 4.1 and 4.1.2. Second, to account for the potential role of outlier scenarios on company performance, the variability of results within the given range of percentage change impacts is observed according to the coefficient of variation. The coefficient of variation measures the standard deviation in NPV changes for each company relative to the mean change. As a standardised measure, it allows for comparison of the variability of NPV changes between companies irrespective of the size or individual profile of one company over another. It is calculated as the ratio of the standard deviation to the mean of NPV for each company.

Disagreement in company–level performance is technology dependent. Previous analysis from Figure 4 shows the relationship of NPV results across all power companies in the dataset, with large clusters of companies showing agreement between the MESSAGEix and the REMIND scenarios in the first and third quadrants, representing positive increase and negative loss in NPV respectively. However, agreement in company performance under the two shock scenarios in the first and third quadrants is not random across companies but related to technology type. This is also true for companies in the second and fourth quadrants representing disagreement in company performance between the two scenarios, where disagreement in how a company performs is also related to uncertainty in a shock scenario depending on the type of technology. Therefore, to more systematically observed the dispersion of NPV changes across scenarios, companies are separated according to technology.[36] The comparative analysis of the dispersion and variability of NPV changes for companies is evaluated across scenarios and according to technology type under the 'Below 2°C' pathway in Figure 5. Companies are disaggregated according to six different technologies: three types of thermal energy for oil, coal, and gas, one for renewables including solar and wind, and separately for nuclear and hydroelectric. From the dispersion and variability of company performance by technology, there are three trends that can be observed.

First, transition renewables (solar, wind) show gains in NPV, whereas fossil fuels (oil, gas, coal) show losses. This is that similar to what has been observed in the previous Figure 4, there is clustering of agreement across scenarios based on the technology type. For each technology, nearly all companies show a positive increase in NPV.

Second, scenarios with wider dispersion in company NPV change also show higher variation. Across plots in Figure 5, it is generally observed that the higher the range in NPV change is associated with a greater absolute value in the coefficient of variation. These trends

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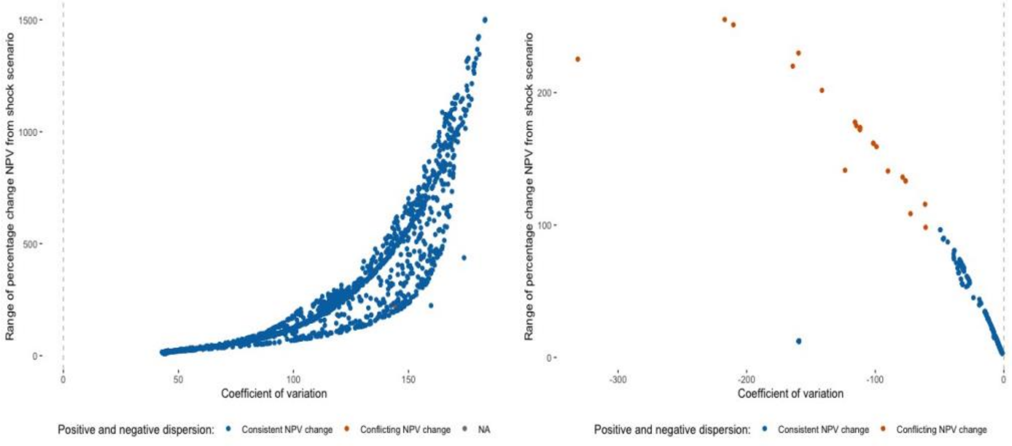
[36] Future trends on energy production by technology are extracted from each of the shock scenarios. For each technology, scenario, and pathway, there are different trajectories which are applied to each company. Further discussion on technology– specific trends for each scenario and pathway can be found in section 8.1.

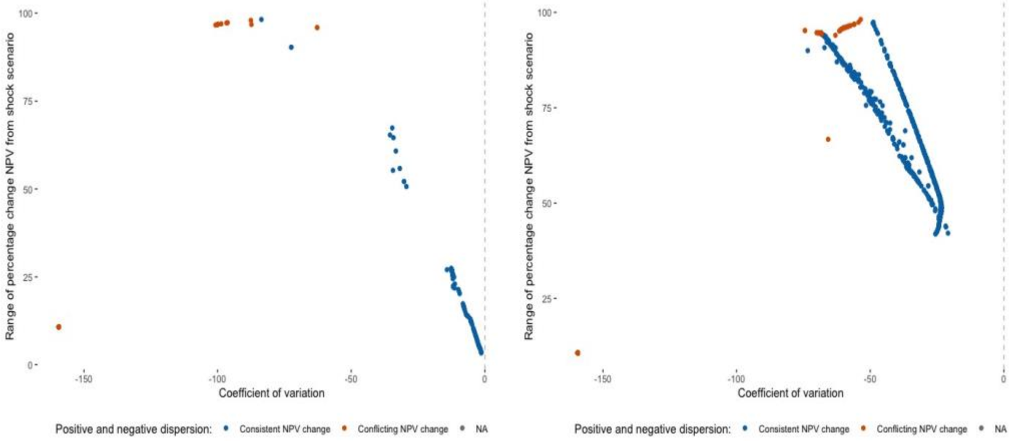
are most clearly observed for oil, gas, and coal, which exhibit clear trends in the relationship between the range of percentage change and the coefficient of variation.

The trend is similar for renewables, but all renewable companies show an improvement in NPV across scenarios in Plot 5a. Additionally, while there are clear trends and broad agreement in company performance across scenarios for oil, gas, and coal, this is not the case for hydro and nuclear in Plots 5e and 5f which do not exhibit any clear trend or relationship between range in percentage changes and variation in NPV. This suggests that there is a general consensus across ‘Below 2°C’ scenarios in the modelling of key technologies such as oil, coal, gas, and renewables, while modelling for the use of hydro and nuclear is less well established or agreed upon in the scenarios.



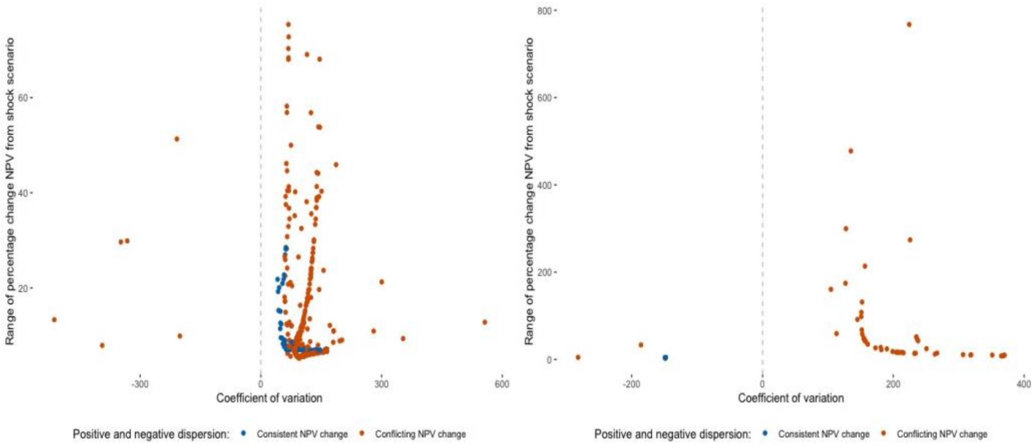
(a) Renewables

(b) Coal



(c) Oil

(d) Gas



(e) Hydro

(f) Nuclear

Fig. 5: *Coefficient of variation in NPV by range of percentage change in NPV across 'Below 2C' scenarios. The x–axis shows the coefficient of variation, which can be positive or negative based on the average NPV performance of the company across all scenarios. The y–axis shows the total range of percentage change in NPV as the largest minus the smallest percentage NPV change for a company, with the higher value indicating the wider the range in company performance across the 'Below 2°C' scenarios. Blue coloured data points indicate consistency for the company as either showing positive NPV change across all scenarios, or all negative. Orange coloured data points indicate inconsistency, where some scenarios show positive NPV changes for the company, while others show negative.*

Third, plots in Figure 5 show that company variability and dispersion are consistent across scenarios, being either in agreement of positive or negative impacts under the shock scenario. Plots in Figure 5 identify whether a company's NPV performance is consistent or inconsistent in positive or negative change across scenarios. Blue coloured data points indicate consistency for the company as either showing positive NPV change across all scenarios, or all negative. Orange coloured data points indicate inconsistency, where some scenarios show positive NPV changes for the company, while others show negative. For the three fossil fuel types and for renewables, most of the data points are coloured blue, indicating that all 'Below 2°C' scenarios show consistent negative or positive performance.

