Climate Policy and Sovereign Debt: The Impact of Transition Scenarios on Sovereign Creditworthiness*

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Abstract

This paper links climate science with sovereign risk assessment to produce a single forward-looking measure of *country-level* climate change risk. We combine the Network for Greening the Financial System (NGFS) climate scenarios with a sovereign credit ratings model to simulate the impact of climate change on credit ratings, cost of debt and probability of default. For the first time, we extend beyond the physical risks of extreme weather events to explicitly incorporate risks associated with transitioning the global economy towards Net Zero. Across the sample of 48 countries and under a scenario of high (low) physical and transition risks, we find average downgrades of 3.9 (2.7) notches and mean increases in the cost of debt of 123 (76) basis points and default probability of 10.4% (6.2%). Counter-intuitively, ratings, default probability, and cost of debt appear insensitive to scenarios in some countries, with important implications for the usefulness of NGFS scenarios across central banks.

JEL Classifications: C53, E6, G20, H63, Q51, Q54.
Keywords: Sovereign debt, credit ratings, climate policy, transition risks, climate change.

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1 Introduction

Climate change presents macroeconomic risks through at least two channels, the direct physical consequences of extreme weather events (physical risks) and the economic risks associated with transforming the global economy from a fossil-fuel based regime to a Net Zero one (transition risks). The IMF estimates that meeting Net Zero by 2050 will require green investments to rise from $900bn in 2020 to $5tn annually by 2030.[1] If there is any hope of meeting these investment needs, sovereign debt markets will need to play an important role. Indeed, the weighted average cost of capital is one of the primary determinants of investment in renewable energy capacity. At the same time, climate change is already curtailing economic output with impacts on tax revenues and ultimately the ability of sovereigns to service debt (Klusak et al., 2023). Established in 2017, the Network for Greening the Financial System (NGFS) is a consortium of 159 central banks and supervisors dedicated to sharing best practices and mobilising private finance to support the Net Zero transition. To coordinate research efforts, the NGFS developed a suite of transition scenarios to ensure consistency and comparability in modelling and research efforts. We use these scenarios to estimate the impact of physical and transition risks on sovereign credit ratings, the probability of default, and the cost of public borrowing across a sample of 48 economies.

Globally, public debt now totals $97 trillion[2] and little is known about how the energy transition might impact the price of government bonds. But major holders of public debt, governments, central banks, mutual funds, pension funds, and insurance companies will increasingly require credible information describing the implications of physical and transition risk for sovereign debt markets. Understanding how the risk profile and associated value of sovereign debt is expected to change in relation to climate risks is crucial for the stability of the financial system.

Our central contribution is to integrate climate science into sovereign risk assessment to quantify country-level climate change risk under a range of policy-relevant scenarios designed and used by a consortium of central banks. Integrated climate risk is difficult to quantify, that is the combination of both physical and transition risks. Studies suggest that corporate and sovereign bond investors may be highly sensitive to the choice of transition scenario (Battiston and Monasterolo, 2020; De Angelis et al., 2024). We make a first attempt to apply the NGFS scenarios to simulations of sovereign credit ratings and document three key findings. First, a Fragmented World scenario results in a 3.9 notch downgrade by 2050, on average. Second, we show that some countries are motivated to make careful climate-policy choices because of the implications for their creditworthiness and subsequently fiscal health. Other countries face a moral hazard dilemma and either face no downgrade (or equally large) regardless of their climate- policy choices. Finally, we argue that our results have both practical and policy implications for long-term investors and sovereigns respectively.

Our analysis relies on one key assumption regarding the underlying rating process. We expect credit rating agencies to be concerned with 'counterfactual ability to repay debt'. The sovereign credit rating scale is ordinal. Countries can be categorized as highly creditworthy, in default and various points in between. The rating agencies determine this by considering a range of factors, however key amongst them is economic performance and GDP. Even though countries can grow at a 'steady state' this might not necessarily lead to an improvement in their rating. On the other hand, it may also be reasonable to claim that a country which fails to grow at all would likely observe a deterioration in its credit rating. So, a country which grows at a slower rate, because of climate change, does so at the expense of macroeconomic fundamentals, which can then impact its creditworthiness. We bring this assumption into our empirical work by exploiting the cross-sectional variation in credit rating assignment, and levels

[1] See IMF article 'World Needs More Policy Ambition, Private Funds, and Innovation to Meet Climate Goals' for more details.

[2] See IMF article entitled 'Global Public Debt Is Probably Worse Than it Looks'.

of economic performance to try and capture how changes to long-term economic performance may direct countries higher or lower on the rating scale.

