The Adaptation Imperative: Climate Change and Sovereign Credit Risk*

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Abstract

This paper examines how climate change affects sovereign credit ratings and borrowing costs under the latest IPCC climate scenarios. We integrate country-specific income-loss estimates from Mohaddes and Raissi (2025) into the IMF's Q-CRAFT macro-fiscal framework and apply a Random Forest emulator to predict rating trajectories. We also use the CDS-spread mapping from Aizenman et al. (2013) to translate these rating changes into borrowing-cost effects. Results show negligible rating impacts under the Paris-aligned scenario but significant downgrades (up to 2.8 notches) and increases in borrowing costs (30 basis points) under high-emission, slow-adaptation pathways by 2100 for the G20 countries. Monte Carlo simulations highlight substantial tail risks and cross-country heterogeneity, with tail outcomes producing downgrades of up to six notches by century end. We further extend the analysis to unrated economies and incorporate acute physical risks from climate-related natural disasters, using DIGNAD to estimate their cumulative GDP effects over 30 years and feeding these into the Q-CRAFT and the Random Forest emulator to project ratings. Disaster exposure can induce 1–3 notch downgrades by 2050 for highly vulnerable emerging economies.

JEL codes: C45, G24, H63, Q54.
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1 Introduction

Climate change poses challenges to macro-financial stability and sovereign creditworthiness. This paper studies the impact of physical climate risks on sovereign credit ratings and borrowing costs, with a modelling chain consisting of climate change-GDP impact assessments under the latest Intergovernmental Panel on Climate Change (IPCC) scenarios, a forward-looking macro-fiscal framework for risk analysis designed by the International Monetary Fund (IMF), a Random Forest model of sovereign credit ratings, and a mapping of rating changes into borrowing costs.

Previous research has studied the effect of climate change on sovereign risk across a number of dimensions. Most closely related to this study is the work by Klusak et al. (2023). They simulated the effects of physical climate risks on sovereign credit ratings for 109 countries through 2100 under different warming scenarios, using Representative Concentration Pathways (RCPs). Burke et al. (2025) added transition risks into this analysis by considering the Network for Greening the Financial System (NGFS) scenarios and policy-driven decarbonization pathways. Both papers identify an important concern, that the macroeconomic impacts of climate risks (both physical and transition) do not translate into credit outcomes for all countries homogeneously, and some are more sensitive than others.

Despite these advances, two critical gaps remain. First, both studies rely on earlier generations of climate-macroeconomic models, which offer limited granularity on adaptation dynamics and temperature variability-factors increasingly recognized as key determinants of long-run climate impacts (Mohaddes and Raissi, 2025). Second, neither framework fully integrates the fiscal feedback loop: how climate-induced GDP losses and increased risk premia propagate through public debt dynamics, potentially amplifying sovereign risk. To support informed policymaking, it is essential that these gaps are addressed.

This paper extends Klusak et al. (2023) and Burke et al. (2025) primarily in two ways. First, we rely on counterfactual results of Mohaddes and Raissi (2025), which provides country-specific estimates of income losses from rising temperatures for 174 economies under the latest IPCC scenarios, explicitly accounting for adaptation and temperature variability. These richer inputs allow us to capture heterogeneity across income groups and assess the fiscal and credit benefits of adaptation strategies. Second, we embed these climate-adjusted macro counterfactuals and rating-implied risk premia into the International Monetary Fund's Q-CRAFT (Quantitative Climate Risk Assessment Fiscal Tool), a forward-looking macro-fiscal framework that quantifies primary deficits, interest costs, and debt under different climate scenarios. This integration enables us to measure the direct effect of climate change on sovereign ratings as well as their indirect fiscal consequences through higher interest bills and debt accumulation.

A further contribution of this paper is the extension of the sovereign credit risk analysis to economies that are not currently rated by major Credit Rating Agencies (CRA). Existing climate-sovereign risk studies are almost entirely limited to rated sovereigns, creating a systematic blind spot among countries with lower incomes and limited adaptive capacity. To address this gap, we construct synthetic baseline ratings for unrated economies using macro-fiscal variables from the Q-CRAFT, complemented by institutional quality measures that capture dimensions typically embedded in CRA methodologies. This global extension allows us to assess the distribution of climate-related credit risks across the full spectrum of countries-particularly those most vulnerable to both chronic climate change and acute physical risks.

In addition to chronic warming scenarios, we also examine how acute physical risks from climate-related natural disasters may affect sovereign creditworthiness. While recent work has begun to explore how extreme events influence debt sustainability, the long-term macro-fiscal implications of climate-related natural disasters of varying probabilities and intensities remain underexplored. We incorporate Annual Average Loss (AAL) estimates from the Coalition for Disaster Resilient Infrastructure (CDRI) into an updated DIGNAD (Debt-Investment-Growth and Natural Disasters) framework to generate long-run annual GDP losses from the entire distribution of natural disasters. These disaster-induced AALs are then fed into the Q-CRAFT to produce disaster-adjusted macro-fiscal paths and rating projections through the Random Forest emulator. This enables us to quantify how exposure to disasters can compound

climate-related sovereign risk, especially for highly vulnerable emerging and developing economies.

Our paper finds that climate change-induced rating impacts are felt most sharply in warmer, and more slow to adapt scenarios. For the G20 economies, the SSP1–2.6 scenario (consistent with the Paris agreement temperature goals) does not lead to any material change in credit ratings before the end of the century. In contrast, an unadapted 90^{th} percentile SSP3–7.0 scenario (i.e., a hot world) implies an average downgrade of about 1.2 notches by mid-century, rising to 2.8 notches by century-end. This corresponds to an increase in the average cost of debt of approximately 19 and 30 basis points, respectively. Since average changes may not necessarily communicate risk, we also conduct a Monte Carlo analysis revealing that the 90^{th} percentile unadapted SSP3–7.0 scenario may result in downgrades of up to 6 notches. For some countries this corresponds to an increase in the cost of debt of 470 basis points by 2100.[1]

Our extended analysis reveals meaningful implications for both unrated economies and countries exposed to acute physical climate risks. For unrated economies, the synthetic rating framework shows that many low-income and climate-vulnerable countries would experience rating trajectories broadly consistent with their development levels, but also significantly more sensitive to climate-induced income losses than the rated sample. When natural disaster risks are incorporated, these vulnerabilities become more pronounced. Using AAL estimates within the DIGNAD model, we find that recurrent climate-related natural disasters can generate sizable and persistent GDP losses, which propagate through Q-CRAFT into higher debt burdens and weaker fiscal positions. As a result, several highly exposed emerging and developing economies face additional downgrades of 1–3 notches by 2050.

Our research is related to a growing literature concerned with climate-macroeconomic impacts (Mohaddes and Raissi, 2025; Kahn et al., 2021; Bilal and Känzig, 2024) as well as how climate change might affect sovereign debt (Klusak et al., 2023; Phan and Schwartzman, 2024; Cappiello et al., 2025; Andersen, 2025; Bernhofen et al., 2025; Bassa and Cont, 2025; Burke et al., 2025). Recent theoretical work by Bassa and Cont (2025) focuses on how their model's risk forecasts can be translated into rating agency style assessments, and Phan and Schwartzman (2024) shows how climate-related disasters can impact sovereign defaults. We contribute to this literature by exploiting cross-sectional variation in sovereigns' ratings histories to model expectations about how climate-induced macroeconomic conditions may influence future credit ratings. Our work is also connected to empirical work that investigates the role of climate change in outcomes for sovereign risk. Credit Ratings Agencies (CRAs) are paying greater attention to physical climate risks and their role in a sovereign's ability to repay debt (Cappiello et al., 2025). We argue that because climate change inevitably slows growth and inflates debt, the specific attention CRAs pay to Environmental, Social, and Governance (ESG) scores may be secondary to these primary macroeconomic effects.

2 Methodology

This section describes how our modeling chain comes together to establish climate-adjusted sovereign credit ratings, while accounting for fiscal feedback loops and an updated set of climate change-macroeconomic assessments aligned with the latest IPCC scenarios and the IMF's Q-CRAFT framework.