However, the opposite is the case for hydro and nuclear, with nearly all data points showing orange, representing disagreement in positive or negative performance between the six scenarios in the 'Below 2°C' pathway. Disagreement in NPV change under hydro and nuclear also reflects the uncertainty with which different scenarios treat the uptake of these technologies in reaching the 'Below 2°C' pathway, which is also apparent in the lack of a relationship between the range in company performance and variation in NPV. For these technologies, there can be large disagreement between scenarios based on phase–out or build–up. This in turn affects whether the profit reduction mechanism embedded in the TRISK framework is applied to the company or not, which is premised on the loss of profits for companies that have not strategically planned to build out the relevant technologies.[37] Hence, while broad trends and can be observed from assessing the impact of shock scenarios on company performance according to technology type, given the wide range in percentage change for companies, as well as the high levels of variation in NPV, this represents significant differences in scenario assumptions for each technology. Findings show that differences in distribution of NPV change by scenarios from sections 4.1 and 4.1.2 represent significant uncertainty for company performance.

There is a high degree of variability in individual company performance based on the choice of scenario being applied. This is the case for a subset of oil, coal, and gas companies, as well as nearly all hydro and nuclear companies. The range in company performance and variation has been so high for some technologies that it yields almost no insights of company performance with a range in percentage change NPV being essentially 0 to 100 percent, and in some cases showing both positive and negative NPV impacts. Hence, given the differences in the distribution of NPV changes according to each scenario, the choice of climate scenario can lead to significantly different assessments of climate transition risk for different types of companies.

3.2.2. Net Zero 2050 pathway

In order to compare results in company performance under the 'Below 2°C' pathway, measures of variation and percentage change in NPV have similarly been compiled for the same set of companies, but stress tested under the more stringent objective of reaching Net Zero by 2050 pathway.[38] The trends in variation and range of percentage change of NPV are shown in Figure 6. Broadly, trends show similar findings as described from section 4.2 under the 'Below 2°C' pathway. However, there are some key differences under the more stringent 'Net Zero 2050' pathway that are worth highlighting.[39]

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[37] The amount of deducted profits depends on a ratio calculated within TRISK, which compares a company's projected forward looking production plans over the next five years with the required production for the same period. The required production is defined as a climate–aligned production trajectory, which in turn is given by the selected target scenario. The goal of this mechanism dampens the profits for companies that have not strategically planned to build out the relevant technology. Although this mechanism is still primarily influenced by the choice of scenario, it can lead to variations in outputs even when scenarios show only small differences, particularly for technologies such as hydro and nuclear. Thus, without this TRISK mechanism, the outputs calculated for nuclear, and hydro could be partly different and its critical to be aware of the model mechanisms that can affect the results alongside to the scenario uncertainty.

[38] There are a different number of scenarios included under the 'Net Zero 2050 scenarios' than for those categorised as 'below 2C'. This could lead to higher variation and range in distribution due to the inclusion or exclusion of extra scenarios. Based on the categorisation of scenarios in Table 1, the Oxford scenario is only features in the 'below 2C' scenario and not for 'Net Zero 2050'. As a check for robustness of findings, the same analysis has been done for the 'below 2C' pathway but excluding the Oxford scenario so that the same number of scenarios are included under each pathway. Results are in appendix section 8.3. Findings are the same for 'below 2C' with or without the Oxford scenario.

[39] Evaluation of the differences in stringency between 'below 2C' scenarios and 'Net Zero 2050' scenarios is further discussed in section 8.2.

First, for renewables (solar, wind), and some fossils (oil, gas), the variability reduces with a faster transition. For renewables, oil, and gas companies in Plots 6a, 6c, and 6d, the level of absolute value variation is lower, with the maximum absolute value coefficient of variation under all three technology types being less than 80. In contrast, under the 'Below 2°C' pathway, the maximum absolute value variation is typically greater than 150. This finding demonstrates that for these three technologies under the more stringent 'Net Zero 2050' pathway, there is greater alignment of scenarios in the assessment of company performance compared to the less stringent 'Below 2°C' pathway. A similar study analysing climate scenario trajectories has also found a narrowing of policy choices across scenario providers with more stringent targets.[40] Therefore, for gas, oil, and renewables, there is consensus across scenarios that a faster and more orderly transition would lead to a more aligned and consistent determination of market risk. This is particularly true in the case of gas and renewables. Under the 'Below 2°C' pathway, scenarios show wide disagreement in performance and risk of companies, represented by the larger number of disagreeing positive and negative performing companies, and by the much higher levels of variation at nearly 100 in absolute value variation. By contrast, under the 'Net Zero 2050' pathway, the same companies do not show any disagreement in performance, with all showing consistent loss in NPV, with the level of variation generally less than 20 in absolute value. Additionally, renewables show much lower variation of their positive NPV change at less than 60 under 'Net Zero 2050' compared to more than 150 under 'Below 2°C' scenarios. The range in percentage increase is also less variable for renewables at less than 200 under 'Net Zero 2050' and greater than 1000 under 'Below 2°C'.

Second, for coal, nuclear, and hydro the variability does not reduce with a faster transition, where the alignment of scenarios for gas, oil, and renewables is contrasted with the performance of coal, hydro, and nuclear in Plots 6b, 6e, and 6f. For these three technologies, there are similarly high levels of variation and uncertainty in the range of performance between the 'Net Zero 2050' and the 'Below 2°C' pathways. The wide-ranging variation in NPV greater than 200 in absolute value is driven by the disagreement in positive or negative performance between scenarios of the same pathway, indicating disagreement and uncertainty between scenarios on the uptake of hydro and nuclear as alternative technologies under either pathway.

For coal, the set of scenarios shows wide uncertainty in the rate and progress of coal phase out. Hence, in contrast to evidence from gas, oil, and renewable technology companies, which show alignment between scenarios and reduced market risk under a more stringent and

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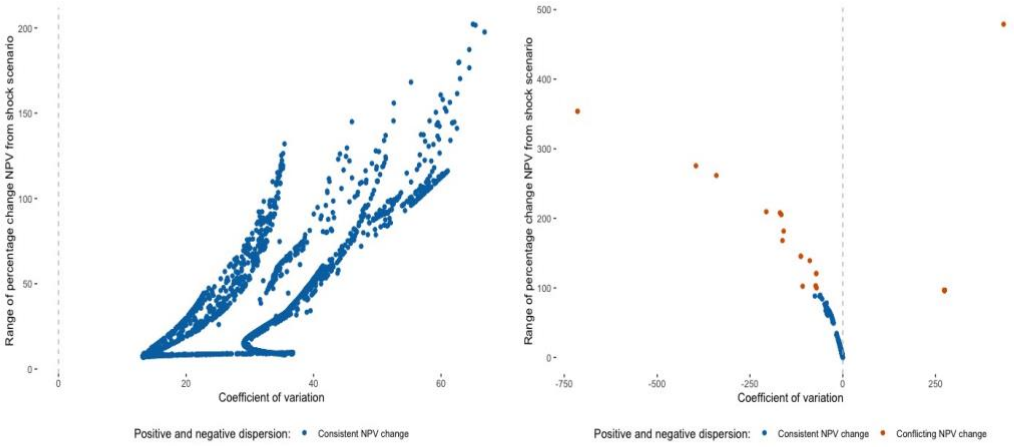
[40] Keywan Riahi et al. "Locked into Copenhagen pledges: Implications of short-term emission targets for the cost and feasibility of long-term climate goals". In: *Technological Forecasting and Social Change* 90 (2015), pp. 8–23.