Our work contributes to a growing literature concerned with the macroeconomic impacts of climate change: growth at the cross-country (Kahn et al., 2021) or within-country level (Mohaddes et al., 2023), fiscal impacts (Tol, 2023), and financial markets (Zhou et al., 2023; Monasterolo, 2020) amongst other things. While our work is closely aligned with research on climate change which is at the intersection of sovereign debt (Beirne et al., 2021), fiscal policy (Tol, 2023) and central bank action (Dikau and Volz, 2021), we deviate from these works by attempting to integrate forward-looking scenarios of climate policy into measures of sovereign debt risk, namely credit ratings. In this way our work is most closely aligned to Klusak et al. (2023) and De Angelis et al. (2024). However, we deviate from these papers in a number of ways. First, our work is unique to Klusak et al. (2023) in the sense that we focus on policy-relevant scenarios of climate change, which are inclusive of both transition and physical risk. Second, in doing so we also extend the model of Klusak et al. (2023) to accommodate outputs from IAMs. More specifically, we present a reproducible methodology, which can be integrated with the Network for Greening the Financial System (NGFS) policy scenarios. This enables a more integrated approach to sovereign risk assessment which is consistent with the developments in climate econometrics and integrated assessment modelling.

Third, we also deviate from the work of De Angelis et al. (2024) by integrating measures of climate risk into sovereign credit ratings, rather than credit default swap spreads. This enables our research to speak in terms of a standardized metric of sovereign credit risk, but also take advantage of its ordinal nature to exploit cross-sectional variation in credit rating assessment. Our results support those of De Angelis et al. (2024), whereby we observe similar variation across the scenarios presented by the NGFS.

Finally, there is increasing interest in measuring climate policy and energy-related uncertainty (Gavriilidis, 2021; Dang et al., 2023; Barnett et al., 2020). Our results show that for some countries, there is much less risk associated with climate change pathways than for others. Our work also contributes to ongoing policy and social debates about the role of government, central banks and financial regulators in measuring and mitigating climate-related financial risks. Central banks and financial regulators are evaluating investor exposure to climate-related financial risks. The European Central Bank, the Bank of England and more recently, the Federal Reserve System have produced scenario analyses aimed at evaluating the exposure of banks' loan books to climate change. Furthermore, we are motivated by the recent Bank of England analysis which supports the use of tree-based machine learning techniques to evaluate the impact of climate-related risks on fixed income instruments.[3]

We combine data from the NGFS with macroeconomic data and information about sovereign credit ratings from S&P Ratings Direct. From the NGFS, we obtain the GDP projections for five key policy scenarios (Below 2°C, Net Zero 2050, Delayed Transition, Nationally Determined Contributions and Fragmented World) across the three IAMs (GCAM, MESSAGEix-GLOBIOM and REMIND-MAgPIE). Each of the five scenarios describes a different amount of both physical and transition risk. Scenarios characterized by low physical and transition risks, such as Below 2° C and Net Zero 2050, are categorized as Orderly scenarios. Scenarios with high physical risks but low transition risks include the Nationally Determined Contributions (NDCs) scenario. Scenarios with high transition risks and low to medium physical risks fall under the Delayed Transition pathway. Lastly, the Fragmented World scenario is characterized by both high physical and high transition risks. For further information and a full description of the scenario narratives see Section 2.4.

We apply these scenarios to a model of sovereign credit ratings developed by Klusak et al. (2023). We then evaluate this model in an out-of-sample setting and adjust the input data to reflect the outputs of the

[3]See Bank of England article 'Measuring climate-related financial risks using scenario analysis' for further details.

IAMs. We obtain sovereign credit rating estimates for 48 countries, across each of the five scenarios and three IAMs for 2050. To validate our assessment, and ensure that our simulated downgrades represent exposure to the spectrum of climate-related risks captured by Integrated Assessment Models, we regress our country-level downgrades on the log total emissions for each country. We select total emissions over per capita emissions since we are trying to capture 'polluting' economic activity within an economy, and any attempt to regulate this will likely impact the country's whose emissions are highest, the most. This thinking is also broadly consistent with the work by Bolton and Kacperczyk (2021), who show that return premiums on equities are more sensitive to total corporate emissions than to emissions intensity. We find that under a Net Zero 2050 scenario, higher total emissions (by 1 standard deviation) are associated with a simulated downgrade of 0.95 notches.[4] In other words, if a country moves from the 10th percentile of polluters to the 90th percentile, we can expect a lower credit rating of approximately 2.4 notches (0.95 x 2.56 = 2.43). This result supports our underlying model as it reveals an association between our output and simple measures of a country's exposure to stringent climate policy.