2.1 Q-CRAFT

The Quantitative Climate Risk Assessment Fiscal Tool (Q-CRAFT) is an Excel-based modeling framework developed by the IMF's Fiscal Affairs Department to quantify the long-term macro-fiscal risks posed by climate change (Tim and Rahman, 2024). It projects key macroeconomic and fiscal aggregates (such

[1] These numbers are obtained from the tails of the Monte Carlo estimates on an analysis of the rating changes and increases in borrowing costs for the G20 countries. SSP-RCP refers to the integrated framework of Shared Socioeconomic Pathways (SSPs) and Representative Concentration Pathways (RCPs). SSPs describe societal futures (population, economy, technology), while RCPs detail GHG concentrations and levels of warming by 2100.

as GDP, primary balance, interest payments, and debt-to-GDP ratios) under alternative climate scenarios through the end of the century. It allows users to explore a range of assumptions regarding global mitigation efforts, adaptation speed, demographic trends, productivity growth, and inflation dynamics. Q-CRAFT can also integrate discrete shocks, such as natural disasters, and assess their implications for fiscal sustainability. Specifically, Q-CRAFT consists of three main blocks:

1. Baseline Macro-Fiscal Framework

   - The baseline scenario is constructed using a production function approach combined with a standard debt dynamics equation:

     $$Debt(t) = Debt(t-1) + PrimaryDeficit(t) + (r(t) - g(t))Debt(t-1)$$

     where r(t) is the effective interest rate and g(t) is real GDP growth.
   - Inputs include demographic projections, productivity growth assumptions, and inflation dynamics. These can be calibrated using national data or IMF's World Economic Outlook.

2. Climate Scenario Impacts

   - Q-CRAFT applies temperature-driven growth shocks to the baseline, based on income loss estimates from Kahn et al. (2021) and Mohaddes and Raissi (2025).
   - Users can select among five climate scenarios, ranging from Paris-aligned mitigation to high-emissions pathways, and adjust adaptation parameters to reflect policy responses.
   - The tool computes the resulting deviations in GDP, revenues, and expenditures, propagating them through the debt dynamics equation.

3. Fiscal Risk Quantification

   - Outputs include time paths for GDP, fiscal balance, and debt-to-GDP ratios under each scenario.
   - Results can be summarized in fan charts or scenario tables for integration into Fiscal Risk Statements and Debt Sustainability Assessments (DSAs).

We rely on the following scenarios: 'Paris' (SSP1-2.6), associated with 1.8°C global warming by 2100. 'Moderate'(SSP2-4.5), associated with 2.7°C global warming by 2100, reflecting current implementation of global mitigation policies. 'High' and 'Hot' are both SSP3-7.0 scenarios, but the latter uses the 90^{th} percentile of temperature increases among all climate models that use SSP3-7.0. These two scenarios are associated with 3.6°C to 4.4°C global warming by 2100. We also consider two additional scenarios which have in-built adaptation assumptions on the 'hot' scenario. 'Hot adapted' has the same temperature increases, but countries adapt to it more quickly (in 20 years). Similarly, 'hot unadapted' has countries responding to climate change more slowly (in 50 years).

This paper relies on various measures from Q-CRAFT to act as inputs into the sovereign credit rating framework described in the following section.

2.2 Sovereign Credit Ratings Emulator

Sovereign credit ratings are expressed on an ordinal scale, representing the ability and willingness of a sovereign to repay public debt. Empirically, these categories have stable correlations with default probabilities and credit spreads, highlighting their usefulness to markets (S&P Global Ratings, 2024). This section outlines the process by which we construct a model for predicting ratings.

Following Klusak et al. (2023), and in contrast to theoretical frameworks such as Bassa and Cont (2025), we adopt an empirical approach centered on a machine learning methodology optimized for predictive accuracy. Our work is informed by a growing body of literature applying non-parametric techniques to credit risk (Markellos et al., 2016; De Moor et al., 2018), as well as research linking these methods to sovereign ratings and environmental change (Burke et al., 2025; Klusak et al., 2023; Holden et al., 2024; Bernhofen et al., 2025; Agarwala et al., 2022). This approach offers two advantages. First, it mirrors Credit Rating Agencies' practices by emulating their output through observed data. Thus, our non-parametric model captures the relationship between macroeconomic outcomes and rating assessments without imposing a predetermined functional form. Second, by focusing on credit ratings rather than default risks (Phan and Schwartzman, 2024), we gain a granular understanding of a sovereign's shifting capacity to access commercial debt-a metric more sensitive to slow-moving temperature increases.

We develop a predictive model that links key macro-fiscal variables to sovereign credit ratings. We utilize Standard & Poor's sovereign ratings as our dependent variable, mapped onto a standard 20-notch numerical scale.[2] Unlike Environmental, Social, and Governance (ESG) scores, credit ratings show high inter-provider correlation (Berg et al., 2022), offering a more consistent benchmark for analysis. Our independent variables consist of a suite of macro-fiscal indicators that are frequently cited in rating actions by CRAs as fundamentals (Cantor and Packer, 1996; Afonso et al., 2011). We recognize GDP per capita (PPP) as a key variable, given its well-documented and substantial influence on sovereign creditworthiness as communicated by CRAs (Klusak et al., 2023; Bassa and Cont, 2025).

Our predictive model is based on a Random Forest regression. Originally described by Breiman (2001), the algorithm constructs a forest of n independent decision trees, where each tree is trained on a bootstrap sample of the original data. To de-correlate the trees and prevent overfitting, the algorithm considers only a random subset of predictors at each node split. Each split is determined by identifying the variable and threshold that minimizes the Mean Squared Error (MSE). For instance, a node might split on log GDP per capita at a threshold of 10 to categorize entities by credit rating above 12/20 from those below. Our model is a combination of 2,000 decision trees and our estimates are based on the average outcomes of all trees. This process of averaging over a large number of models and randomisation in each tree, contributes towards a more robust, stable prediction than a single tree could achieve (Athey and Imbens, 2019). An illustrative specification of the model in this paper is as follows:

$$CR_i = GDPpc_{it} + \boldsymbol{X}_{it} + \mu_{it} \tag{1}$$

where CR represents the average sovereign credit rating, $GDPpc$ is log GDP per capita (PPP), $\boldsymbol{X}$ is the vector of control variables obtained from Q-CRAFT namely primary expenditure (%NGDP), interest expenditure (%NGDP), primary balance (%NGDP), overall balance (%NGDP) and Debt to GDP(%). The focus of this model is to estimate the sovereign rating by exploiting the between-country variation in rating assignment and macro-fiscal conditions. We avoid introducing within-country variation on the dependent variable by relying only on the average ratings for each country from 2020.[3] We pursue this approach for two reasons. First, our aim is to understand how fundamental changes in a country's macro-fiscal conditions driven by climate change alter its long-term creditworthiness. Within-country variation (the focus of traditional fixed-effects models) is often too narrow to capture these changes. While a fixed-effects framework would find this specification infeasible due to the lack of within-unit variance, the Random Forest algorithm allows us to estimate the model successfully. Second, a descriptive analysis of

[2]This scale is represented in Table 5. The empirical literature on sovereign credit ratings often relies on either a 20-notch, or much larger scale which accounts for more incremental changes to a sovereign's creditworthiness (e.g. changes to a country's 'outlook' status) (Klusak et al., 2024). This approach does not offer any additional insight into our model for two reasons. First, we apply a regression technique, rather than a categorical assessment, so we estimate continuous rating outcomes anyway. Second, this may reduce our predictive accuracy since it may appear as though there are bigger gaps in our data simply by spreading the same number of observations across a larger scale.

[3]This number will be the credit rating for country i from 2020. Where countries have been assigned different ratings in this period, we obtain the average of those ratings.

the ratings data reveals that within-country variation is often very limited. Descriptive analysis confirms that sovereign ratings are remarkably "sticky." Of the 149 sovereigns assessed since 1941, 11% have never seen a rating change, and 34% have moved by two notches or fewer over their entire history. Even in a more contemporary period (2020–2025), 80% of countries that experienced a rating action remained within a narrow 2-notch band (69 countries out of 86 with a ratings change). By averaging ratings, we mitigate short-term "noise" and focus the model on the structural determinants of credit risk.