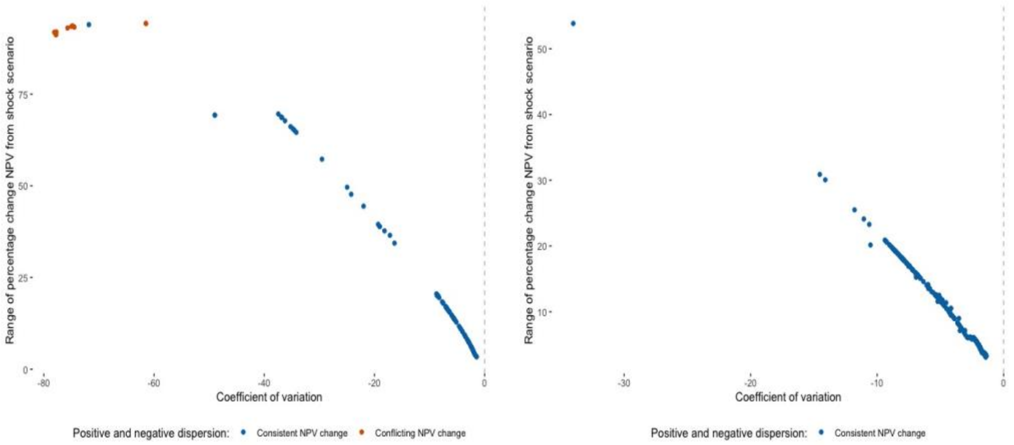
orderly transition, the wide ranging variation and inconsistent company performance for coal, hydro, and nuclear across scenarios and pathways suggest a higher degree of uncertainty and market risk for either uptake or phase out, irrespective of the stringency of the pathway.

The comparative results under different climate scenarios and pathways yields important findings for the assessment of transition risk. For financial institutions seeking to understand the market risk of their portfolio of power companies, the unknown and potentially high stringency policies that may be required to attain specific climate goals are assumed to introduce greater market risk and higher volatility with increasing stringency. However, stress testing a global set of power companies using the TRISK framework has shown the opposite to be true. Comparing a broad set of scenarios and providers under two different pathways has shown that there is greater uncertainty in the assessment of company performance under less stringent pathways since scenarios model a wider range of trajectories and a larger carbon budget. However, under a more specific target or narrow policy ambition, there are fewer trajectories for meeting a smaller carbon budget, and hence there is less uncertainty and lower market risk.



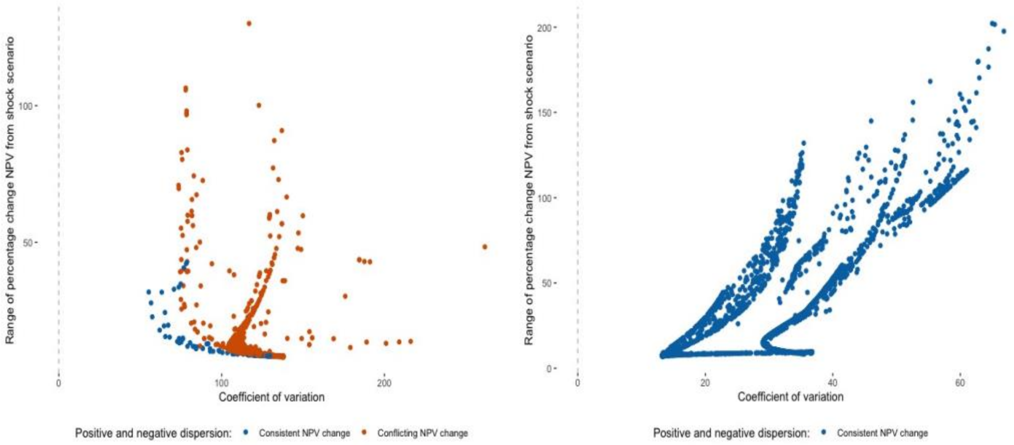
(a) Renewables

(b) Coal



(c) Oil

(d) Gas



(e) Hydro (f) Nuclear

Fig. 6: *Coefficient of variation in NPV by range of percentage change in NPV across 'Net Zero 2050' scenarios. The x–axis shows the coefficient of variation, which can be positive or negative based on the average NPV performance of the company across all scenarios. The y–axis shows the total range of percentage change in NPV as the largest minus the smallest percentage NPV change for a company, with the higher value indicating the wider the range in company performance across the 'Net Zero 2050' scenarios. Blue coloured data points indicate consistency for the company as either showing positive NPV change across all scenarios, or all negative. Orange coloured data points indicate inconsistency, where some scenarios show positive NPV changes for the company, while others show negative.*

The additional uncertainty related with climate stress testing models coupled with low climate ambition could potentially affect the risk assessment of lending institutions and thereby impact the viability and operations of these institutions in terms of their investments and returns. This could subsequently lead to a sharp rise in risk premium and cause instability to the financial system. Therefore, a focus on more stringent climate scenarios could help to strengthen the financial system by reducing market risk, whereas further delays and less ambitious targets can lead to higher systemic risks.

While comparative analysis of company performance under a 'Below 2°C' pathway and a 'Net Zero 2050' pathway leads to clear differences in market risk based on policy stringency, this has only been found for some technologies. Regardless of the pathway, there is still wide-ranging uncertainty in the performance of coal, hydro, and nuclear companies. Hence, while findings demonstrate that alignment with more ambitious and stringent climate goals can lead to reduced uncertainty and volatility in the assessment of market risk for gas, oil, and renewable companies, the choice in both the pathway and the scenario is still the main driver of uncertainty. Consequently, the wide ranging and inconsistent assessment of company performance between scenarios and pathways means that the greatest determinant of transition risk assessment is the choice in the scenario and pathway itself.

4. Results: Impact on probability of default

4.1. Key findings

In the previous section, we showed that market risk for individual firms based on Net Present Value change can significantly vary with the choice of climate IAM models even when these follow the same narrative pathways. However, variability in the choice of model does not only impact firm value change but can also be propagated to financial institutions' loan books. Within the TRISK framework, the financial institution credit risk impact is estimated using Merton–type structural model of credit risk, which explicitly models the firm Probability of

Default (PD) as the likelihood of a company asset value falling below a default threshold (value of liabilities) within a certain time horizon.

NPV change is used to determines the transition–risk related impact on company asset value and it is therefore the most significant driver of risk in the credit risk model. The PD is estimated both for under baseline and shock scenario assumptions and the resulting risk parameter of interest is the absolute difference between ‘baseline PD’ and ‘shock PD’, that is a ‘PD change’, in a similar fashion as the NPV change is created. The relationship between NPV change and PD change is therefore direct which would suggest that the company–level scenario model outcome variation should be very similar both for NPV change or PD change. It is important to highlight that TRISK outputs PD change in absolute terms, while the NPV change is represented as a percentage change.

