The debt burden of tropical cyclones and climate change

June Choi[1,*], Renzhi Jing[2,3], Christopher W. Callahan[1,4],
Marshall Burke[1,5,6], Noah S. Diffenbaugh[1,2]

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Abstract

Addressing climate change, through both mitigation and adaptation, is anticipated to require global investments of more than $6 trillion annually by 2035. However, many countries face significant barriers to accessing the finance needed for these investments, due to low or absent credit ratings, large debt burdens, and high borrowing costs. There is concern that climate change, through its economic impacts, may amplify these barriers, potentially locking countries into a "vicious cycle" in which mounting economic losses further constrain countries' capacity to invest in adaptation and mitigation. We provide evidence that the cost and availability of capital for many countries have already been shaped by their historical exposure to tropical cyclones (TCs) and warming temperatures. Our empirically derived estimates suggest that, across all TC-exposed countries, debt-to-GDP ratios are on average 30% higher due to the cumulative effects of TCs since 1990. GDP levels are on average 10% lower due to the combined impacts of TCs and warming temperatures across all countries. We estimate that because of these impacts, hotter countries are more likely to receive credit ratings below investment grade (< BBB–), and borrowing costs are at least 1 basis point (0.01%) higher in 28 countries and 5 basis points higher in highly-exposed countries. Future increases in temperature and TC activity will likely worsen countries' credit, potentially undermining both countries' abilities to address climate change and their long-run development prospects.

*junechoi@stanford.edu; 1. Doerr School of Sustainability, Stanford University; 2. Woods Institute for the Environment; 3. Stanford School of Medicine; 4. O'Neill School of Public & Environmental Affairs, Indiana University 5. Center on Food Security and the Environment; 6. National Bureau of Economic Research

1 Introduction

Efforts to reduce greenhouse gas emissions and adapt to the impacts of climate change are estimated to require global investments of more than US$6 trillion annually by 2035 (Bhattacharya et al. (2024)). Among emerging markets and developing countries (EMDCs), excluding China, estimated investment needs are US$2.4 trillion by 2030—more than ten times the climate finance that these countries currently receive (Climate Policy Initiative (2025)). While increasing financial support to developing countries has been a key priority in global climate negotiations since 2009 (UNFCCC. Conference of the Parties serving as the meeting of the Parties to the Paris Agreement (CMA) (2024)), the bulk of climate finance has remained concentrated in advanced economies while the rest of the world has received only a small share, and largely in the form of debt (Extended Data Fig. 1).

The large regional disparity in finance flows is not new (Lucas (1990)), but likely persists due to differences in the strength and quality of institutions, the maturity of financial markets, and other indicators of economic development which are ultimately reflected in sovereign credit ratings (United Nations, Inter-agency Task Force on Financing for Development (2022), Kowalewski et al. (2025)). Ratings issued by agencies such as Standard & Poor's, Moody's, and Fitch continue to play an influential role in shaping the lending decisions of global investors, despite concerns regarding the role of rating agencies in contributing to the global financial crisis in 2009. Because sovereign ratings serve as ceilings for domestic economic actors, a downgrade at the sovereign level can significantly raise financing costs across the entire economy (Almeida et al. (2017)). Low-rated sovereigns face the difficult choice of borrowing from international capital markets and being exposed to currency risks, or borrowing from domestic markets at potentially higher rates at short-term maturities. On the other hand, countries without a credit rating are effectively locked out of international capital markets (fig. 1, United Nations, Inter-agency Task Force on Financing for Development (2022), UNCTAD (2024)). These constraints are compounded by high sovereign debt levels which are projected to reach 100% of global GDP by 2030 (International Monetary Fund (2024)). Among low-income countries, interest payments currently exceed their combined health and education spending and are estimated to contribute to net negative transfers to Multilateral Development Banks (MDBs) (G20 Independent Expert Group (2023)). Most of these countries have been in sovereign debt default over the past two decades (fig. S1, Beers et al. (2021)).

There is growing evidence that many of these countries also face substantial macroeconomic risk from climate change itself, especially lower-income and hotter countries that are differentially exposed and vulnerable to a range of climate threats and their impacts (Burke et al. (2015), Burke et al. (2018),Nath et al. (2023), Bilal and Känzig (2024), Acevedo et al. (2020), Mohan and Strobl (2021)). As global warming approaches 1.5°C above pre-industrial levels (Masson-Delmotte et al. (2021), Diffenbaugh and Barnes (2023), Bevacqua et al. (2025)), there is growing concern that credit ratings and the overall ability of countries to access financing will be negatively impacted by these economic impacts of a warming climate, contributing to a "vicious cycle" by which impacted countries are increasingly challenged to secure the finance necessary for addressing climate change and other development objectives (Kling et al. (2018), Volz et al. (2020)). Consistent with these growing concerns, data show a strong correlation between countries' credit ratings, mean temperatures, and tropical cyclone (TC) exposure, with hotter and more TC-exposed countries more likely to have speculative grade ratings (< BBB-) (fig. 1). It is projected that climate change will increase the likelihood of major category TCs and TC-induced precipitation, although significant uncertainties remain regarding TC formation and overall frequency (Masson-Delmotte et al. (2021), Knutson et al. (2020), Knutson et al. (2015), van Oldenborgh et al. (2017), Sobel et al. (2016), Bhatia et al. (2022)). Concern about the vicious cycle is especially acute for small island states such as Jamaica, Barbados, and Grenada, where TCs are the primary source of negative financial shock (fig. 1, fig. S7). Because of their small land area, high population density, coastal infrastructure and exposure to sea level rise, a small island state's entire economy can be exposed to the impacts of a single TC event (Brownbridge and Canagarajah (2024), Hsiang and Jina (2014)). Small island states also face higher reconstruction costs and significant constraints in mobilizing post-disaster financing due to their remote locations (Slany (2020)).