Note that the variables on the right hand side of the regression are still allowed to vary over time within-country. Whilst our data and modelling approach is still quite similar to the work of Klusak et al. (2023), our means of estimating the model varies. Klusak et al. (2023) estimate one Random Forest regression for the period 2015-2020, after which they adjust the levels of macro-fiscal variables to reflect the climate-induced changes in GDP given by Kahn et al. (2021). In contrast, our framework employs a dynamic rolling estimation of the Random Forest model. We leverage the Q-CRAFT's baseline scenario (with no climate impacts) as an evolving benchmark. In this baseline, economies are assumed to maintain their prevailing sovereign ratings. Using this assumption, we estimate the Random Forest regression on baseline macro-fiscal data over an initial six-year window (2030–2035). The resulting "baseline model" (trained on 2030–2035 data) is then used to simulate sovereign credit ratings for the last year (2035) under each of the IPCC climate scenarios. Next, we shift the estimation window forward by one year (re-training the Random Forest model on the baseline data for 2031–2036) and use this updated model to project ratings for 2036. We repeat this procedure iteratively up to the year 2100. This rolling estimation approach ensures that each year's prediction is anchored in a climate-neutral condition, allowing the baseline to evolve over time in line with macro-fiscal trends in the Q-CRAFT. By continuously recalibrating the rating model as new baseline data become available, we capture time-varying relationships and mitigate the risk of model drift. While this strategy is more computationally intensive than a one-off estimation, it aligns with the forward-looking nature of our analysis and mirrors how rating agencies update their assessments as economic conditions change. Moreover, integration with the Q-CRAFT framework makes this feasible: the internally consistent baseline projections from Q-CRAFT provide a reliable moving target for re-estimation. The result is a dynamically updated credit rating simulator that reflects both the absolute macro-fiscal changes and the relative cross-country dynamics at each step, thereby improving the policy relevance of our climate-risk assessments.

2.3 Model Accuracy

We validate the predictive accuracy of the model using out-of-sample tests. Specifically, we conduct a back-testing exercise on the initial baseline (2030–2035). The full dataset of sovereign observations from this six-year window is randomly divided into a training set (e.g. 70% of observations) and a testing set (the remaining 30%). We train the Random Forest on the training subset, then use the fitted model to predict credit ratings for the held-out observations in the testing subset. By comparing these predictions against the actual S&P ratings in the baseline data, we can gauge the model's out-of-sample accuracy. We repeat this procedure using several train-test splits (e.g. 80/20, 70/30, 60/40) to ensure robustness.

Table 1 presents the model's predictive accuracy-defined as the percentage of ratings correctly predicted within a three-notch margin-across three increasingly restrictive configurations (Panels A through C). We show that while the model captures nearly all ratings within a three-notch threshold, it achieves an exact 'hit rate' for approximately half of the sample.

2.4 From Rating Actions to Borrowing Costs

Debt crises often result in non-linear increases in bond spreads as initial macroeconomic shocks are compounded by endogenous feedback (Gibson et al., 2017; Delatte et al., 2014). This process is frequently self-reinforcing: a downgrade can worsen the very economic conditions that triggered it, leading to a

Table 1: Numerical Values for ± Notches (up to ±3)

Notch	% Accurate	Notch	% Accurate
Panel A: 80% training sample			
±0	62.14	±2	97.57
±1	90.78	±3	100
Panel B: 70% training sample			
±0	57.56	±2	97.97
±1	91.28	±3	99.71
Panel C: 60% training sample			
±0	48.3	±2	96.12
±1	86.65	±3	98.54

This table reports the % accuracy of our model over different ratios of a training and testing sample. Panel A reveals the results of an 80:20 sample, Panel B a 70:30 sample and Panel C a 60:40 sample. These are reported when rounding our results to full notches.

cascade of further rating actions (Manso, 2013). The relationship between rating changes and market spreads is also non-uniform as it is strongly moderated by the issuer's existing rating level (Aizenman et al., 2013). Consequently, the impact on borrowing costs depends as much on an issuer's starting position on the 20-notch scale as it does on the severity of the climate or economic shock itself.

Rather than estimating causal effects, we focus on mapping the simulated rating changes to spread movements, agnostic of the specific transmission channels. Previous studies have often utilized a 'constant returns to downgrades' approach (Klusak et al., 2023), which may fail to capture the well-documented non-linearities in the rating-spread relationship (Agarwala et al., 2022). To address this, we adopt the parameters estimated by Aizenman et al. (2013) to establish changes in spreads. Specifically, we utilize their model of Credit Default Swap (CDS) spreads as a proxy for the risk premium. This is theoretically sound, as the CDS spread represents the basis between the risk-free rate and the sovereign bond yield; an investor holding a covered CDS effectively sees their return neutralized to the risk-free rate. This methodology offers three distinct advantages. First, it obviates the need for prior assumptions regarding baseline risk-free rates or absolute market risk levels. Second, it reflects realistic market dynamics- acknowledging that a transition from AAA to AA+ is significantly less consequential than a shift from BBB- to BB+, which crosses the critical investment-grade threshold. Third, unlike alternative non-linear models that may rely on overly aggregated data (see Burke et al. (2025) and Agarwala et al. (2022) for examples), the parameters estimated by Aizenman et al. (2013) are more granular. The resulting expression is as follows:

$$\Delta CDS_{it} = -282.51\Delta CR_{it} + 14.23(\Delta CR * RatingLevel)_{it} \tag{2}$$

We utilize this relation to quantify the shifting cost of debt across different rating thresholds. To illustrate the non-linearity of the model, consider a 1-notch downgrade from AA+ (19) to AA (18). Under our specification, this transition results in a modest spread increase of 12 basis points ($= 282.51 + (14.23 \times -19)$). In contrast, a downgrade of the same magnitude at a lower credit level-moving from BBB (12) to BBB- (11)- precipitates a significantly sharper increase of approximately 125 basis points.

3 Results

We begin by evaluating the impact of climate change under various IPCC scenarios on credit ratings through 2100 for 125 countries.[4] Figure 1 shows the distribution of these ratings changes. Notably, while mean ratings remain relatively stable across scenarios, there is a compression in the upper quartile and overall range as global warming intensifies. A key finding is the small ratings-variance observed between

[4]This is the sample of countries who already have a history of credit rating assessment with S&P

the Paris-aligned, Moderate, High, and even "Hot Adapted" scenarios. Moving from SSP1-2.6 to SSP3-7.0 has minimal impact on ratings, even at the 90^{th} percentile of SSP3-7.0, provided global economies adapt rapidly to a warming climate. Significant downgrades only materialize when incorporating the slower adaptation assumptions of Mohaddes and Raissi (2025). We also show the distributions for the years 2035 (Figure 7) and 2050 (Figure 8). It is perhaps most striking that the difference in ratings across scenarios only begins to materialise in 2050, again, for the more 'slow to adapt' scenarios.