Selected scenario pairs demonstrate higher agreement on PD change compared to NPV change. Figure 7 illustrates selected bilateral relationship of TRISK results for PD change between pairs of scenarios for the Net Zero 2050 pathway. The x–axis represents the change in PD (in percentage points of PD difference) for GCAM or MESSAGEix while the y–axis represents the change in PD (in percentage points) for REMIND, WEO, and IPR FPS scenarios.[41] The immediate finding is that contrary to NPV change impacts, the selected scenario pairs agree relatively more on PD change.

When assessing the distance of PD change impacts from this 45–degree line, the scenario pair that shows the most dispersed distribution, and therefore a significant disagreement in PD change, is GCAM and WEO. However, the distribution of PD change for all selected scenario pairs while clustered around 0 on the x-axis is shown to have a wide range of impacts on along the y–axis. This means that for a significant number of companies, very low or 0 PD change impact may correspond to a wide range of impacts in another scenario. The variability of credit risk scenario impacts hence appears to be less characterised by conflicting signs of scenario impacts but rather about a conflicting severity of PD change – low impact in one scenario corresponds to a large impact in another. The green and yellow quadrants where companies show disagreement in PD change includes a small number of companies that fall into these quadrants, which confirms the suggestion that the main risk in assessing resilience to climate transition when expressed in PD terms is in the conflicting severity of impacts.

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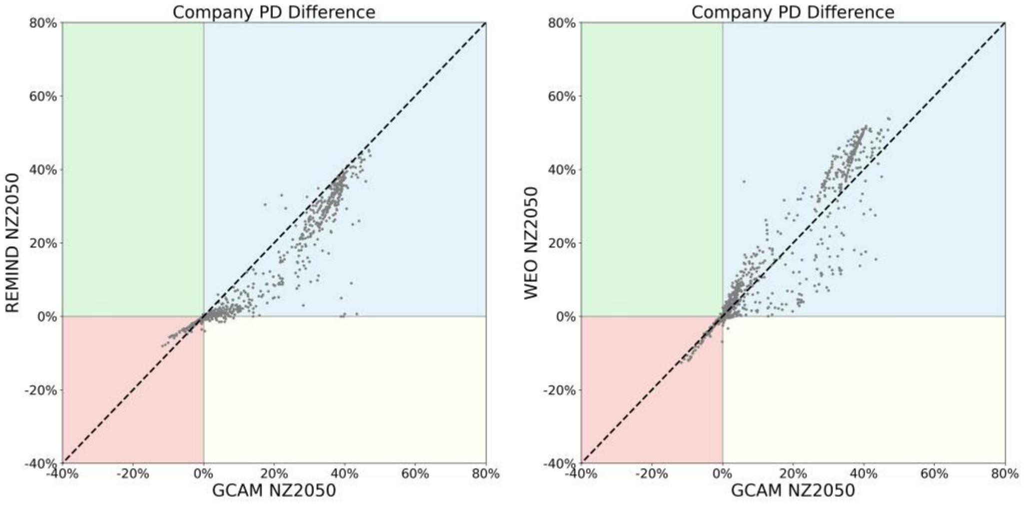
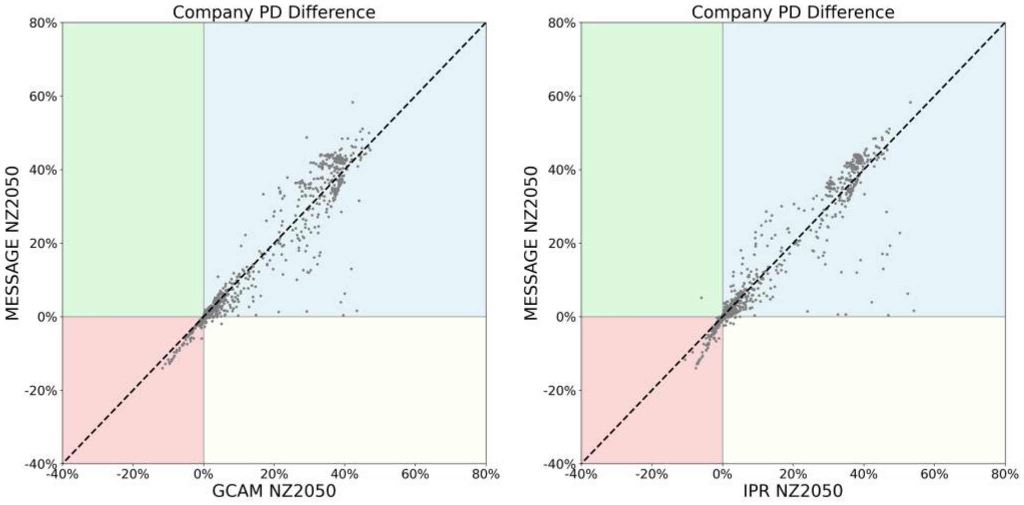
[41] The blue and red quadrants indicate agreement between scenarios where companies are shown to either improve in positive PD change under both scenarios in the blue quadrant or lose with negative PD change under both scenarios in the red quadrant. Again, the bilateral pairs of scenarios are shown as a scatter Plot of the relative change in company PD change from the TRISK model under the two scenarios, where the 45–degree line represents agreement in the company PD change between the two scenarios.



(a) GCAM – Remind

(b) GCAM – WEO



(c) GCAM – Message

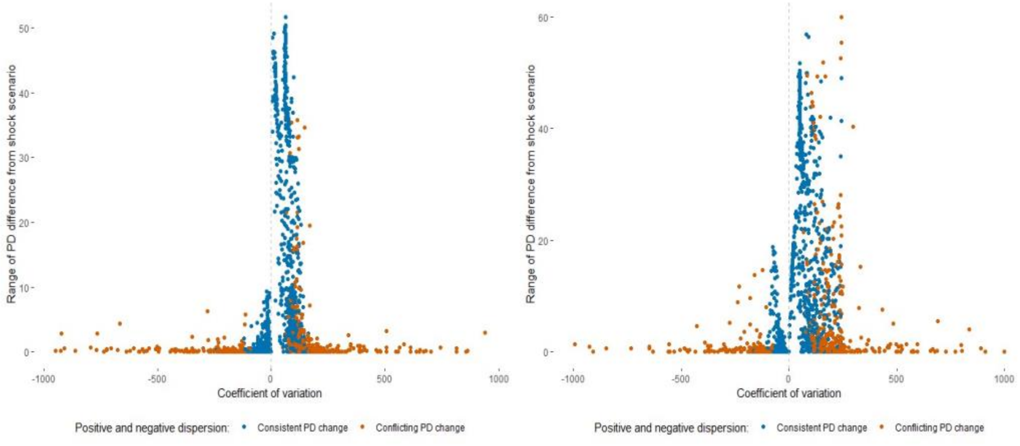
(d) IPR – Message

Fig. 7: *Distribution of company change in probability of default by scenario pairs for Net Zero 2050 pathway*

Figure 8 shows a comparative analysis of the dispersion and variability of NPV changes for companies is evaluated across the NZ0 and B2Ds scenario for the Power sector. As there are only Power sector companies in our sample and TRISK outputs PDs on company–sector level there is only one Figure for each policy ambition. Figure 8 identifies whether a company's PD change is consistent or inconsistent in positive or negative change across the scenarios of the same policy ambition. Blue coloured data points indicate consistency for the company as either showing positive PD change across all scenarios, or all negative. Orange coloured data points indicate inconsistency, where some scenarios show positive PD changes for the company, while others show negative.

From the Figure, the majority of the data points show consistently negative or positive impact (blue data points for agreement across scenarios) both for the ‘Below 2°C’ and ‘Net Zero 2050’ scenarios. This finding holds along the full range of PD change. Additionally, the dispersion of climate scenario model PD change impacts appears to show a narrower distribution for scenarios under the ‘Net Zero 2050’ climate ambition compared to the ‘Below 2C’ pathway. This finding is consistent with what has been observed under NPV effects that show a narrower range in variation under the more stringent ‘Net Zero 2050’ pathway compared to the less stringent ‘Below 2°C’.