We document a number of key results. The Net Zero 2050 scenario results in the fewest number of sovereign downgrades, approximating 2.7 notches on average, while the Fragmented World scenario produces a sample average downgrade of approximately 3.9 notches. Second, there are some countries that, despite facing significant GDP losses across the scenarios, may experience stable ratings, a phenomenon often referred to as ratings stickiness. These economies are typically concentrated towards the lower end of the ratings scale. Put crudely, if a country is already in default, climate change will not help, but neither will it make it a 'defaulter' default. This finding indicates that several countries might face a moral hazard dilemma, whereby adopting policies for addressing climate change may not align with their efforts to bolster credit ratings. These results imply two things. First, international coordination efforts to address climate change need to deal with the fact that some countries simply do not have an economic incentive to implement green policies. Second, the risks from climate change may already be 'baked-in' (Kotz et al., 2024).

2 Data and Methodology

In this paper we make use of two distinct sets of data. First, we rely on macroeconomic and sovereign ratings data to construct a predictive model of sovereign credit ratings. Second, we obtain GDP projections for a range of transition scenarios from the NGFS. We do this for each of the policy scenarios and each of the three Integrated Assessment Models.

2.1 NGFS data

The data we obtain from the NGFS is accessible through the NGFS Phase 5 Scenario Explorer.[5] The NGFS uses three integrated assessment models (IAMs) which our research relies on. These include the following downscaled models to provide country-level estimates, MESSAGEix-GLOBIOM 1.1-M-R12, REMIND-MAgPIE 3.2-4.6, and GCAM 6.0. These models aim to capture complex interactions between the energy system, water, agriculture, land use, climate and the economy and make varying levels of assumptions about the behaviour of individuals and firms. Literature on IAMs has grown rapidly, and models are continuously updated. For a review and discussion of these models see Fisher-Vanden and Weyant (2020). Our approach simulates a rating change for each country, under each scenario, according to the impacts predicted by each IAM. For each country, under each scenario, we report the average

[4] We use a 20-notch ratings scale, where 20 corresponds to AAA. See Table 5 for the rating symbol and the corresponding numerical ratings.

[5] This data is available here.

Table 1: Descriptive Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Rating	11.23	5.10	1.00	20.00
ln GDP per capita	9.21	1.28	6.03	11.70
GDP growth	0.01	0.09	-0.41	0.29
Net General Government Debt / GDP	35.06	63.78	-489.79	172.82
General Government Balance / GDP	-2.44	3.98	-21.05	21.57
Narrow Net External debt / CARs	53.03	123.69	-708.18	461.29
Current Account Balance / GDP	-1.14	8.33	-63.50	36.31

Notes: This table shows the descriptive statistics for our model training data. This ranges from 2015 to 2020, for 123 different countries and a total number of observation equalling 723. The sovereign credit rating variable is on the 20-notch scale, where AAA=20.

rating change found across the three IAMs.[6] By incorporating the three IAMs in this way we draw robust insights across models and reduce sensitivity to model-specific error. The NGFS rely on the outputs from the IAMs to act as inputs to the global econometric model NiGEM (National Institute Global Econometric Model). NiGEM provides simulations of the GDP pathways we use in our model.

2.2 Macroeconomic data

We obtain macroeconomic and sovereign credit ratings data from S&P Ratings Direct. We rely on data from Standard & Poor's (S&P) as it is generally regarded as the rating agency to lead Moody's and Fitch in rating revisions and often leads to a greater market impact (Almeida et al., 2017). Our database is a year-country panel from 2015-2020. This period excludes two severe sovereign risk events, namely the Global Financial Crisis and the Covid-19 Pandemic. The impact of these events on our ratings model may be that we underestimate the impact of climate related losses on sovereign credit ratings. Researchers have variously documented the impact of systemic events on credit ratings. Whilst the empirical evidence suggests that ratings remain relatively stable during these periods (Teixeira et al., 2018; Tran et al., 2021), the economic fundamentals do not. As such, this would impact on the accuracy of our model out of sample. Finally, we make our variable selection based on the criteria that we aim to maximise our predictive accuracy of sovereign credit ratings, whilst not limiting our ability to integrate expectations of how we might expect those variables to change in response to climate transition. Table 1 presents the summary statistics for our macroeconomic data.