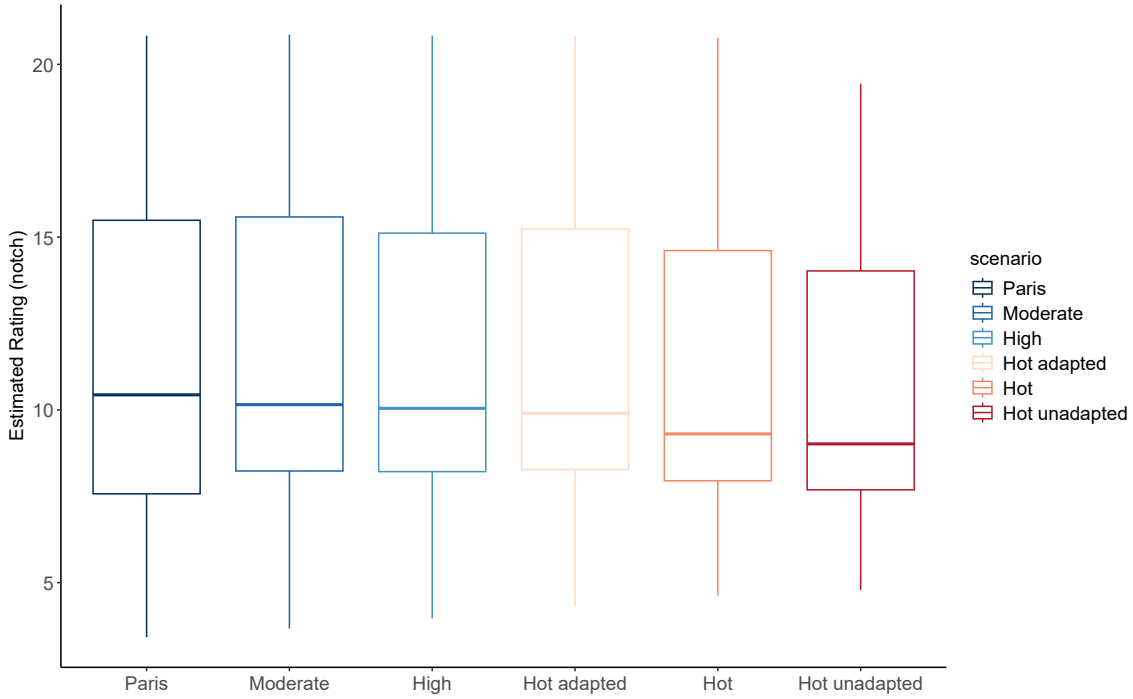


Figure 1: Global rating distributions by scenario (2100)

Table 2 details the average changes in ratings (Panel A) and borrowing costs (Panel B) by year and scenario for the G20 countries. Our findings indicate that rating adjustments remain negligible through 2035, beginning to materialize by 2050 and nearly doubling in magnitude by the end of the century across most high-emissions pathways. We corroborate the results of Klusak et al. (2023), finding that sovereign downgrades are largely avoided under a Paris Agreement-aligned scenario. In Panel B, we translate these credit changes into increases in borrowing costs (expressed in basis points) using Equation (2). Under a 90th percentile unadapted SSP3-7.0 scenario, the average downgrade escalates from 1.2 notches to nearly 3 notches by 2100. Consequently, average borrowing costs rise from 19 to 30 basis points. To account for the non-linearities inherent in Equation (2), we report median estimates. This approach mitigates the influence of outliers (e.g., lower-rated countries where marginal, poorly predicted upgrades result in disproportionately large reductions in the cost of debt).

We further examine how adaptation measures affect global credit rating trajectories. Figure 2 shows the p-values on a test of significance that the observed rating changes are statistically different from zero across countries. We show that by century-end only rating changes observed from the 'Hot' and 'Hot unadapted' scenario are statistically distinguishable. These results highlight the mitigating effect of the adaptation mechanisms embedded in Mohaddes and Raissi (2025) and Kahn et al. (2021). The rate

Table 2: Summary of Results for the G20

Panel A: Rating Changes (notches)				
Scenario	2035	2050	2070	2100
Paris	0	-0.03	-0.09	-0.33
Moderate	0	-0.16***	-0.29	-0.62**
High	-0.05	-0.46***	-0.64	-1.28**
Hot adapted	-0.02	-0.41***	-0.55	-1.32**
Hot	-0.14	-0.74***	-0.98	-2.03***
Hot unadapted	-0.38**	-1.2***	-1.63**	-2.75***
Panel B: Borrowing Cost Changes (basis points)				
Scenario	2035	2050	2070	2100
Paris	0.00	0.00	-0.00	-1.33
Moderate	-0.03	0.86	1.79	-1.16
High	-0.71	3.68	3.95	3.93
Hot adapted	-0.89	3.77	3.49	5.01
Hot	-0.30	6.70	7.75	26.25
Hot unadapted	4.24	18.95	18.35	29.40

This table reports the results from our model for the G20 countries. We show these results as averages for each scenario against 2035, 2050, 2070 and 2100 Panel A provides an indication of the level of statistical significance of these rating changes from zero with *** = 0.01, ** = 0.05 and * = 0.1. Borrowing cost changes (measured in basis points) in Panel B are calculated using the formula and parameters in Equation 2.

of climate shock absorption serves as a buffer for sovereign creditworthiness; higher adaptive capacity minimizes income losses, thereby preserving fiscal stability and credit ratings.

3.1 Monte Carlo Analysis

Although the Random Forest model uses predictions from 2,000 decision trees to produce a mean estimate, focusing solely on this average can obscure significant tail risks. As noted by Weitzman (2011) and Zenios (2022), climate damage assessments must account for the entire range of possible outcomes, not just the most likely impact. This concern is increasingly echoed by both practitioners (Trust et al., 2024) and academics (Ranger et al., 2023). To address this, we implement a Monte Carlo simulation over our machine learning framework. We train 10,000 unique Random Forest models, each consisting of 2,000 trees, to generate a robust predictive distribution of ratings impacts for the G20 economies.

Figure 3 illustrates the distribution of century-end outcomes by country and scenario. To facilitate a cross-country comparison of uncertainty, we mean-center the estimates at zero. This visualization reveals significant intra-scenario variation across G20 countries, suggesting that certain sovereigns are more sensitive to the models' random variation. This dispersion may stem from two primary sources. First, high variance in a country's historical predictors (such as rapid debt accumulation or GDP growth within the $[t, t-5]$ observation window) can lead to unstable predictions when the Random Forest subsamples the data. Second, high dispersion for specific countries, notably Argentina, Australia, and China, may indicate that their S&P ratings are also influenced by exogenous or "subjective" factors not fully captured by our model's information set (De Moor et al., 2018). In contrast, Turkey, South Africa, and South Korea exhibit the highest degree of model consensus. A clearer pattern emerges across climate scenarios: as we move from SSP1-2.6 to the unadapted 90^{th} percentile SSP3-7.0, the distributions flatten and the uncertainty range expands. This finding confirms that higher temperatures do not merely shift outcomes toward more severe downgrades; they increase the variance of those outcomes as well. The country-level heterogeneity on the x-axis shows that the "climate-induced uncertainty" is not distributed equally, presenting a heightened risk for some sovereigns.

In Table 3, we report the tail outcomes from the Monte Carlo analysis. We focus on the 90^{th} percentile of downgrades and increases in debt costs across various scenarios and the years 2035, 2050, 2070, and 2100. These results indicate that, in worst-case scenarios, an approximate doubling of rating

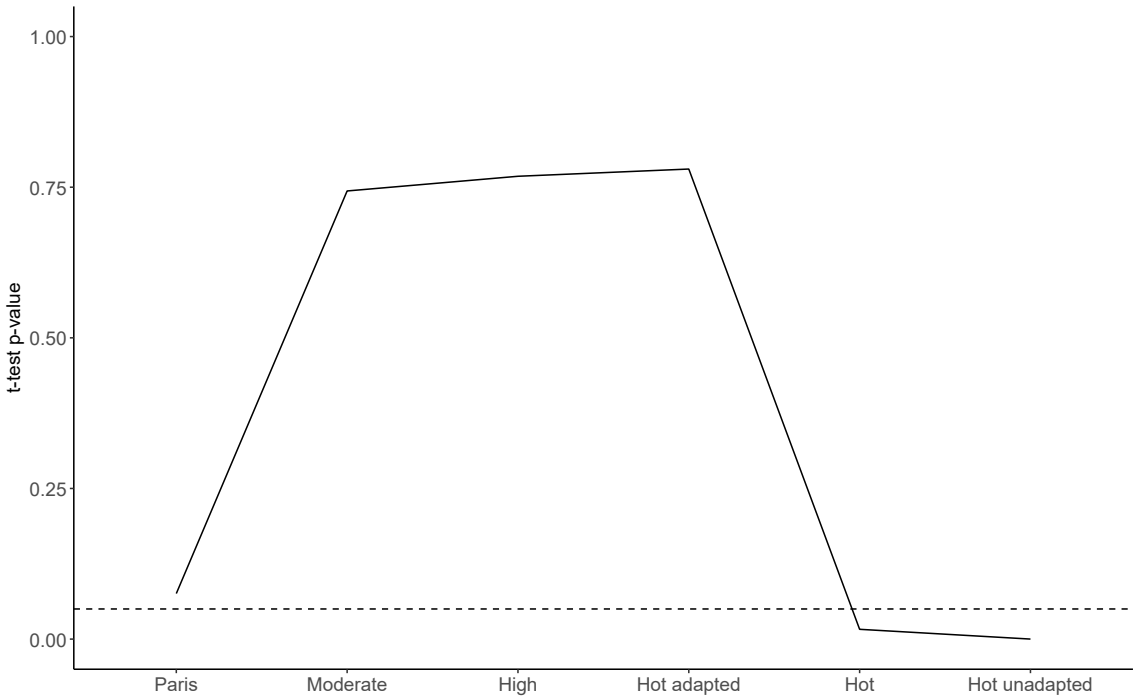


Figure 2: Testing the statistical significance of the rating changes by scenario (2100)