Most notably, both Figures 8a and 8b show a low coefficient of variation for the majority scenario impacts and this again holds true along the full range of PD change. This seems to confirm the suggestion that in PD change terms, the scenarios agree relatively more. It is worth noting, however, that contrary to the technology–based NPV model, the PD model operates only on company–sector where technology–level shocks are aggregated (more discussion on this point in the next section). Further, if there are conflicting signs and a variation between scenario impacts then it appears mainly in the low ranges of PD difference. This seems, in some degree, to refute the concern associated with the conflicting severity of scenario impacts. As the majority of outliers and conflicting signs appears in the low range of PD differences, the risk of miscalculating climate transition credit risk for a given company due to a choice of a particular scenario are not material overall. But note that there are nevertheless several cases of conflicting signs, especially in for a positive coefficient of variation meaning that for some companies, there may be a highly positive PD change impact in one scenario corresponding to a small negative PD change impact in another.



(a) Net Zero 2050, Power sector

(b) Below 2°C, Power sector

Fig. 8: *Coefficient of variation in PD by range of difference in PD value across 'Net Zero 2050' and 'Below 2°C' scenarios*

4.2. Additional considerations: Role of input data and model assumptions

This paper has so far outlined how the credit risk impacts differ for climate scenarios with the same policy ambition using TRISK as a consistent climate stress testing model framework. However, there are several input data and model assumptions inherent to the TRISK methodology which may, on their own, contribute the variability of financial risk impacts and which hence need to be highlighted.

First, whereas the Net Present Value change is estimated for each profit–generating and technology–specific business unit of a company, the PD change model operates only on whole– company level and only sector level. This is because the key input into the discounted cashflow model are technology level profit pathways and therefore is used to estimate NPV change for each profit–generating business unit of a company. For example, for a firm operating in the Power sector and active in Renewables, Nuclear, and Coal power generation technologies, the NPV is estimated separately each for those Renewables, Nuclear and Coal technology–specific business units. On the other hand, the Merton structural credit risk model estimates the transition risk impact on the probability of default of whole companies. This is achieved by aggregating the NPV impact across all business units (weighted for their relative size) and then use the NPV change as data input on the impact on company valuation in the Merton model to derive a single, company–level PD change. This means that some of the technology–specific shocks are aggregated to sector level in the PD model which may relatively reduce the technology–specific scenario variability as shown in the PD change analysis.

Second, contrary to NPV change estimation, the credit risk PD change model relies on an additional data input which is company financial risk profile on top of the production and scenario data inputs used in the NPV model. Although the firm–level financial data is applied consistently across both B2DS and NZ0 scenario model runs for all technologies, it may alter the distribution of individual firm PDs impacts for each scenario run as PD change in not only function of the selected climate baseline and shock scenario but also the individual firm’s financial risk position as it enters the model. Further, the firm–level financial data is dependent on either the data self–reported by companies for which there may be some concerns on accuracy or assumptions on companies that need to be accounted for in the absence of corporate-reported data. Without accurate or complete corporate reported data, this can lead to some variation in credit risk impacts due to uncertainty from individual firm data.

Third, there are likely other transmission channels which would be expected to impact the scenario variability, but which are currently not represented in the TRISK model framework.[42] In particular, the credit risk model in current state assumes a scenario–independent asset volatility. The Merton model uses total NPV value change of a firm as the only driver of risk. However, it is reasonable to assume that company value volatility may spike in response to a climate transition shock, particularly in the case of a negative production shock leading to reduced profits and dividends. This calls for a stochastic representation of the scenario–dependent company volatility which would act as additional risk channel.[43] However, such a representation is not currently incorporated in the model and is left for further development.

Fourth, it is worth bringing to attention several challenges related to the choice of the credit risk model. The Merton model is useful in the TRISK framework for mainstream applicability and its coherency with the output produce by the NPV change model. But there are important questions that need to be raised about the suitability of the Merton credit risk framework for climate financial risk analysis. For instance, the Merton framework assumes a normal distribution of the shock and company value as well as perfect competition and efficient financial markets without frictions. However, a standard normal distribution contrasts with the expected realised distribution of climate risk impacts which is likely to have sharper peak and fatter tails. In the context of climate risk, tail–risk loss events related to extreme but plausible

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[42] Lucia Alessi and Stefano Battiston. “Two sides of the same coin: Green taxonomy alignment versus transition risk in financial portfolios”. In: *International Review of Financial Analysis* 84.1 (2022), pp. 1–19.

[43] Alan Roncoroni, Stefano Battiston, and Luis O.L. Escobar-Farfan. “Climate risk and financial stability in the networks of banks and investment funds”. In: *Journal of Financial Stability* 54.100870 (2021), pp. 1–27.

climate transition are not well represented by the Merton model. Further, the normal distribution of company value is assumed to be scenario independent which again, in the context of varying scenario impacts needs to be reconsidered.

5. Conclusion

This paper evaluates the financial market risk calculated across five different climate scenario models using a consistent bottom–up climate stress test to show that there is significant variation in the market valuation of a set of global power companies as measure by Net Present Value change. Additionally, results show that when company NPV effects are aggregated to financial impacts, the variability in company NPV changes has a significant impact on the assessment of credit risk as measured by probability of default change, although variability is lower.

When using the TRISK model to produce NPV changes across a global set of 3,419 power companies, the resulting distribution of NPV changes shows significant differences in company performance, premised on the shock scenario applied to the stress test. Although there is broad alignment in NPV change according to Spearman correlation for bilateral scenario pairs, a more formal comparison of the shape of the distribution using the Wilcoxon signed–rank test shows that, in nearly all cases, a company's NPV under one scenario significantly differs from the performance of that same company under another scenario, even when the scenarios are based on the same narrative of the future temperature target or policy ambition.

To test whether variability in climate stress test outcomes is related to differences in climate scenario models based on the type of energy technology, this paper looks at the dispersion of company technology impacts across all five scenario models according to each energy technology type, based on either a more stringent 'Net Zero 2050' policy ambition, or a less stringent 'Below 2°C' narrative. We identify several consistent broad trends across all scenario models for both levels of climate policy ambition such as increasing NPV change for renewables, or decreasing NPV for oil, coal, and gas companies, more importantly though, there is a clear evidence of a high degree of uncertainty and variability in individual company performance based on the choice of scenario being applied. Findings show that the uncertainty is higher for the scenarios of the 'Below 2°C' climate policy ambition than the 'Net Zero 2050' ambition. Overall, there are six main implications to our findings:

1. **The choice of scenario model can lead to significantly different assessments of climate transition risk for companies.** This is represented both in the significant differences in the distribution of NPV changes based on the input shock scenario used, as

well as how it creates disagreements in company performance for different technologies, with some technology level impacts indicating opposite valuations, highlighting that many companies are losing value in one scenario, but gaining value in another scenario.