2.3 Methodology

We apply a random forest estimation to a combined dataset of sovereign credit ratings and macroeconomic data. Our model follows Klusak et al. (2023) and is consistent with central banks use of tree-based algorithms to simulate sovereign credit ratings.[7] We apply a random forest estimation to the following model:

$$Rating_{it} = GDPpc_{it} + \Delta GDP_{it} + GPV_{it} + \mu_{it} \tag{1}$$

Where, $Rating_{it}$ is the level of sovereign creditworthiness from 1-20 (20 being the highest attainable credit rating of AAA, on the S&P scale), $GDPpc_{it}$ is the level of GDP per capita, ΔGDP_{it} is the growth rate and GPV_{it} represents a vector of government performance indicators produced by S&P,

[6] The NGFS provide several justifications for their decision to employ multiple IAMs. These include a greater ability to capture model uncertainty, exploit model-specific properties (e.g. REMIND-MAgPIE offers more detail for industry, compared to GCAM which offers it for buildings). Our procedure therefore retains the NGFS's intent. For further details, please see the NGFS scenarios portal.

[7] See, for instance, Bank of England.

these include; narrow net external debt to current account receipts, current account balance to GDP, general government balance to GDP and net general government debt to GDP.

Estimating a panel model enables us to more accurately reflect out of sample estimates, as a single credit rating is not necessarily achieved by only a narrow set of parameters. The random forest model works in a similar way to a single decision tree. The algorithm splits into nodes by selecting a variable from the pool, and at a value which gives the most efficient split of the data. Our specification splits on residual mean squared error. This is expanded in a random forest setting to 2,000 decision trees. However, to avoid overfitting, the algorithm selects a random subsample of the training data and available variables for each tree to estimate. There has been a growth in the use of machine learning techniques in energy economics (Ghoddusi et al., 2019), and in economics more widely (Athey and Imbens, 2019). We leverage these methods to provide accurate, out-of-sample estimates for sovereign creditworthiness.

Once we have a fitted model for estimating sovereign credit ratings, we are able to evaluate it. We perform a standard machine learning process to do this. We fit the model to 70% of our historical data. We then estimate the model, out of sample, on the remaining 30% of our data. In this exercise we correctly estimate the actual sovereign credit rating, within 2 notches, 90% of the time. This score increases to 97% within 3 notches.[8] Figure 1 reveals how accurate we are for each country in the sample. The orange dot represents the country's average sovereign credit rating over the sample period. The blue dot represents our model's estimate, coupled with its error bound.

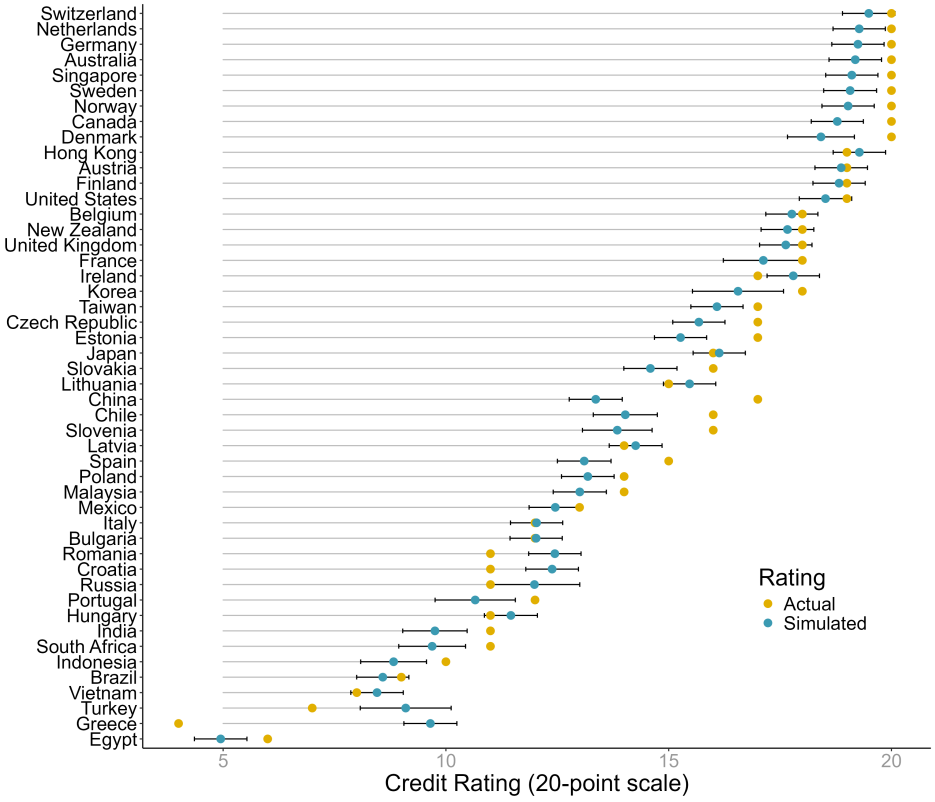


Figure 1: Out of Sample Accuracy by Country

Notes: The orange dot depicts the actual rating, and the blue dot depicts the simulated rating from our model. The black whiskers depict the error bound for our estimate.