Table 3: Monte Carlo for the G20

Panel A: 90^{th}pc Rating Changes (notches)				
Scenario	2035	2050	2070	2100
Paris	-0.02	-0.23	-0.54	-1.37
Moderate	-0.10	-0.42	-1.67	-2.86
High	-0.43	-1.37	-3.36	-3.96
Hot adapted	-0.25	-1.20	-2.73	-3.46
Hot	-0.62	-2.07	-3.69	-4.70
Hot unadapted	-1.37	-2.77	-4.37	-6.11
Panel B: 90^{th}pc Borrowing Cost Changes (basis points)				
Scenario	2035	2050	2070	2100
Paris	2.26	11.42	24.06	115.77
Moderate	5.88	45.24	96.46	190.44
High	23.64	127.06	253.75	305.13
Hot adapted	17.06	101.77	232.99	312.82
Hot	51.09	159.48	335.14	464.29
Hot unadapted	88.78	219.47	373.56	469.01

This table reports the results from our Monte Carlo analysis for the G20 countries. Panel A provides shows the 90^{th} percentile change in downgrades and Panel B shows the corresponding borrowing cost changes (measured in basis points).

downgrades can increase borrowing costs by at least tenfold, highlighting the pronounced non-linearities and the expanded uncertainty that emerge in higher-emission, slower-adaptation scenarios.

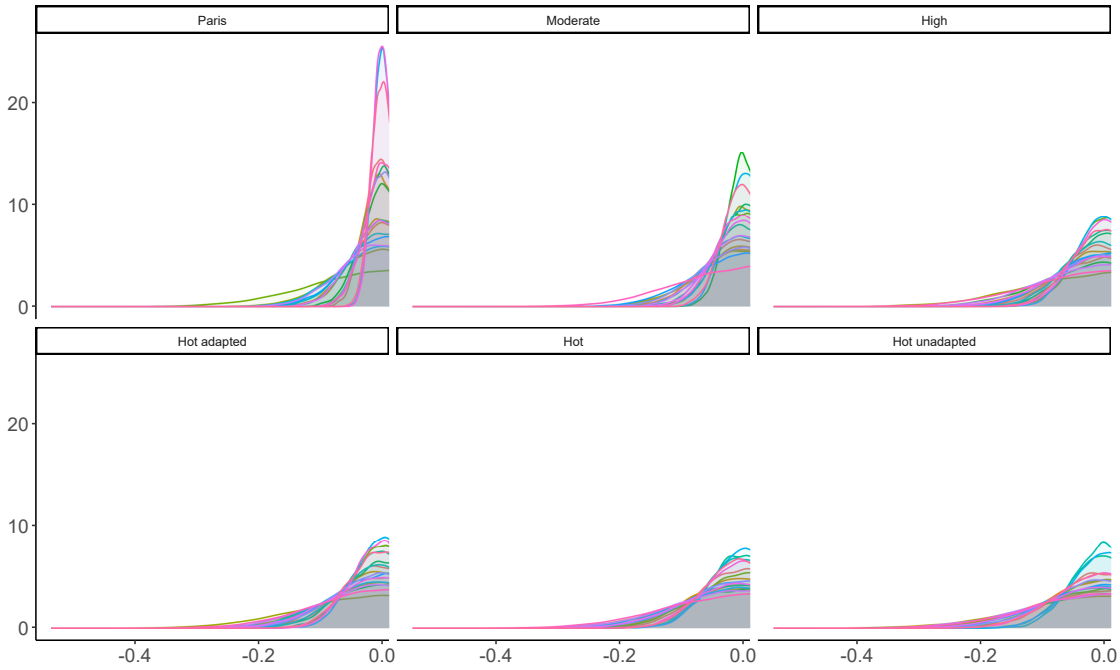


Figure 3: 2100 Monte Carlo Analysis by Scenario for the G20

3.2 What is driving the changes in credit risk?

To illustrate the mechanics of our Random Forest regressions and the drivers of our sovereign rating projections, we conduct a variable importance analysis. Following the methodology of Athey and Imbens (2019), we check what happens to the model's mean square error if we randomly impute values for different variables. As illustrated in Figure 4, GDP per capita emerges as the dominant macroeconomic determinant of credit ratings. While our baseline model achieves a Root Mean Squared Error (RMSE) of approximately 1.07 notches, the random imputation of GDP per capita increases this error by 5.7 notches. The other variables in the model range between 1 and 2.5 notches in their importance. These results confirm that while sovereign ratings are multi-dimensional, they remain fundamentally anchored to a nation's position on the income ladder.

A further way to understand the inner workings of a Random Forest model is through *ceteris paribus* (CP) profiles. These profiles illustrate the partial relationship between a specific feature and the predicted rating while holding all other variables constant. While conceptually similar to regression coefficients, CP profiles offer a more nuanced view: whereas a least-squares coefficient assumes a uniform global effect, the Random Forest captures local effects that vary depending on the specific combination of a country's other macroeconomic features. Instead of a single summary statistic, the CP profile generates a functional curve. Figure 5 visualizes these profiles for individual countries, specifically highlighting the relationship between GDP per capita and credit ratings. In this analysis, Argentina and China (indicated by black lines at the bottom and top, respectively) demonstrate distinct sensitivities. China's profile appears notably "flatter" than Argentina's, suggesting that because China performs well across a wider range of macroeconomic dimensions, its rating is less sensitive to marginal fluctuations in GDP per capita alone. This finding aligns with the cross-country sensitivity analysis in Klusak et al. (2023).