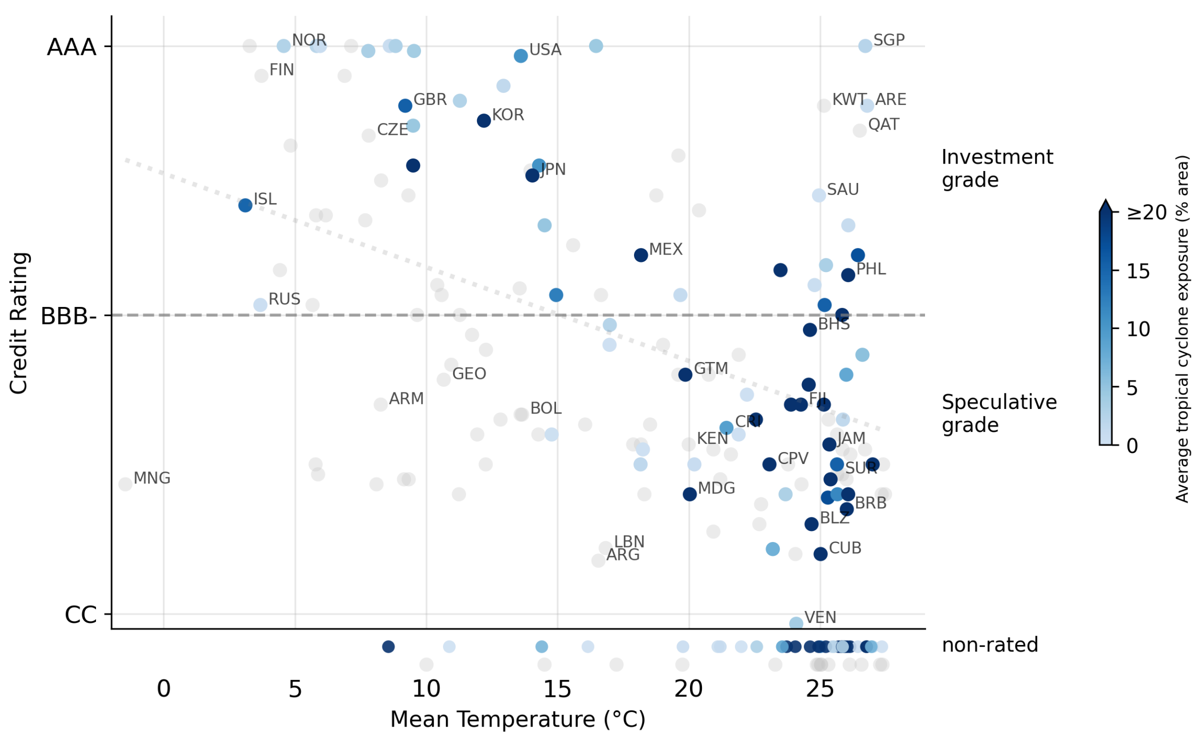


Figure 1. Scatter plot of country mean temperatures, average tropical cyclone exposure, and sovereign credit ratings in 2019. Mean temperatures are on the x-axis, and credit ratings on the y-axis are the average of ratings from the "Big Three" agencies (S&P, Moody's, Fitch). Colors indicate the average tropical cyclone exposure in terms of land area affected. Scatter plot along the x-axis shows the temperature distribution and tropical cyclone exposure of 46 countries that have never received an official rating from the three major credit rating agencies.

A growing body of research investigates how the actual and perceived risks of climate change may impact sovereign ratings and bond yields. These studies largely focus on the temperature-GDP impact channel, the association between ratings and aggregate indicators of climate risk vulnerability (Cevik and Jalles (2020), Bolton et al. (2023), Klusak et al. (2021), Beirne et al. (2021)), or the impact of disasters in general (Fisera et al. (2023), Deryugina (2022)). Some studies use theoretically modeled estimates to understand how the combination of high sovereign debt and TCs may slow post-disaster recovery, impact governments' ability to issue debt and increase borrowing costs (Phan and Schwartzman (2024), Bakkensen and Barrage (2025), Mallucci (2022)), without explicitly accounting for the temperature-GDP impact channel. Meanwhile, empirical evidence on the impact of TCs has been mixed, with some finding that severe TCs do not increase debt nor cause long-run impacts on GDP growth (International Monetary Fund (2014), Cavallo et al. (2013)), and others finding long-run growth impacts (Hsiang and Jina (2014), Cabezon et al. (2015), Brownbridge and Canagarajah (2024), Slany (2020)).

This study provides the first global assessment of how historical exposure to TCs and long-term country-level warming has shaped the cost and availability of capital. We do this by empirically estimating how combined impacts of TCs and rising temperatures affect debt and GDP. We further provide evidence of how these impacts have shaped countries' credit ratings and borrowing costs, which may compound countries' debt burdens and limit their capacity to respond to climate change.

We first estimate the impact of TCs and warming temperatures on two macroeconomic variables that are key determinants of sovereign credit ratings: the debt-to-GDP ratio (hereafter "debt ratio") and GDP (Cantor and Packer (1996), Afonso et al. (2011)). The debt ratio is a widely used indicator for understanding a country's debt burden that facilitates cross-country comparisons by scaling debt relative to economic output. It also serves as an important indicator for understanding a government's capacity to implement fiscal policy measures in response to financial crises or economic downturns (Romer and Romer (2019), Jordà et al. (2016)). To estimate the impacts of TCs and temperature on debt ratios and GDP, we employ a local projection model commonly used in applied macroeconomic settings to investigate the long-run impact of exogenous shocks (Methods).

Next, to understand how the macroeconomic impacts from TCs and temperature change could affect countries' credit rating and borrowing costs, we estimate a range of regression and machine learning-based prediction models that relate credit ratings to observed macroeconomic factors. We then combine these models with our estimates of the impact of TCs and temperature on the macro-economy to estimate counterfactual credit ratings and borrowing costs had these shocks not occurred.