The next step in the analysis is to estimate sovereign credit ratings out of sample on data which reflects the macroeconomic environment projected by the IAMs. GDP per capita and the growth rate

[8] The replication package is available upon request.

are given directly by the outputs from NiGEM. To identify reasonable values for the remaining four government performance variables we rely on data from S&P, which shows how these values are expected to change under shocks to GDP based on historical data from countries exposed to various acute climate-related events. We estimate a third order polynomial to bivariate relationships and interpolate estimates to populate our input data. Given a complete dataset which reflects a projected macroeconomic environment, we estimate our sovereign credit ratings out of sample.

With simulated sovereign credit ratings, we can rely on data from S&P and FRED to estimate the relationships between the rating categories, default probabilities and cost of debt premiums respectively. This final step provides a more detailed economic and financial interpretation for the credit rating and reveals how small changes in a low-rated country have a much bigger impact on cost of debt and default probability, than a similar sized change in the rating of highly-rated sovereigns. See Figure 2 for a graph of the relationship between credit ratings and probability of default.

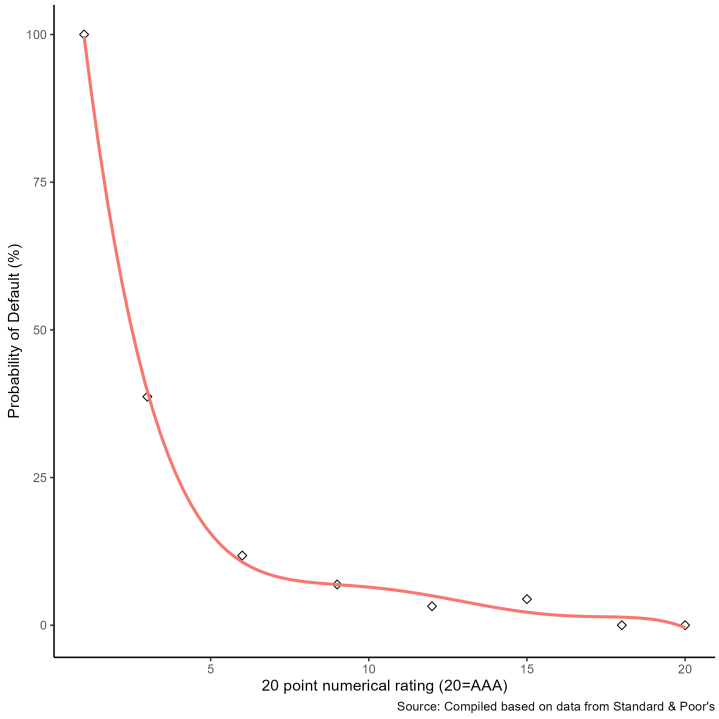


Figure 2: Soverign Credit Ratings and the Probability of Default

2.4 NGFS Scenarios

Table 2 shows a brief outline of the NGFS scenario categories, pathways, make up of physical vs. transition risk, a brief description and the average 2050 GDP loss. Net Zero 2050 assumes the immediate introduction of ambitious climate policy and a significant role for carbon dioxide removal technology. The Below 2°C scenario is less strict, but still assumes a dual role of climate policy and some deployment for carbon dioxide removal technology. Delayed transition is characterised by slower introduction of climate policies (2030), limited use of carbon removal and subsequent higher carbon prices. There is also higher variation in policies across countries. Nationally Determined Contributions (NDCs) have a modest policy ambition, and the losses in this scenario are primarily driven by physical risks. Fragmented World assumes delayed and divergent climate policy globally. Some countries are exposed to more transition risks than others, everyone faces high physical risks. The results of country-level GDP losses are also

Table 2: NGFS Scenarios

Scenario Category	Scenario Name	Physical/Transition Risk	Description	Average GDP Losses (%) by 2050
Orderly	Net Zero 2050	Low/Low	Limits warming to 1.5C. Strict climate policy and innovation schedule	-5.62
Orderly	Below 2°C	Low/Low	67% chance of limiting global warming to below 2°C	-6.99
Disorderly	Delayed Transition	Low/High	Global emissions do not decrease until 2030. Strong policies are then needed to limit warming below 2C	-8.46
Hot House World	NDCs	High/Low	All pledged policies	-8.82
Too little, too late	Fragmented World	High/High	Delayed and divergent climate policy ambition globally. High physical risk everywhere	-9.24

Notes: This table shows the range of NGFS scenarios accessed from NGFS Phase 5 Scenario Explorer. The NGFS uses three integrated assessment models (IAMs) including MESSAGEix-GLOBIOM 1.1-M-R12, REMIND-MAgPIE 3.2-4.6, and GCAM 6.0.

presented in Figure 3. These are the downscaled estimates produced for each IAM from the NiGEM macroeconomic model.