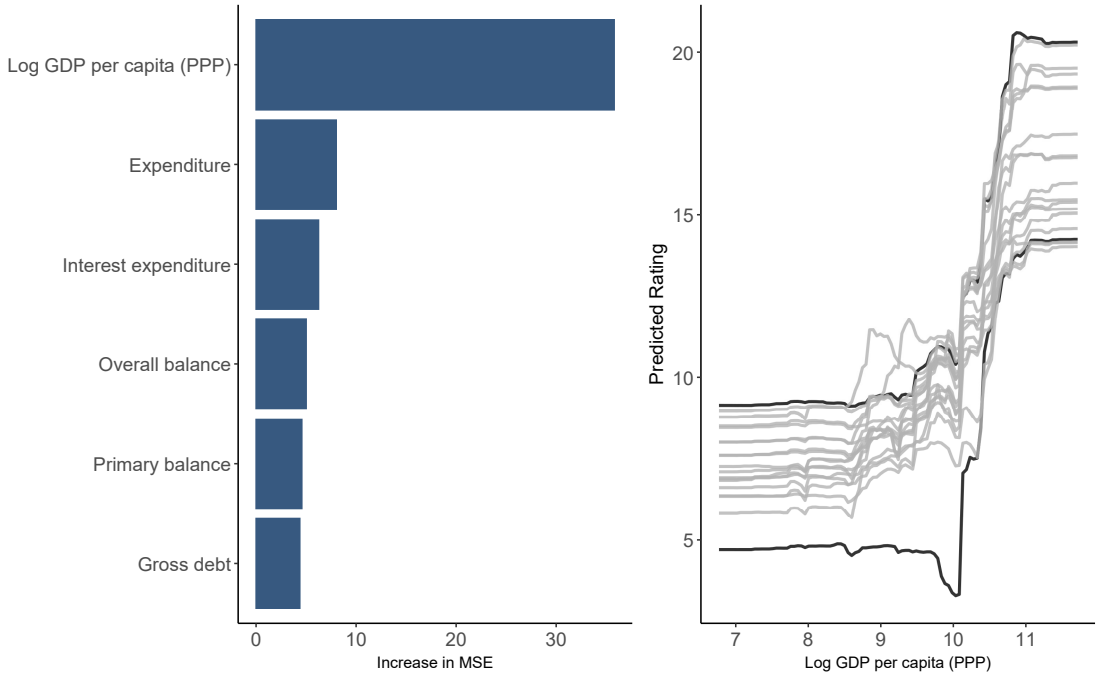


Figure 4: Determinants of Credit Ratings Changes

4 Extended Sample

Previous research on climate-driven sovereign risk has largely been constrained to economies with formal credit ratings from major CRAs (Klusak et al., 2023). This selection criterion creates a substantial void in our understanding of climate impacts on unrated nations. A lack of rating is often a proxy for lower levels of development and limited adaptive capacity. By excluding these nations, a significant "blind spot" remains regarding the global distribution of climate risk. In this section, we address this systemic gap by extending our analysis to a global scale. We generate "synthetic" baseline ratings for all previously unrated economies using historical data from the Q-CRAFT and supplemental sources. This expanded dataset allows for a more equitable assessment of climate vulnerability across the full spectrum of global development. This exercise enables us to extend our analysis to 160 countries.

The focus of this section is to obtain an accurate prediction of the credit rating for unrated economies. Because these synthetic ratings serve as benchmarks for climate scenario extensions, we are not bound by the restrictions of the ratings model in Equation (1). Therefore, we augment our macro-fiscal variables from the Q-CRAFT with a qualitative proxy for geopolitics and institutions inherent in CRA assessments. We introduce the World Bank's *Rule of Law* index as a primary feature. This addition is grounded in the findings of De Moor et al. (2018), who demonstrate that institutional quality is a decisive factor in sovereign creditworthiness, particularly in jurisdictions where traditional fiscal data may not fully capture governance risks.

Validating predictions for unrated economies is challenging, as "true" ratings do not exist for comparison. To circumvent this, we employ an experimental validation framework based on synthetic missingness. First, we take our existing data for countries that receive ratings from S&P. We then randomly impute missingness for a subsample of countries. At this point, we can apply our model to estimate the

Table 4: Numerical Values for ± Notches (up to ±9)

Notch	% Accurate	Notch	% Accurate
±0	15.79	±5	94.74
±1	43.61	±6	96.24
±2	62.41	±7	97.74
±3	82.71	±8	99.25
±4	89.47	±9	99.25

This table reports the % accuracy of our model in the context of missing data. We estimate ratings for a random selection of countries (between 20% and 30%), up to 1,000 times. We then compute the country-level average predicted rating for each of these iterations and report the overall frequency of accuracy in notches in this table.

missing ratings that we can benchmark against the retained true value from S&P. Given that 35 out of 160 countries in our broader sample are unrated (a missingness ratio of approximately 22%), it is vital that our model maintains accuracy at this scale. To ensure our results are not an artifact of a single random split, we execute a Monte Carlo cross-validation with 1,000 iterations. In each run, we randomly impute missingness for 20% to 30% of the rated sample (approximately 25–38 countries). This iterative process allows us to generate a robust distribution of error metrics, ensuring our estimation technique remains reliable when extended to truly unrated economies.

Due to the iterative nature of our exercise, nearly every country in our sample is subjected to "missingness" across the 1,000 runs. Table 4 presents the aggregate performance metrics from this validation. Our model demonstrates strong predictive power, successfully recovering the hidden ratings within a two-notch margin approximately 62% of the time. It is important to distinguish these results from the statistics in Table 1. While the initial metrics relied on standard out-of-sample testing (removing individual observations), the exercise here employs a more stringent "out-of-country" validation. In this setup, an entire country's historical presence is removed from the training set, ensuring the model can generalize to sovereigns with no ratings. This rigorous test confirms the model's suitability for estimating ratings for truly unrated economies.

Figure 5 illustrates the country-level predictive accuracy across the credit spectrum. The observed patterns reflect a well-documented phenomenon in the machine learning literature: predictive performance often degrades at the boundaries of the covariate space (Athey and Imbens, 2019). Because the model has fewer observations to learn from at the extreme ends of the rating scale, its ability to generalize suffers from a lack of data support. However, these boundary effects do not significantly compromise the overall integrity of our global extension. The number of sovereigns with ratings below 5 (10) or above 16 (30) is relatively small. Consequently, while uncertainty is higher for the highest- and lowest-rated nations, the model remains highly robust for the vast majority of the global sample.

5 Climate-related Natural Disasters

Another gap in the literature concerns the fiscal implications of climate-related natural disasters. Specifically, there is limited evidence on how sovereign credit ratings and the cost of debt servicing evolve in response to acute physical risks. While recent guidance from major agencies indicates that disaster exposure is a material component of creditworthiness assessments (Fitch Ratings, 2022; Moody's Investors Service, 2017), quantifying this relationship remains challenging. Understanding these implications is essential for informing strategic decisions regarding the scale and timing of adaptation investments.

Bernhofen et al. (2025) make the first attempt to analyze how acute physical risks influence fiscal stability through a case study of Thailand. Their methodology utilizes a one-off flood risk and an adaptation framework grounded in probabilistic catastrophe modeling. Our research deviates from this approach

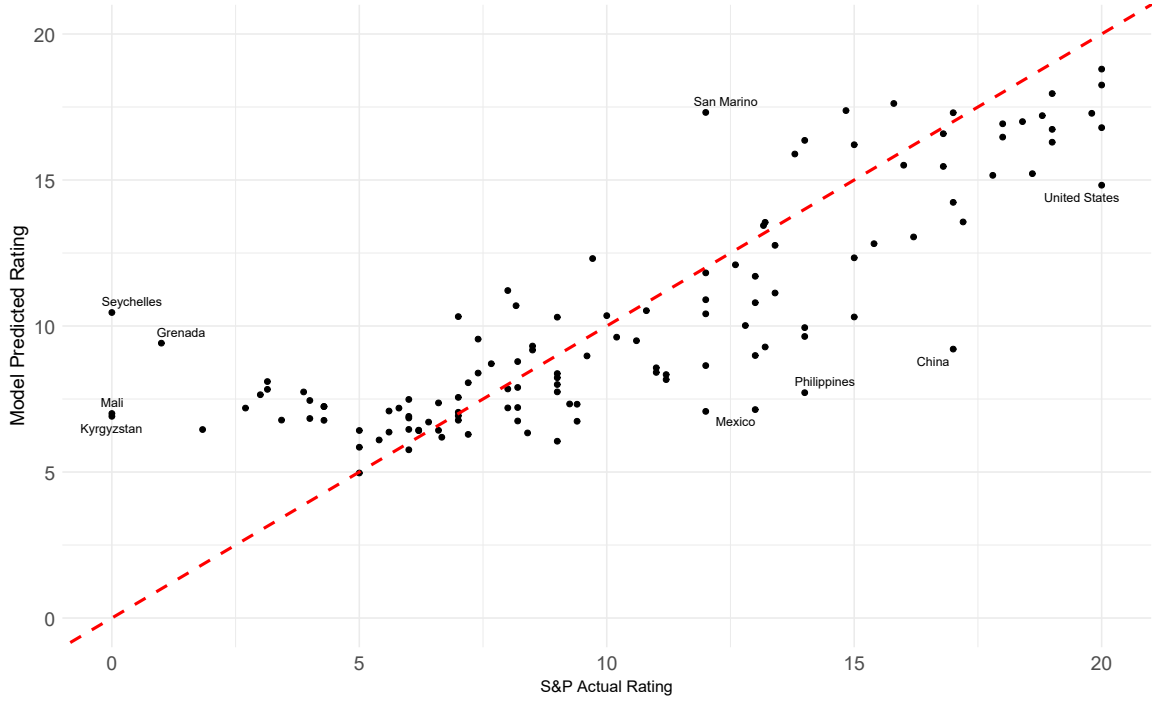


Figure 5: The observed S&P rating (x-axis) against those predicted by our model (y-axis)

in a number of ways. First, we focus on the expected value of capital losses in 30 countries[5] across all disaster types, each with different probabilities and intensities, using an Annual Average Loss (AAL) metric. The Coalition for Disaster Resilient Infrastructure (CDRI), which is an international coalition of countries, United Nations agencies, multilateral development banks, the private sector, and academic institutions, provides AAL estimates for many countries and enables a comprehensive assessment of disaster risk by capturing the full distribution of potential losses. In other words, while Bernhofen et al. (2025) focus on a point on the Loss Exceedance Curve (LEC), the AAL metric from the CDRI represents the integral of the LEC. Thus, it facilitates a risk-adjusted projection of macro-fiscal aggregates.