2. **There may be a link between climate policy ambition and the variability of model outcomes based on types of energy technologies,** with more ambitious climate policy scenarios ('Net Zero 2050') possessing generally less variation in outcomes than the less ambitious ones ('below 2°C) both in the NPV change and the PD change outcomes.[44]
3. **Variability and disagreement in company performance is highly dependent on the type of energy technology.** Findings have shown that shock scenarios show broad agreement between in the change in company performance for renewables, oil, gas, and coal, however widespread disagreement in the performance of hydro and nuclear. For renewable companies between pathways and across scenarios, they show an improvement in performance with positive NPV changes. For most coal, oil, and gas companies, most scenarios show agreement in NPV losses. In contrast, scenarios show widespread disagreement with a high degree of both positive and negative NPV changes for hydro and nuclear companies, and wide-ranging variation and distribution of NPV changes.
4. **Some climate scenario models demonstrate significant outlying disagreement compared to other scenarios.** Analysis of both overall distributions and company performance based on technology type have identified climate models such as the Oxford model and MESSAGEix that have a wide difference in the distribution of NPV changes relative to other scenario models used in the stress test. The magnitude of these differences in company performance could be due to several factors underlying the climate model itself, such as differences in modelling assumptions.
5. **The high variability between scenarios for the same climate policy ambition highlights the black–box nature of models.** This is particularly true due to the assumptions used to derive those technology level trends from mainstream climate scenario providers.[45] Although it is expected that different scenario providers show some degree of difference in trajectory for the same temperature target or policy ambition, how these differences in trajectories are further propagated through subsequent financial risk analysis, or the extent to which it would be expected, has not been established. We propose that a follow up analysis of the technology level output trends and input parameter assumptions is performed using an input-output model.
6. **Analysis of the effect of scenario variability in the probability of default outcomes shows relatively smaller variations than those indicated by NPV change.** Aggregating

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[44] A caveat to this finding is the fact that we are only comparing two climate policy ambitions in this paper. To further support this claim, a follow–up analysis would need to consider climate scenarios from a broader range of climate policy ambitions.

[45] Tang and Pianosi, *An input-output sensitivity analysis of climate-economy integrated assessment models*, op. cit.

company performance under NPV to company–sector across energy technologies broadly shows lower levels of variation in PDs at all levels of dispersion, with less variation in PD under the more stringent ‘Net Zero 2050’ pathway compared to the ‘Below 2°C pathway. However, there is still widespread disagreement in PD outcomes with several companies showing high variation in PD across scenarios at relatively low differences in distribution of PD change, most likely due to the large number of companies that show disagreement in positive or negative PD performance.

While this paper has identified several findings affecting the assessment of climate risk based on the input of different climate scenarios and models, this has been applied to a consistent climate stress test. There are several frameworks for climate stress testing that have been developed, including different methods for inferring climate scenario shocks on companies and financial institutions from a variety of scenario models. For ease and efficiency, the 1in1000 TRISK climate stress testing framework allows for a very direct method of translating climate scenario technology pathways to corporate valuation impacts. Despite this, the credit risk model adds an additional layer of complexity; TRISK first calculates NPV impacts and then uses those as a subsequent input into an add–on credit risk model. Hence, there is a more direct link between the scenario pathways and NPV change impacts than between the scenarios and PD differences. The additional modelling layers such as the add–on credit risk model, additional data sources and several assumptions specific to the Merton framework may increase the risk that some variability is attributed to those additional layers rather than the differences in source climate scenarios.

The use of the 1in1000 TRISK stress testing framework is designed to be as transparent a framework as possible for the analysis of different input scenario models. For subsequent research, further work needs to be done to transparently test additional model assumptions to determine the degree to which credit risk variability can be attributed to stress test model assumptions. The need for the consideration of multiple scenarios, as well as reverse stress testing approaches to address issues of transparency has been similarly highlighted by other studies.[46] **The variability of climate scenario trends can have significant implications for how they are applied as inputs to climate stress testing frameworks.** Climate financial scenarios considered in this analysis rely on pathways derived from Integrated Assessment Models. The literature on IAMs has emphasised that future trends from these models should be treated as indicative of broad climate financial outcomes, rather than as precise forecasts of what will happen under certain conditions. However, a growing number of corporate or supervisory climate stress test exercises have been using climate scenarios and models as

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[46] David Aikman, Romain Angotti, and Katarzyna Budnik. “Stress testing with multiple scenarios: A tale on tails and reverse stress scenarios”. In: *European Central Bank Working Paper Series* 2941 (2024).

predictive forecasts to inform supervision, regulation, and policymaking. However, findings from this paper demonstrate that the results of any financial stress test, regardless of the complexity, consistency, or transparency, are highly dependent on the climate scenario that is being input into the stress test. This has important implications for financial institutions, highlighting the need to consider a broader range of climate scenarios and the application of several future trends due to the potential for biases in climate scenarios, and the uncertainty in the assessment of risk from the stress testing framework itself.

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7. Appendix

7.1. Technology trends

Evaluation of company performance under different shock scenarios is based on forecasts of energy technology changes in production. Production forecasts are taken from each shock scenario. The TRISK model calculates technology trajectories in two distinct ways based on high or low carbon energy technologies. For carbon–intensive technologies, trajectories are based on the implied growth rates taken from the scenario trajectory. In contrast, for low carbon technologies, the trajectories are derived from the technology's relative share in relation to the total sectoral production over time. This approach is used to better capturing the build–out of companies that operate multiple technologies within the power sector, as well as for those planning production expansions in the coming years but with no production realised in the starting year.

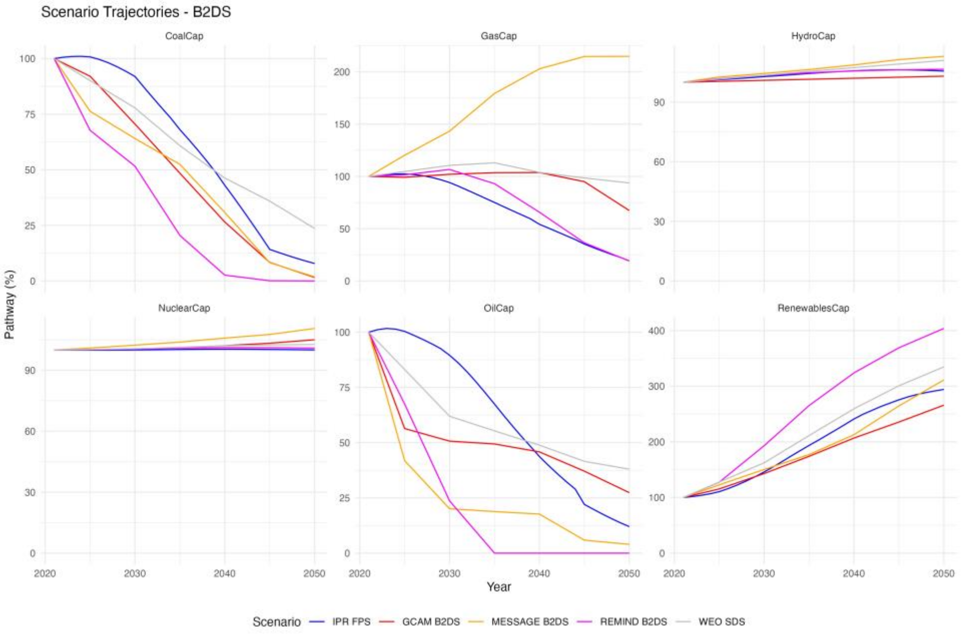


Fig. 9: *Forecast trends for energy technologies according to different scenarios under the Below 2°C pathway.*

Analysis in Sections 4.2 and 4.2.2 are based on different company NPV changes for each technology trend, for each scenario. Figure 9 shows the forecast trends for each technology under the 'Below 2°C' pathway. While there are differences in the trends, they do not show variability to the same extent that variability is observed in company performance, as they all show consistent increasing or decreasing trends over time. Additionally, Figure 10 shows the technology trends for the ‘Net Zero 2050’ pathway. The trends are similar to those for the ‘Below 2°C’ pathway in that they show widespread agreement in either increasing or decreasing trends over time.