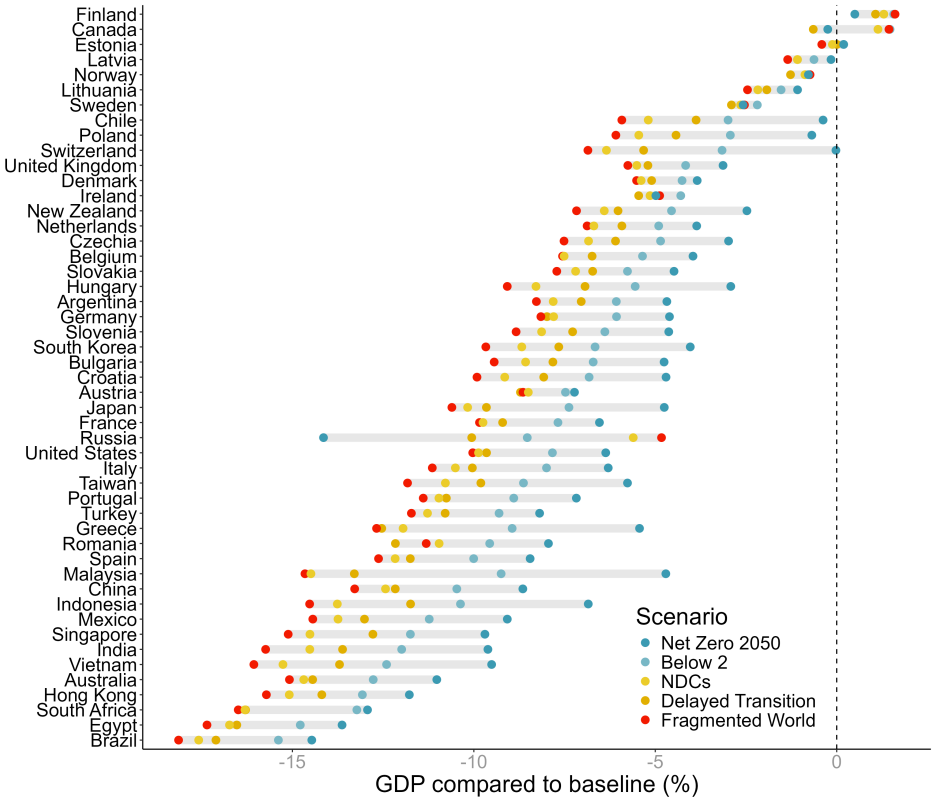


Figure 3: GDP Losses by Scenario in 2050

Notes: This figure shows the downscaled GDP deviation from baseline figures by country. These results are averages from each of the three IAMs.

3 Empirical Results

In this section we present the results of our random forest simulations. Figure 4 shows the average sovereign credit rating downgrades by scenario in 2050. A natural grouping of the scenarios emerges. A Fragmented World scenario poses the most significant threat to sovereign creditworthiness. Disorderly transition scenarios follow closely (Delayed Transition and NDCs) and orderly transitions provide the most beneficial outcome. Similarly, density plots demonstrate that scenarios with higher average downgrades also exhibit fatter tails. These results are largely consistent with those presented by De Angelis et al. (2024). While orderly scenarios may prove the most costly in the short term, the longer term economic outcomes are better under these scenarios. Furthermore, only taking the average downgrade from these scenarios may obscure the extent of the fiscal risks facing those countries which are most exposed (i.e. those in the tail).