We obtain the annual GDP impact of these capital losses over a 30-year horizon through an updated version of the DIGNAD model, which has been adapted to simulate the effects of recurring climate-related natural disasters using AALs. Second, applying GDP loss estimates from recurrent natural disasters to the ratings model developed in Section 2 requires a different interpretation of the results than in Bernhofen et al. (2025). While their work isolates the immediate, transitory impact of an extreme "tail-risk" event using DIGNAD, our study focuses on translating the AALs to cumulative GDP reductions, reflecting how a longer term exposure to acute physical risks on average, may result in a lower credit rating. We continue to rely on the Q-CRAFT to generate disaster-adjusted debt trajectories, fiscal balances, and interest costs, which are then used to quantify sovereign ratings changes.

[5]We identify these 30 countries using data from EM-DAT (2000–2024) and AAL estimates from CDRI. Specifically, we retain countries in the top global quartile on at least one of three indicators: (i) average annual population affected (at least 1.64% of the population), provided they experience major disasters in at least 10 percent of years; (ii) modelled AAL from natural disasters exceeding 0.46% of the capital stock; or (iii) modelled AAL exceeding 1.69% of GDP. Taken together, these thresholds capture both the human exposure and the macro-financial relevance of disaster risk.

5.1 Results

Figure 6 shows the accumulated GDP losses (%) by 2050 on the x-axis and the rating change in notches on the y-axis. We also represent the accuracy of the model's initial ratings assessment for each country by the size of the dots, with larger ones representing higher accuracy.[6]

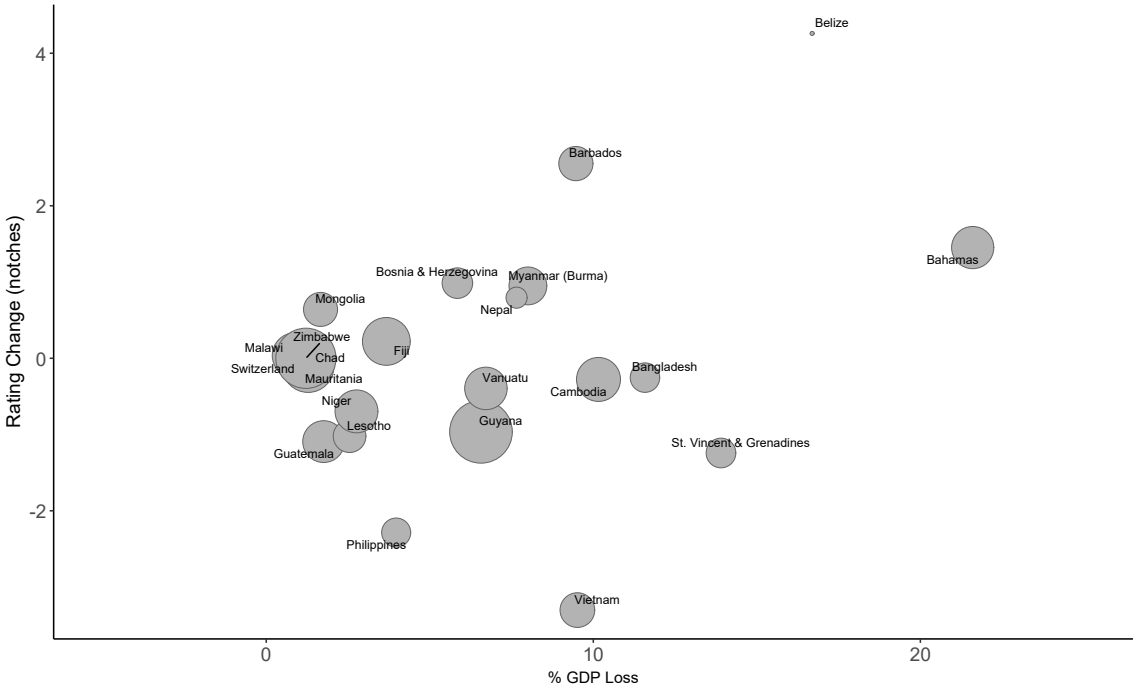


Figure 6: Disaster-induced GDP losses against rating downgrades (30-year horizon)

If we take the annual average losses, and simulate their GDP impacts through DIGNAD in addition to the effects of slow-moving temperature increases, we can measure the extent of further ratings changes. Our analysis reveals that the most vulnerable economies include Vietnam, Saint Vincent and the Grenadines, the Philippines, Guyana, and Guatemala. Each experiencing a downgrade between 1 and 3 notches. An important caveat to this analysis is that it is reasonable to assume that these countries' incomes (and ratings) are already low as a consequence of long-term exposure to natural disasters. As a result, this exercise may involve some degree of overlap.[7] An alternative interpretation is to view these results in reverse: they approximate the potential rating improvements that could occur if adaptation

[6] We calculate the accuracy by taking the absolute distance between our model's estimate in the baseline scenario against it's historical rating average. To have this represented where larger numbers indicate more accuracy we compute the ln reciprocal of that figure; $ln[\frac{1}{|CR_{his}-CR_{baseline}|}]$. The logarithmic transformation avoids making relatively small differences in accuracy, i.e. half a notch vs. 2 notches, looking incredibly large due to the reciprocal.

[7] The relationship between slow-moving climate shifts and extreme weather events is not merely one of cause and effect but a dynamic interplay where each can amplify the impacts of the other. For example, a warmer atmosphere holds more moisture, leading to heavier precipitation and more intense storms. Similarly, higher temperatures exacerbate the severity of heatwaves. Changes in global circulation patterns can lead to altered precipitation, exacerbating droughts in some regions while increasing flood risks in others. The gradual increase in sea levels contributes to more destructive storm surges during hurricanes and tropical cyclones, leading to increased coastal flooding. The IPCC AR6 Physical Science Report highlights a clear increase in frequency and intensity of extreme weather events as global average temperatures rise. Moreover, the report shows that the impacts of climate change on extreme weather events exhibit significant regional

efforts could fully offset future income losses. However, there are limits to adaptation benefits. At the macro level, Aligishiev et al. (2022) show that adaptation would not be able to reduce the expected damages from extreme weather events by more than half under current climate scenarios before the cost of investments outweigh their benefits. This is also corroborated by Kahn et al. (2021).

5.2 Discussion

Estimation of the impact of natural disasters on sovereign credit ratings faces several empirical challenges. Countries most exposed to disasters often already have lower incomes and poorer ratings. The mean (median) rating in this sub-sample is 8.4 (7.4). This empirical fact coincides with our methodology that improves in accuracy nearer the center of the covariate space (Athey and Imbens, 2019). This issue is also discussed in Section 4 and represented by Figure 5. At this end of the rating scale, countries have larger variance in their historical rating assignment over time, greater between-country differences in macroeconomic fundamentals, and a wider range of factors determining their rating where the *willingness* to repay debt is more of a concern in the rating assessment than is simply, the ability to repay.