2 Results

We find clear evidence that exposure to TCs affects subsequent debt ratios, with the effect size depending on the amount of land area exposed to high wind speeds (fig. 2). For instance, exposure of ten percent of a country's land area to tropical storm–level winds (>18 m/s) increases the debt ratio by 2.5% after ten years, while equivalent exposure to category 1–3 winds (33–50 m/s) raises it by 3.5%, and exposure to major TCs (>50 m/s) raises it by 5%. Impacts peak 5-10 years after exposure and fade after 15 years. The impact of each wind speed intensity scales with the share of land area exposed (fig. 2, panel b & d), which varies greatly depending on a country's size and average TC exposure. For example, up to 100% of Barbados' land area has historically been exposed to Category 3 or higher winds, compared with less than 5% of the United States (see fig. 3, panel b; fig. S7). Our baseline model includes temperature impacts as controls based on literature documenting robust evidence of temperature impacts on GDP (Methods). We do not detect a clear impact of temperature on the debt ratio separate from TCs, as coefficients are highly sensitive to the inclusion of different samples and time trends (fig. S3).

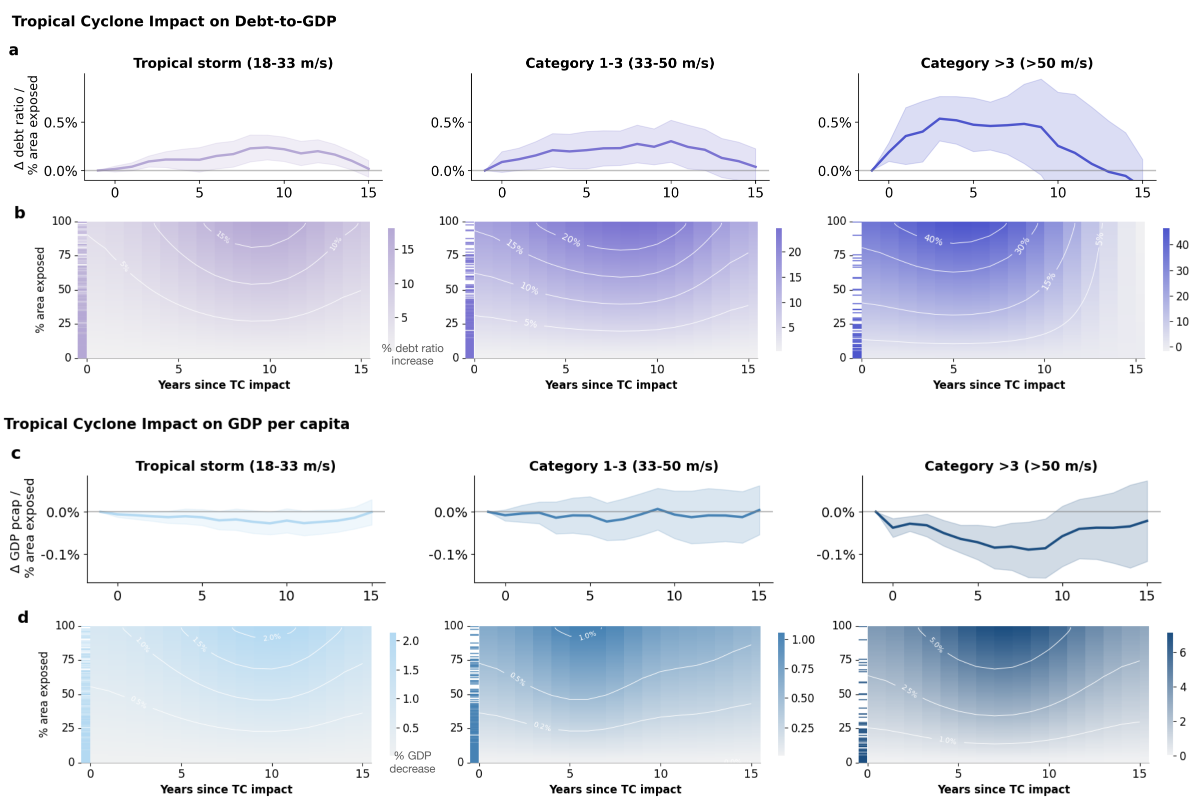


Figure 2. Impact of tropical cyclones on debt-to-GDP ratios and GDP. Panel a plots the response of the debt ratio to 1% of land area exposed to wind speeds of increasing intensity. **Panel b** scales each response estimate by the land area exposed to each wind speed category, from 0 to 100%. The distribution of observed exposure values from the data are shown as rug plots along the y-axis. **Panel c** plots the response of GDP per capita to 1% of land area exposed to wind speeds of varying intensity. **Panel d** scales the response by land area exposed, as in Panel b.

When considering GDP as the outcome, we again find that the impact of TCs depends on the land area impacted by wind speeds of different intensities (fig. 2). Exposure of 10% of a country's land area to tropical storm–level winds (>18 m/s) reduces GDP by 0.2% after ten years, while similar exposure to major tropical cyclones (>50 m/s) reduces GDP by 1% at its peak before returning to trend. We also confirm that, consistent with literature (Burke et al. (2015), Nath et al. (2023)), country-level warming impacts GDP growth and that this impact is independent from TC impacts. A 1°C hotter year relative to the country's mean temperature reduces GDP by 1% after four years, with impacts weakly persisting even after a decade (fig. S4). These impacts are highly dependent on the country's mean temperature, consistent with Burke et al. (2015) and Nath et al. (2023). We test three different methods for isolating temperature shocks, each showing statistically significant and persistent effects of a hotter year lasting up to six years for countries with mean historical temperature of 25°C (fig. S4).