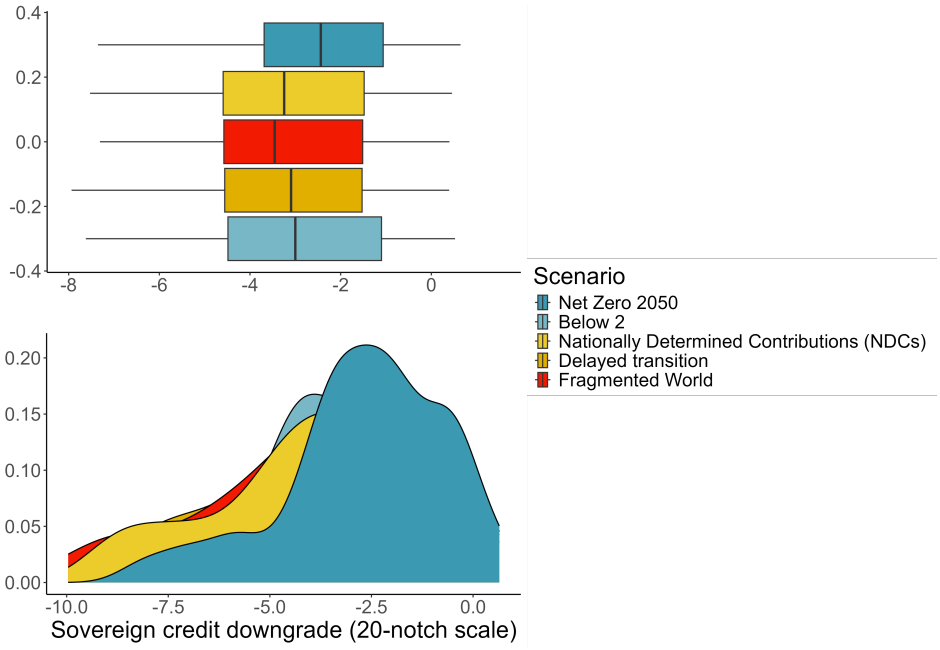


Figure 4: Average Credit Rating Impacts by Scenario in 2050

We present our country-level results for 2050 in Table 3 and Figure 5. In Figure 5 the grey dot shows the actual credit rating and the black whiskers depict the confidence interval around our in-sample estimate of that rating today. These whiskers are centered around the baseline estimate of today's rating which we have removed from the graph for clarity. Our results show that for many countries, scenarios of orderly transition, and in some cases NDCs, may fall within the confidence interval of our model. This means that these countries expect minimal impact on their sovereign risk assessment because of these scenarios. However, almost all countries are exposed to downgrades from the Fragmented World scenario. There are some distinct country-specific patterns which emerge. For instance, Russia faces the most severe downgrade from a Net Zero 2050 outcome. This is largely driven by the GDP estimates given in Figure 3 and stands out as the only country to experience this sort of outcome. Some countries, for instance India, Vietnam and Brazil at the bottom end as well as Norway, Canada, and Finland, among others, at the top end, face little impacts from these scenarios to their sovereign credit ratings. In other words, their sovereign ratings appear to be largely insensitive to the choice of climate policy.

Our results reveal an interesting problem. Not all countries face an equally pressing economic incentive to implement climate policies which benefit the rest of the world. While India pursuing Net Zero by 2050

Table 3: Rating Outcomes in 2050

Scenario	Rating change (notches)	Cost of debt premium (%)	Change to probability of default (%)
Net Zero 2050	-2.69	0.76	6.15
Below 2°C	-3.13	0.89	7.11
Delayed Transition	-3.61	1.10	9.13
NDCs	-3.67	1.12	9.33
Fragmented World	-3.87	1.23	10.36

Notes: Column 1 shows the scenario being estimated, Column 2 shows the average change to the credit rating, Column 3 shows the average change to the cost of debt, and Column 4 shows the average change in the probability of default. The results of our baseline simulations are all significant at the 1% level.

will benefit many other countries, it does little to support India's ability to borrow from international financial markets. How does the international community contend with this issue, and what are the consequences for the NGFS and their scenarios. These scenarios are largely reliant on countries pursuing coordinated efforts. Our results show that not all countries have the same incentive to see this happen.