We illustrate this issue with reference to our result in Figure 6 for Belize (captured in the top right quadrant of Figure 6). In late 2021, Belize received a much improved rating from Standard & Poor's by 4 notches from CC to B-, representing a drop in 10-year default probability from near 100% to approximately 58%. This upgrade was in part a recognition of the debt restructuring which came with an historic blue bond issuance.[8] However, S&P still refer to 'debt repayment culture' in their assessment. This significant variance in rating change, coinciding with a shock to fundamentals that cannot be truly reflected in a new rating because it coincides with other factors, introduces local noise on the macro-ratings curve. This is important for Random Forest estimation because the partial effect of one regressor is dependent upon the values of other regressors, i.e estimates are locally determined rather than through the parameters estimated in a global average effects model. These are important considerations for interpreting our results in Figure 6 and why we reduce the visual significance of countries like Belize, Nepal and Bosnia & Herzegovina.

6 Conclusions

We made several contributions to the literature and reported a range of results on the impacts of climate change, both acute and chronic, on countries' ability to service debt. First, we utilized results from one of the most recent climate-macroeconomic estimates under the latest IPCC climate scenarios, namely Mohaddes and Raissi (2025). Second, we improved upon the work by Klusak et al. (2023) by fully integrating the methodology within the IMF's macro-fiscal framework, Q-CRAFT. This enables us to fully capture the fiscal feedback loop involved in how climate-induced GDP losses propagate into public debt dynamics. Third, we discussed how our results have implications for adaptation policies and heterogeneous effects across countries. Our results show that the greatest losses are felt in a scenario consistent with 90^{th} percentile of SSP3-7.0 scenario, with extremely-slow adaptation. We argued that when economies adapt much more quickly to this same climate scenario, the impact on credit rating outcomes become negligible. We extended our approach to countries not yet in receipt of ratings from Standard & Poor's and evaluated the uncertainty space through a Monte Carlo analysis. Finally, we also integrated our model with natural disaster data from CDRI and a modified version of DIGNAD to evaluate the impact of acute physical risks. These results show that for countries prone to disaster-induced GDP losses, rating downgrades could increase by 1 to 3 notches within the next 30 years.

variability, with some areas more prone to specific types of events than others. In this paper, while the annual average losses are constructed under unchanged climate conditions, these are unlikely reflected in baseline Q-CRAFT projections.

[8] This is documented both by S&P and The Nature Conservancy

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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	

This table shows the S&P sovereign credit rating scale. In this study, when we make reference to notch changes in a rating, we refer to this scale.

A Global Rating Distributions for 2035 and 2050

Figures 7 and 8 replicate the global rating distributions across scenarios for 2035 and 2050, respectively. In 2035, the box plots reveal very limited dispersion across climate pathways: medians and interquartile ranges are nearly indistinguishable, suggesting that early in the horizon climate-induced income losses have not yet translated into material differences in sovereign credit ratings. By 2050, however, divergence becomes more apparent, particularly in the High, Hot adapted and Hot unadapted scenarios, where the upper tail compresses and the lower tail extends, indicating a gradual erosion of credit quality for more exposed sovereigns. The Paris-aligned and Moderate scenarios continue to display tightly clustered distributions with negligible shifts, underscoring that meaningful rating impacts only begin to emerge in the more severe, slower-to-adapt climate pathways by mid-century.

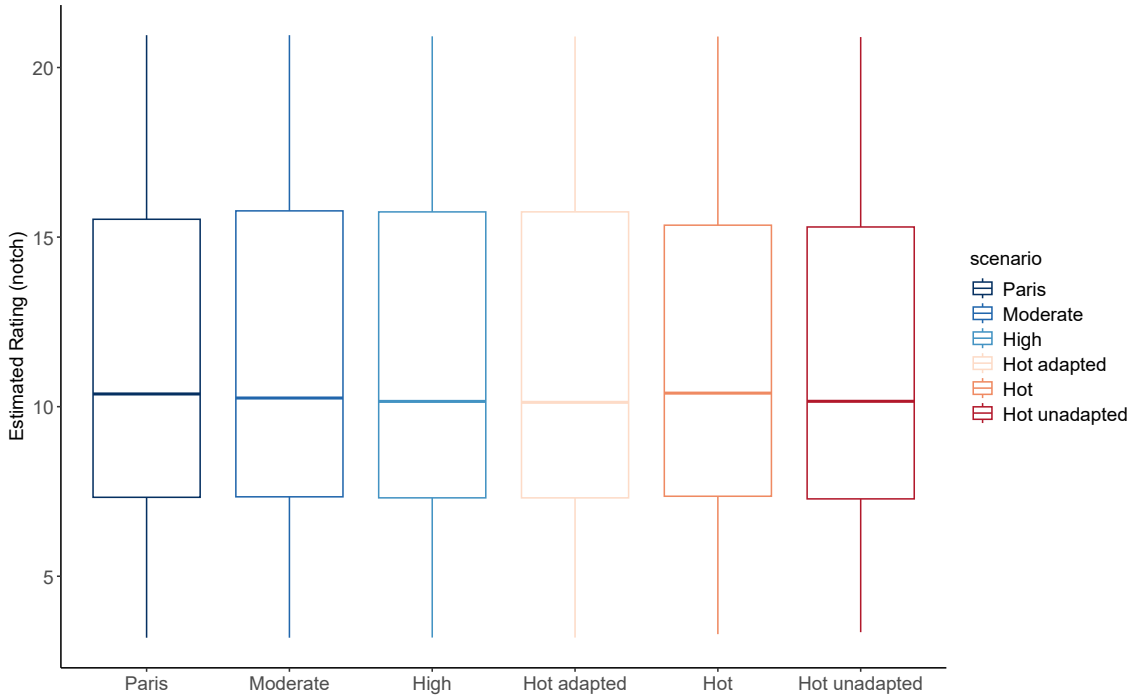


Figure 7: Global rating distributions by scenario (2035)

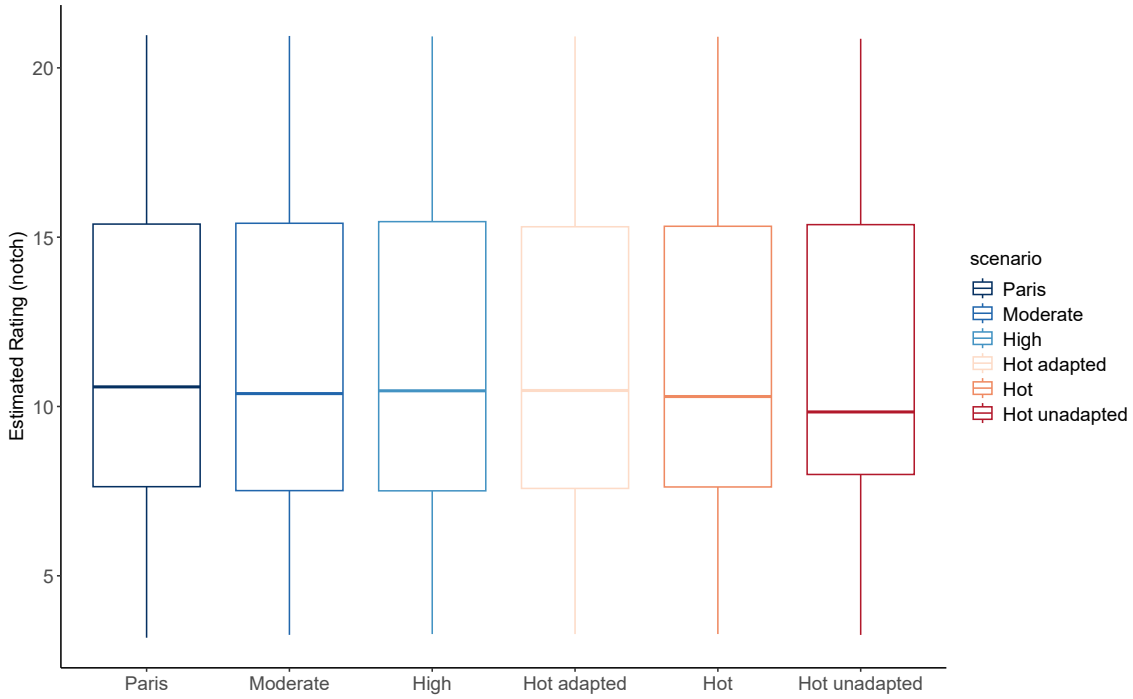


Figure 8: Global rating distributions by scenario (2050)