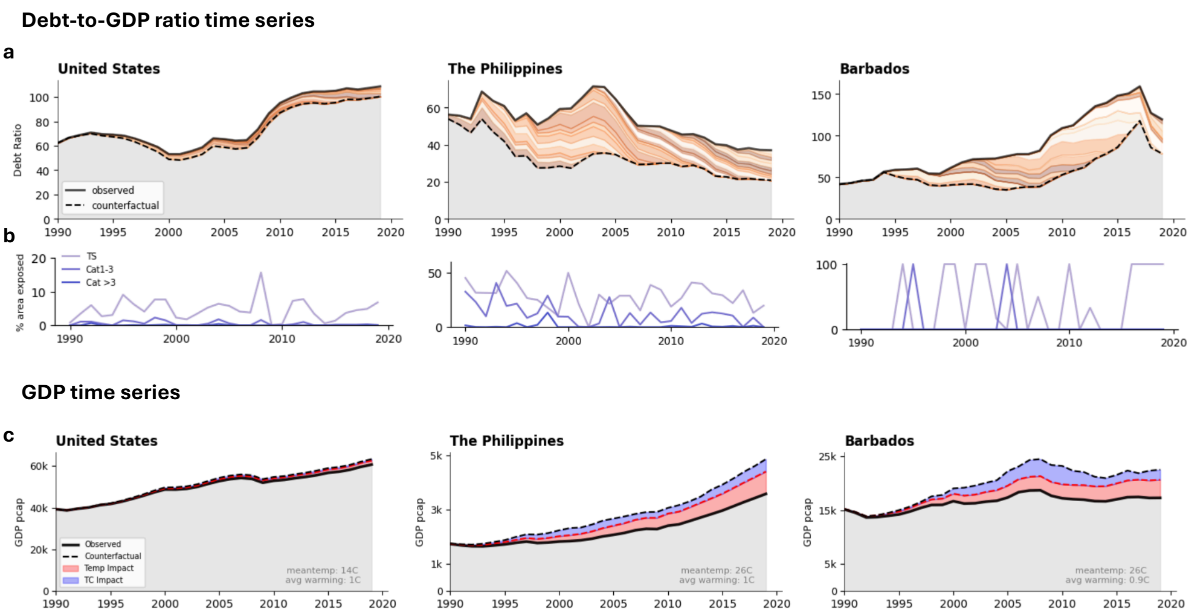


Figure 3. Panel a (observed vs counterfactual debt ratio time series) plots the time series of the observed debt ratio (black line) and counterfactual debt ratios (colored bars) for three countries with varying exposures. Each shaded bar represents the cumulative impact of all tropical cyclones in a given year. The black dotted line represents the counterfactual time series after removing the impact of all storms from 1990 onward. **Panel b (exposures)** plots the land area exposure values for each wind speed category. The color bars and axes ranges are different in each subplot. **Panel c (observed vs counterfactual GDP time series)** plots the time series of the observed GDP (black line) and counterfactual GDP that removes the impact of all tropical cyclone occurrences (blue) and temperature impacts (red) from 1990 onwards. The black dotted line plots the counterfactual scenario with both tropical cyclone and temperature impacts removed.

We then use these estimates to calculate counterfactual GDPs and debt ratios had observed warming and TC landfalls since 1990 did not occur. We find that, on average across TC-exposed countries, debt ratios in 2019 are 30% higher due to observed TCs, and GDP levels are approximately 10% lower due to the combined impacts of TCs and country-level warming (fig. 3, fig. 4). Among small island sovereign states, on average 50% of the public debt burden in 2019 is attributable to TCs, and GDP levels are 20% lower due to the combined impact of TCs and country-level warming. A map showing the global distribution of debt ratio impacts is shown in fig. 4 (GDP impacts are shown in fig. S6). In terms of GDP impacts, country-level warming accounts for a larger share of impacts than TCs (fig. 3, panel c).