Under both pathways, the only technology trend that shows a difference in trajectory compared to other scenarios is the positive increase in the amount of gas produced under the MESSAGEix IAM, whereas all other scenarios show a decrease in gas production. Despite this difference in the direction of the trend in gas production under both pathways, the impact on company performance does not correspond to a higher variation in gas company performance observed in sections 4.2 and 4.2.2.

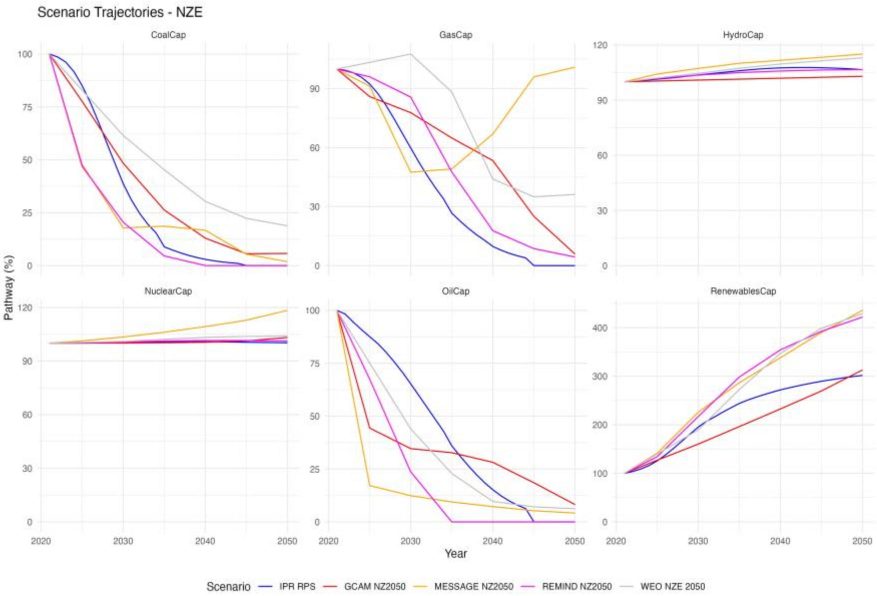
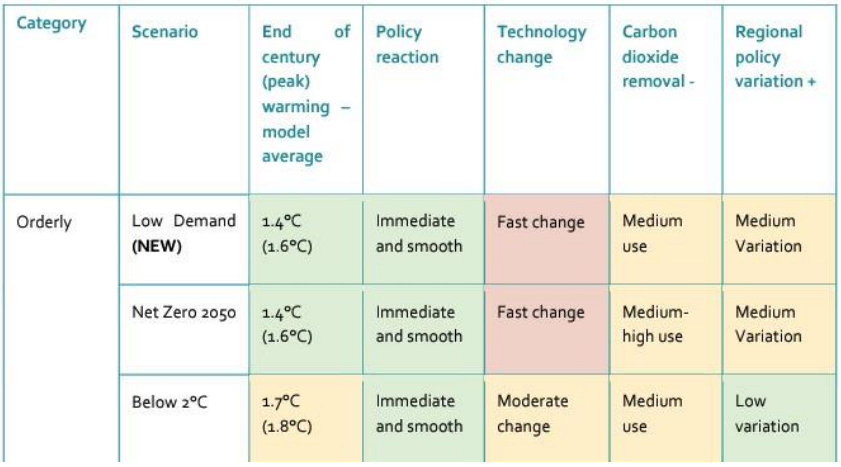


Fig. 10: *Forecast trends for energy technologies according to different scenarios under the Net Zero 2050 pathway.*

Comparisons in technology trends show that even slight differences in production trajectories can be propagated through a climate stress test to represent larger differences in the assessment of company performance and risk. Additionally, while most technology trends show fairly consistent and similar trajectories, this is not always the case, as observed from the assumptions on the uptake of gas under MESSAGEix. Hence, the choice in the climate scenario has significant implications for the assessment of climate risk based on technology type, and individual company performance.

7.2. Climate pathway stringency

Comparisons of climate stress tests have focused on broad categorisations of scenarios according to climate policy ambition, policy timing and coordination, technology evolution, and temperature target. While these categories are broad and include several assumptions and uncertainties that are modelled differently for each IAM, which leads to different trajectories, they have been grouped together according to similar themes and parameters for how the future green transition will unfold.



Category	Scenario	End of century (peak) warming – model average	Policy reaction	Technology change	Carbon dioxide removal -	Regional policy variation +
Orderly	Low Demand **(NEW)**	1.4°C (1.6°C)	Immediate and smooth	Fast change	Medium use	Medium Variation
	Net Zero 2050	1.4°C (1.6°C)	Immediate and smooth	Fast change	Medium-high use	Medium Variation
	Below 2°C	1.7°C (1.8°C)	Immediate and smooth	Moderate change	Medium use	Low variation

Fig. 11: *NGFS scenario narrative pathways according to key assumptions. Green is “low risk”, yellow is “medium risk”, and red is “high risk”.*

Analysis in this paper has focused on differences in stringency between a ‘Below 2°C’ pathway, and a ‘Net Zero 2050’ pathway, with the former being less stringent than the latter. The theme of these two pathways have been taken from the scenarios provided by NGFS, which comprises 3 of the 6 IAM scenarios used in this analysis from Table 1, being GCAM, REMIND, and MESSAGEix. The other three scenario providers used in this analysis, IEA, IPR, and Oxford, do not make the exact same distinctions between the two pathways as that made by NGFS, but broadly fit the same narrative framework of either reaching Net Zero by 2050, and the other achieving the more modest goal of maintaining a Below 2°C global average surface temperature warming by the end of the century.

Under Net Zero 2050 scenarios, global warming is limited to 1.5°C through a series of stringent and coordinated climate policies and innovations, with global Net Zero being achieved by mid–century. In contrast, the Below 2°C pathway is less ambitions, and gives a longer timeline to achieving climate goals by end of century rather than by mid-century. Rather than having a global policy coordination for Net Zero, it is assumed that only 80 percent of countries with stated Net Zero targets reaching them by the end of the century. Under this set of scenarios, it is expected that global warming will reach 2°C by the end of century. Differences in temperature target and policy ambition and coordination are highlighted according to key characteristics by NGFS in Table 11.[47] The ordering of scenario narratives in Table 11 highlights the distinctions between the Below 2°C narrative and the Net Zero 2050 based on differences in policy coordination, ambition, temperature target, and technological evolution. Additionally, differences in policy stringency and transition risk are shown in Figure 12, which shows the total amount of global emissions per year that are expected under each NGFS scenario for either the Below 2°C or Net Zero 2050 pathway. The trends in global emissions for each IAM are coloured according to the narrative pathway, with red for Below 2°C scenarios, and blue for Net Zero 2050.

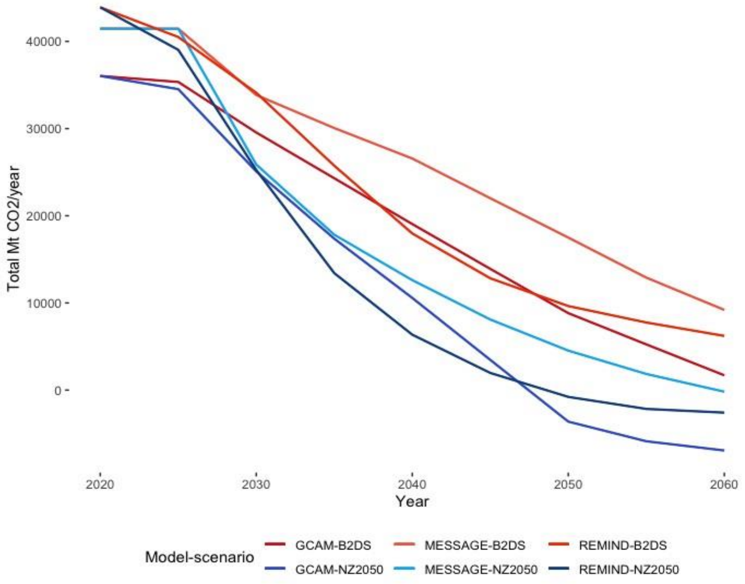


Fig. 12: *Global amount Mt CO2 that is emitted under each NGFS scenario*

First, the trajectory of global emissions is different under each IAM, despite sharing the same narrative pathway. Second, all trends show a reduction in emissions towards the mid century. Third, differences in stringency according to both narrative pathway and scenarios are observed by the amount of emissions that are allotted under each trajectory. For all three scenarios under the Below 2°C target, they project a greater amount of global emissions than for all scenarios under the Net Zero 2050 pathway. Hence, between the two, the carbon budget

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[47] Christoph Bertram et al. *NGFS Climate Scenarios Database*. Technical Documentation. Network for Greening the Financial System Macrofinancial Workstream, June 2020, pp. 20.