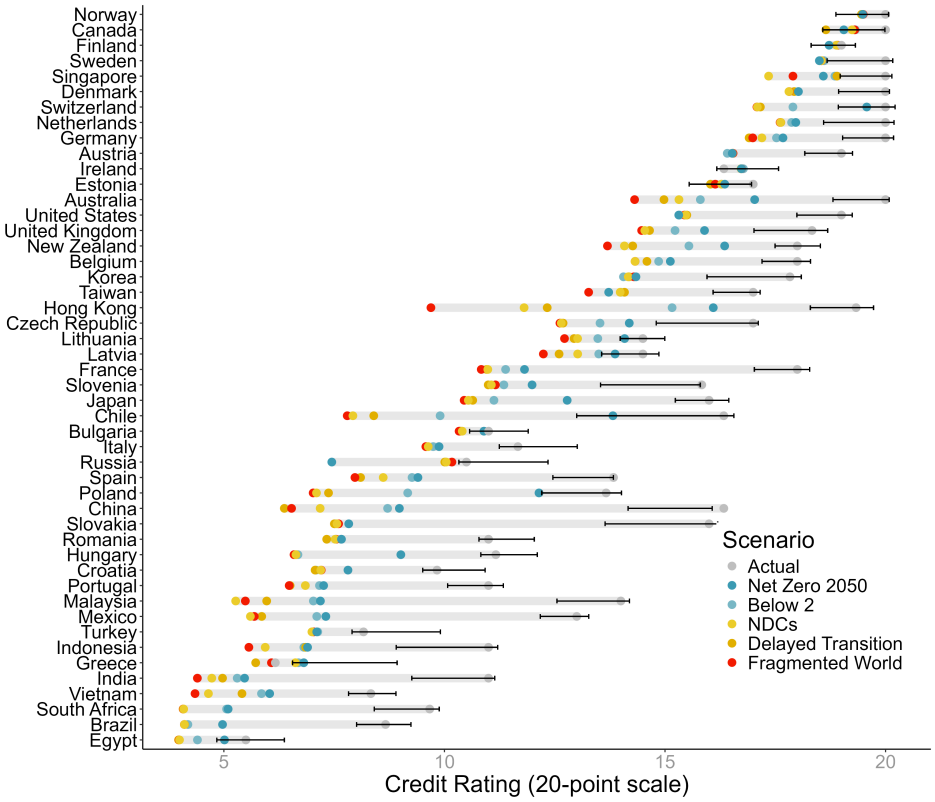


Figure 5: Sovereign Credit Ratings by Scenario in 2050

Notes: The grey dot and whiskers represent the actual rating and our in-sample confidence interval around that rating.

4 Are we capturing elements of transition risk?

Despite evidence that markets are beginning to price-in climate transition and policy risk (Bolton and Kacperczyk, 2021; Monasterolo, 2020) and that physical risks are affecting fixed-income instruments (Goldsmith-Pinkham et al., 2023; Beirne et al., 2021), the balance of expert opinion is that this remains incomplete. Consistent with a survey of 861 finance academics, professionals, public sector regulators

Table 4: Regression of Simulated Downgrades on Emissions

Scenario	β	t-value	t-value (robust)	R^2
Below 2°C	-0.80	-2.57	-2.66	0.11
Delayed Transition	-0.86	-2.42	-2.29	0.10
Fragmented World	-0.86	-2.22	-2.20	0.08
NDCs	-0.87	-2.37	-2.42	0.09
Net Zero 2050	-0.95	-3.49	-3.70	0.20

Notes: This table shows the results of our regression of simulated downgrades on standardized log total emissions ($\Delta Rating_i = \beta lnEmissions_i + \mu_i$) for 2020. We do this for each of the five scenarios. Column 2 reveals the β estimate for the regression, Columns 3 and 4 show the t-value and robust t-value respectively, and Column 5 shows the model fit.

and policy economists, our results imply this repricing has not fully materialised (Stroebel and Wurgler, 2021).

$$\Delta Rating_{i,NGFS} = \beta lnEmissions_{i,2020} + \mu_i \tag{2}$$

In this section, we demonstrate that our downgrades do indeed reflect aspects of transition risk. Consistent with Bolton and Kacperczyk (2021) we proxy for transition risk by using country-level log total emissions to estimate the following regression model in Equation 2, for 2020 emissions data. Our results show, that for the Net Zero 2050 scenario, countries with higher emissions (by 1 standard deviation) are associated with a 0.95 notch downgrade in our model. In other words, countries at the 10th percentile of polluters compared to the 90th percentile, have a different simulated credit rating of approximately 2.4 notches (0.95 x 2.56 = 2.43). We present the results of this analysis in Table 4, amongst the other scenario estimations. Furthermore, we also observe the fit of this relationship to be better in scenarios characterized by higher levels of transition risk, as one might expect.

5 Concluding remarks

This paper studies how sovereign creditworthiness may change in response to various scenarios of climate transition. To address this issue we combine macroeconomic data, sovereign ratings data and projected GDP pathways of 48 countries under five different scenarios of climate transition. We construct a predictive model of sovereign credit ratings and simulate rating downgrades under the five different scenarios 2050. We document three key findings. First, on a global average, a Fragmented World scenario results in a 3.9 notch downgrade by 2050. Second, we show that some countries are motivated to make careful climate-policy choices because of the implications for their creditworthiness. Whereas other countries face a moral hazard dilemma and either face no downgrade (or equally large) regardless of their climate- policy choices. Finally, we argue that our results have both practical and policy implications for long-term investors and sovereigns respectively.

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Table 5: S&P Credit Rating Scale

Long-term Foreign Currency Issuer Rating Symbol	Numerical Rating	Grade
AAA	20	Prime
AA+	19	High
AA	18	
AA-	17	
A+	16	Upper-medium
A	15	
A-	14	
BBB+	13	Lower-medium
BBB	12	
BBB-	11	
BB+	10	Speculative
BB	9	
BB-	8	
B+	7	Highly speculative
B	6	
B-	5	
CCC+	4	Substantial risks
CCC	3	
CCC-	2	
CC	1	Extremely speculative / In default
C	1	
D/SD	1	