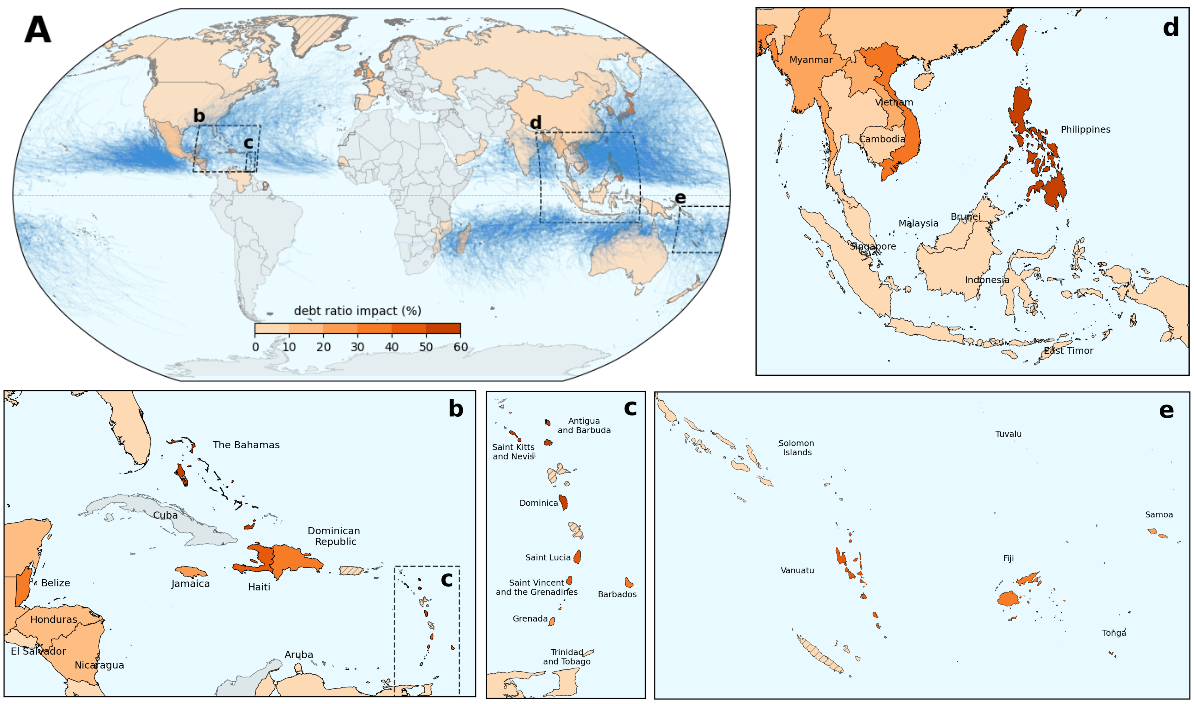


Figure 4. Share of countries' debt ratio in 2019 attributable to tropical cyclone exposure from 1990 onwards. Panel A shows the global map, where blue lines show tropical cyclone tracks from 1990-2019. **Sub-panels b-e** provide a zoomed-in view of regions that are highly exposed to tropical cyclones. Hatch marks indicate sovereign territories and dependencies without a debt record, and grey indicates countries either without tropical cyclone exposure or debt records.

Next, we investigate how the long-run impact on debt ratios and GDP may be affecting sovereign credit ratings and borrowing costs today. To do this, we predict the probability distribution of counterfactual ratings that countries would have been assigned based on their counterfactual debt ratios and GDP in 2019 (Methods). We estimate that 85 countries are more likely to be assigned below–investment-grade ratings (<BBB-) and 93 countries are less likely to receive a rating upgrade as a consequence of these macroeconomic impacts (fig. S16).

These rating changes are associated with a change in the borrowing costs of countries, here measured as the basis point difference in the coupon rates of sovereign bonds (Methods). Many countries with below investment-grade ratings are likely incurring additional borrowing costs of 1 to 35 basis points due to the impact of TCs and warming temperatures (fig. 5). The additional borrowing costs are greater for countries that predominantly issue bonds in local currency than for countries issuing in a dominant currency (USD, EUR, GBP, CHF, CAD)(Extended

Data Fig. 2).

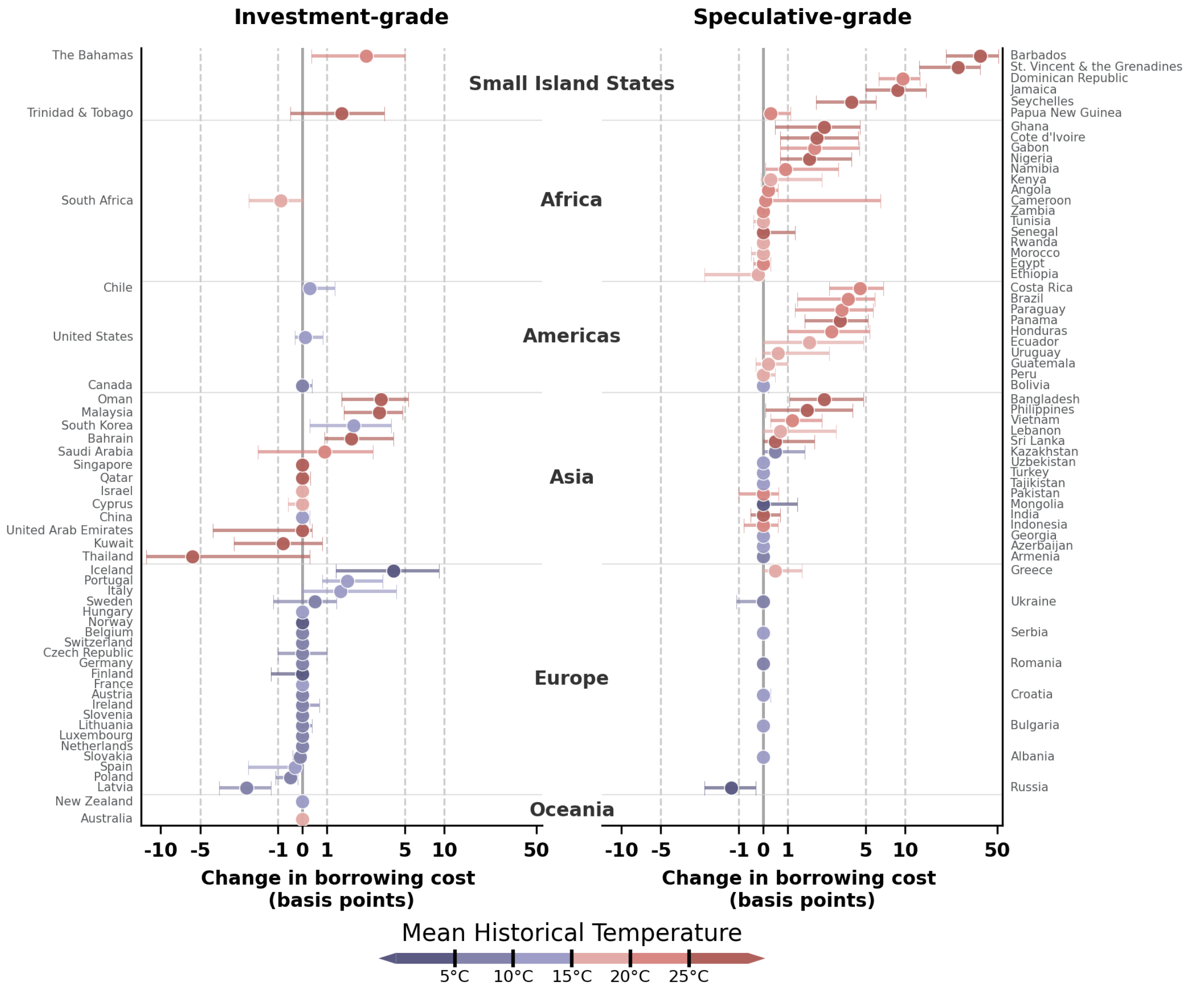


Figure 5. The change in borrowing cost attributed to historical tropical cyclones and climate change. Values are plotted separately for countries with investment-grade (left) and speculative-grade ratings (right), and non-rated countries. Colors are based on each country's mean historical temperature. Error bars show the inter-quartile range of predictions derived from 500 randomized training samples in the rating prediction model, with each sample holding out 20% of countries.