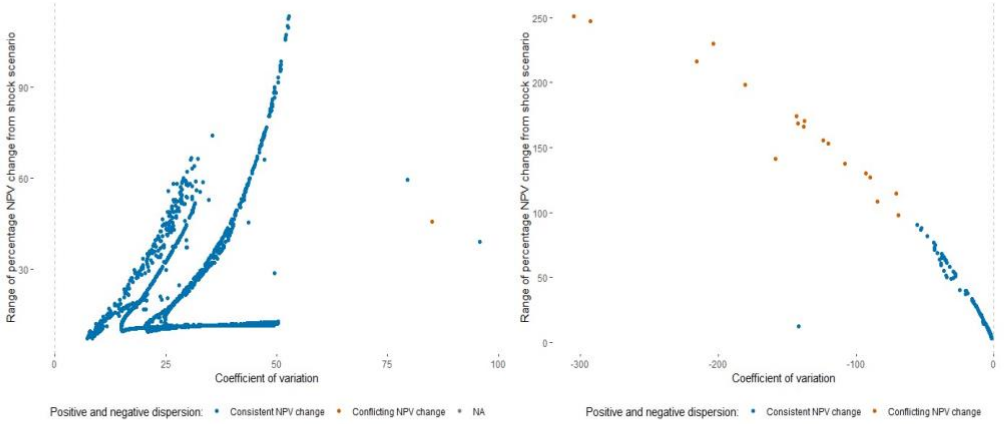
for all Net Zero 2050 scenarios is smaller than for all Below 2°C scenarios, thus the stringency is higher under the Net Zero 2050 pathway. Given the broad characteristics of how these two narrative pathways have been described by NGFS, as well as the amount of carbon budget allotted under each, there is a clear distinction in the level of policy stringency and coordination between the two. Premised on the differences between pathways, this paper has found that, given the uncertainty in modelling future pathways, there is more agreement and less risk to companies and financial institutions under more stringent and ambitious climate scenarios, rather than those that delay action and policy coordination later in the century.

7.3. Sensitivity to the Oxford scenario

The focus and part of the main findings of this paper have been on the identification of differences in the variability of company performance, and hence market risk, based on the stringency of scenarios according to pathway, with a focus on the Net Zero 2050 goal, or more broadly ensuring a Below 2°C global average surface temperature warning by the end of the century. Table 1 shows the categorisation of different climate scenarios, and their providers based on their broad objectives in terms of policy ambition and temperature target.

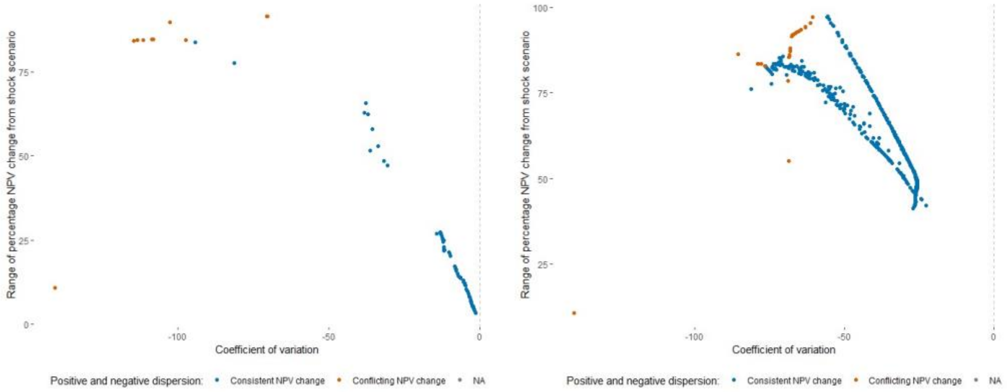
From the table, the study has included one extra scenario that is categorised under the ‘Below 2°C’ pathway compared to the ‘Net Zero 2050’ pathway. Since much of the analysis in this paper is premised on the extent of variation and dispersion in company performance under a stress test based on the choice in climate scenario, it is possible that the presence of more scenarios under one pathway relative to another could significantly affect the results. Therefore, as a measure of robustness of the analysis, the same analysis previously applied in Sections 4.2 and 4.2.2 is replicated here for the ‘Below 2°C’ pathway, but omitting the Oxford scenario, since it is the only one that is present only under ‘Below 2°C’ and not under ‘Net Zero 2050’. Results are shown in Figure 13.

The Oxford scenarios only show a significant impact on NPV variability on renewables. Results of the range and variation in NPV impacts for power companies according to technology type along the y and x axis respectively show essentially no change in either the dispersion of scenario impacts on NPV, nor in the coefficient of variation. The only case where there is some change in results compared to the inclusion of the Oxford scenario is for renewables, Plot 13a. The exclusion of the Oxford scenario shows a different pattern in the dispersion and variation of company performance, and a lower level of variation. Across all other technology types, when using the same scenario providers as analysed under ‘Net Zero 2050’ as here for ‘Below 2°C’, findings remain the same showing a wider range in NPV change, and a higher coefficient of variation for the less stringent pathway, than for the more stringent ‘Net Zero 2050’ pathway.



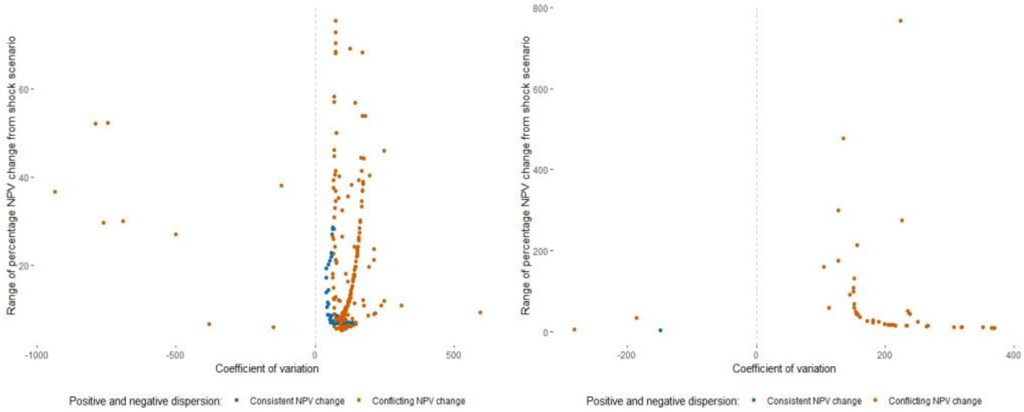
(a) Renewables

(b) Coal



(c) Oil

(d) Gas



(e) Hydro

(f) Nuclear

Table 3: *Difference in distributions of TRISK results on NPV change based on shock scenario for Net Zero 2050 pathway*