3 Discussion

The scale of investment required to reduce emissions and adapt to the impacts of climate change is estimated at trillions of dollars annually in the coming decade (Bhattacharya et al. (2024)). Global policy efforts have emphasized the critical role of the private sector in mobilizing finance at this scale, yet many countries face persistent challenges in accessing capital markets due to weak or non-existent credit ratings, large debt burdens, and high borrowing costs (see fig. 1,Extended Data Fig. 1, Bhattacharya et al. (2024)). Understanding the dynamic impact of TCs and warming temperatures on countries' overall debt burdens and the additional costs that this imposes is important to ensure the design of policies that can deliver climate finance equitably and in a manner that supports each country's needs.

We provide a global-scale estimate of how past exposure to TCs and warming temperatures may have impacted countries' borrowing costs today, including predictions for countries that have never received a credit rating. While research suggests that climate risks may already be reflected in credit ratings, or may lead to downgrades in the future (Cevik and Jalles (2020), Bolton et al. (2023), Klusak et al. (2021)), they do not clarify the underlying macroeconomic channels through which credit ratings may be affected. Cappiello et al. (2025) suggest that countries with high exposure to physical risks (e.g. temperature anomalies and disasters) or transition risks (e.g. dependence on fossil fuel revenues) are associated with lower credit ratings. Other studies directly estimate climate change impacts on bond yields, albeit for a limited sample of countries for which these data are available (Kling et al. (2018), Beirne et al. (2021)). We find that hotter countries with low credit ratings today have an increased likelihood of experiencing a rating downgrade and higher borrowing costs, while some colder countries with higher credit ratings today have an increased likelihood of a rating upgrade as warming temperatures positively impact GDP growth. Meanwhile, countries that do not have a credit rating today may find it increasingly difficult to attain one.

Our analysis also contributes to the literature on the macroeconomic impacts of TCs. Existing estimates of TC damages measure exposure primarily as a function of wind speed (e.g. Hsiang and Jina (2014), Bakkensen and Mendelsohn (2016), Noy (2009)). A frequently cited estimate of TC-induced GDP damages provided by Hsiang and Jina (2014) estimates that an additional m/s of wind speed per unit area causes output loss of 0.09% five years after a storm. The intuition for using wind speed as a metric of TC exposure draws from literature demonstrating that direct losses are a power function of the maximum wind speed affecting a given unit area or property (Pielke (2007), Nordhaus (2010), Emanuel (2005), Emanuel (2011), Southern (1979)). However, the maximum wind speed metric reflects only the peak intensity of a storm and fails to capture the broader spatial extent of exposure that may be more relevant for understanding economic losses.

In contrast, we measure TC exposure as the percent of land area of the country impacted by different wind speeds, to capture the multiple hazards associated with the spatial structure of the storm while also accounting for differences in country size. Our metric thus captures both the scale and distribution of potential damages, and is more suitable for capturing non-linear impacts. It also better aligns with the mechanism by which TCs disrupt economic activity and trigger reconstruction costs, following widespread damage to infrastructure, agriculture, and settlements. Our results indeed confirm that there are meaningful debt and GDP impacts in areas exposed to low wind speeds.

A major caveat of our analysis is that we do not directly measure the impacts of TC-induced precipitation or storm surge. While significant uncertainties remain regarding how climate change will impact the frequency or landfall location of TCs, evidence points to the increasing intensity and heavy precipitation associated with TCs globally (Sobel et al. (2023), Masson-Delmotte et al. (2021), Knutson et al. (2015), Khouakhi et al. (2017)). Furthermore, recent events have led to significant damages even in areas exposed to low wind speeds, due to heavy precipitation and inland flooding (Schleypen et al. (2024), Bakkensen et al. (2018)). Likewise, increases in sea level have already led to increasing risk of storm-surge flooding from landfalling TCs (Xi et al. (2023); Lin et al. (2016); Glavovic et al. (2022)), and intensifying precipitation and sea level rise can create non-linear increases in compound flood hazard (Wahl et al. (2015), Moftakhari et al. (2017),Bevacqua et al. (2019)). In our current analysis, we do not directly test the impact of TC-induced precipitation or storm surge separate from the the winds due to the large uncertainties in their measurement and the persistent challenges in both satellite and ground-based precipitation measurements at the global scale. Our exclusive focus on TC winds was necessary in order to maintain global coverage with a consistent exposure metric, with the necessary trade-off being that we do not isolate the impacts of TC-induced precipitation or storm surge separate from TC winds. Because stronger winds are highly correlated with greater precipitation and storm surge, damages attributed to wind intensity partly reflect these non-wind hazards. Even so, disentangling and quantifying damages attributable to wind, precipitation, and storm surge remains an important avenue for future work.

We also provide a novel empirical estimate of TC impacts on a country's debt ratio. Empirical estimates of TC impacts have focused largely on measuring direct losses, GDP, mortality or well-being (Cavallo et al. (2013), Hsiang and Jina (2014), Bakkensen and Mendelsohn (2016), Young and Hsiang (2024), Rappaport (2014), Hallegatte et al. (2016)). Among the few empirical studies that have focused on the debt impact of disasters (Noy and Nualsri (2011); Melecky and Raddatz (2011); Zhang and Chang (2020), see overview in Deryugina (2022)), TCs are not the main focus and these studies rely on a database of damage estimates (e.g. EM-DAT) to identify disaster occurrences, which introduces endogeneity concerns. For instance, only disasters that cross a specific threshold for damage are included in the database (e.g. fatalities greater than 10, damages greater than 0.5% of GDP), which means that estimated impacts may potentially be driven by other factors that led the storm to be included in the database in the first place, rather than characteristics of the storm itself (Botzen et al. (2019)). One study that examines TC impacts using a wind field measure considers only countries in the Caribbean region and uses debt service costs as a proxy for measuring debt burdens (Ouattara and Strobl (2013)). Yet other studies have utilized theoretical models to conclude that recovery and access to capital will be negatively impacted among countries following TCs (Phan and Schwartzman (2024), (Bakkensen and Barrage (2025), Mallucci (2022)). Our study focuses explicitly on the impact of TCs using a physical measure (land area affected by varying wind speed intensities) to directly estimate impacts on the debt burden associated with different storm intensities, and utilize comprehensive debt data available for 190 countries (Mbaye et al. (2018)). Thus, we recover a direct empirical understanding of how countries' debt ratios evolve in the aftermath of TCs across countries with varying exposure profiles.

The differential responses to TCs compared to warming temperatures suggest that these factors impact the economy through different channels. TCs have been associated with capital destruction and the need for increased capital expenditures during the recovery and reconstruction phase (Melecky and Raddatz (2011)). In contrast, warming temperatures have been associated with GDP impacts mainly through the productivity channel, for instance in terms of agricultural yields or labor productivity Burke et al. (2015). This potentially explains why we recover a clear temperature impact on GDP but not for debt ratios, while TC impacts are recovered for both GDP and debt ratios.

There have been increasing calls for sovereign debt relief in recent years, whether through debt cancellations, restructuring, or deferred payment options for countries facing increasing debt burdens (UNCTAD (2023), Government of Barbados (2024), Jubilee Commission (2025)). Several banks have started offering products and new policies for communities impacted by catastrophes (UNEP Finance Initiative, Munich Re (2024)). At the sovereign level, however, no overarching institution exists to coordinate debt relief across official (government) and private creditors. For example, the IMF-led Debt Service Suspension Initiative (DSSI) during the COVID-19 pandemic only included official creditors, and several eligible countries declined to participate due to concerns that doing so could raise their borrowing costs from private creditors (Lang et al. (2023)). Similar concerns have limited the effectiveness of the G20 Common Framework for Debt Treatments (Jubilee Commission (2025), Paris Club and G20 (2020)). Further complicating debt restructuring efforts is that China, now the largest bilateral creditor to many developing countries, is not a member of the Paris Club, which has been the principal forum for sovereign debt negotiations since 1956 (Horn et al. (2021), United Nations Development Programme (2025)).

To address sovereign debt challenges, The Bridgetown Initiative launched in 2022 calls for international financial architecture reform, including debt relief measures, transparency in credit rating agencies, and inclusion of ’debt-pause’ clauses, or debt repayment suspension for countries following disasters (Government of Barbados (2024)). Grenada’s debt-pause clause was the first to be activated in 2024 following Hurricane Beryl, after it was inserted as part of its debt structuring negotiations in 2015 (Asonuma et al. (2018)). Our results suggest these measures could lower sovereign debt burdens by providing immediate liquidity after major TCs, easing the need for new borrowing. For countries with weak or absent credit ratings, a temporary suspension of debt-service payments can free scarce capital for disaster response and reduce reliance on high-cost borrowing. Other policy options may involve increasing the share of concessional lending or grants in climate finance alongside innovative mechanisms such as debt-for-nature swaps.

4 Conclusion

Our findings show that exposure to TCs and warming temperatures over the past three decades has already shaped the cost and availability of capital for many countries. As financing from global capital markets becomes more costly, countries are likely to become further trapped in a "vicious cycle" of debt, unable to access the upfront finance needed to reduce climate impacts in the first place. Ultimately, these results underscore the urgent need to address the growing financial costs borne by countries that have contributed least to historical emissions yet face the greatest impacts of climate change.

Methods

Our approach can be broadly summarized as containing three parts. In the empirical part, we estimate the impact of climate shocks on two key macroeconomic determinants of a country's sovereign credit ratings: the debt-to-GDP ratio and GDP (Cantor and Packer (1996); Mellios and Paget-Blanc (2006); Afonso et al. (2011); see also fig. S14). Building on the empirical results, we then derive counterfactual scenarios for the two variables in the absence of tropical cyclones and rising temperatures. Finally, we train a prediction model to estimate how the macroeconomic impacts may have affected sovereign credit ratings and borrowing costs for countries.

4.1 Empirical model

We employ a local projections (LP) with long differences model (Jordà (2005), Jorda and Taylor (2025)), an approach that is increasingly common in the macroeconomic literature to directly estimate the dynamic and cumulative long-run response of outcomes to a shock (e.g. Bilal and Känzig (2024), Nath et al. (2023), Romer and Romer (2019)). Unlike Vector Autoregressive (VAR) models, LPs estimate impacts sequentially at each step of the forecast horizon with separate regressions, making them more robust to potential biases arising from model misspecification (Montiel Olea and Plagborg-Møller (2021),Montiel Olea et al. (2025), Jorda and Taylor (2025)).

Our main model is specified as below:

$$y_{i,t+h} - y_{i,t-1} = \boldsymbol{\beta}_t^h \cdot \mathbf{tc}_{it} + \boldsymbol{\delta}_t^h \cdot \boldsymbol{\tau}_{it} + \mathbf{x_{it}} + \epsilon_{it} \qquad \text{for } h = 0, 1, \ldots, H \tag{1}$$

The model allows us to estimate the impact of tropical cyclones (β_t) and temperature (δ_t) occurring in year t on outcomes (y) for country (i) at increasing time horizons ($t+h$), controlling for $\mathbf{x_{it}}$ where:

$$\mathbf{x_{it}} = \sum_{l=1}^{n} \boldsymbol{\beta}_l^h \cdot \mathbf{tc}_{i,t-l} + \sum_{l=1}^{n} \boldsymbol{\delta}_l^h \cdot \boldsymbol{\tau}_{i,t-l} + \alpha_i + \gamma_t + \phi_i(t)$$

$$\boldsymbol{\beta}_l^h = \begin{bmatrix} \beta_{1,l}^h & \beta_{2,l}^h & \beta_{3,l}^h \end{bmatrix}, \quad \mathbf{tc}_{i,t-l} = \begin{bmatrix} tc_{1,i,t-l} \\ tc_{2,i,t-l} \\ tc_{3,i,t-l} \end{bmatrix}$$

$$\boldsymbol{\delta}_l^h = \begin{bmatrix} \delta_{0,l}^h & \delta_{1,l}^h \end{bmatrix}, \quad \boldsymbol{\tau}_{i,t-l} = \begin{bmatrix} \tau_{i,t-l} \\ \tau_{i,t-l} \cdot \bar{T}_i \end{bmatrix}$$

$$\phi_i(t) \in \{0,\ \phi_i t,\ \phi_{1i}t + \phi_{2i}t^2\}$$

The vector of coefficients β_t^h and δ_t^h form the impulse response functions (IRF) that estimate the dynamic cumulative effect of the shock occurring at time (t). $\boldsymbol{x}_t$ represents a vector of controls, which includes lags of both tropical cyclone and temperature shocks, α_i and γ_t represent country and year fixed effects, respectively. Country-specific time trends are denoted by $\phi_i(t)$.

To credibly isolate the impact of a shock from a given year, we must account for serial correlations in both the outcome variable and the shock variables (Jorda and Taylor (2025). Even after isolating the shock variable following the methods outlined below (4.2.1, 4.2.2), weak serial correlation can persist in the data. To account for this, we include up to two lags of the lagged difference in the outcome variable ($y_{t-1} - y_{t-2}$, $y_{t_2} - y_{t_3}$), up to 10 lags of the TC shock variables, and 2 lags of the temperature shock variables. Finally, we also test the model using Driscoll-Kraay standard errors to address any spatial and temporal serial correlations in the panel data, which can additionally account for cross-sectional dependencies across units. We additionally test empirical bootstrap and wild cluster bootstrap as alternative methods for generating standard errors. A list of robustness checks conducted are shown in fig. S2 and **??**.

4.1.1 Tropical cyclone exposure

To characterize the tropical cyclone shock, we use tropical cyclone wind fields generated from a parametric wind model (Chavas et al. (2015) that captures the full wind extent of a storm and explicitly accounts for the asymmetrical structure of tropical cyclones (Chen et al. (2023) as it evolves over land (Jing et al. (2024). Wind fields for each tropical cyclone are generated at 30-arcsec spatial resolution (approximately 10×10 km^2). We combine the wind fields from all tropical cyclone occurrences within a year to compute the maximum wind speed experienced over land in each grid cell. Wind speeds are then classified into three intensity categories: 18–33 m/s (tropical storms), 33–50 m/s (Category 1–2 storms), and >50 m/s (major storms, Category 3 and above) according to the Saffir-Simpson Hurricane Wind Scale. For each country and year, we estimate the share of land area exposed to each category of wind speed to ensure comparability across countries of varying sizes.

Let ws_{gy} denote the maximum wind speed in grid cell g during year y, across all storms. A_G denotes the total land area of a country computed as the total number of grid cells falling within country borders. The share of land area exposed to wind speed category $c \in \{1,2,3\}$ in year y is computed as:

$$tc_{c,y} = \frac{1}{A_G} \sum_{g=1}^{G} \begin{cases} 1 & \text{if } ws_{gy} \in T_c \\ 0 & \text{otherwise} \end{cases}$$

where the wind speed categories are defined as:

$$T_1 = (18, 33)\,\mathrm{m/s}, \quad T_2 = [33, 50)\,\mathrm{m/s}, \quad T_3 = [50, max)\,\mathrm{m/s}.$$

This yields $tc_{c,y} \in [0, 1]$, representing the proportion of a country's land area exposed to wind speeds in each category during year y. This measure of tropical cyclone exposure does not exhibit serial correlation, unlike temperature, which we take an additional step to isolate the shock as described below (see fig. S5).

4.1.2 Temperature exposure

We use the ERA5 gridded 2-meter surface temperature dataset (0.25° × 0.25°, 31 km) and construct population-weighted, country-level annual temperature exposures for all years. The population weights are from Rossi-Hansberg and Zhang (2025).

We build on existing literature (Burke et al. (2015), Nath et al. (2023)) showing that the impact of a hotter or cooler year depends nonlinearly on a country's average temperature, and that serial correlations in temperature should be accounted for. We follow Nath et al. (2023) in constructing temperature shocks as the residuals from a nonlinear autoregressive model that includes lagged temperature terms:

$$T_{it} = \sum_{j=1}^{p} \gamma_j T_{i,t-j} + \sum_{j=1}^{p} \theta_j T_{i,t-j} \cdot \overline{T}_i + \mu_i + \mu_t + \tau_{it} \tag{2}$$

The residual τ_{it} is the estimated temperature shock.

In addition, we consider two alternative ways of isolating the temperature shock: accounting for the persistence of shocks by applying a Hamilton filter as in Bilal and Känzig (2024), and simply removing a country-specific time quadratic trend from the temperature time series. In models that do not specify a country-specific time trend or include a linear time trend, isolating the temperature shock through this latter method yields qualitatively similar results as the other two methods (fig. S4).

4.1.3 Economic data

For debt-to-GDP ratio we use the Global Debt Database from the IMF, which provides comprehensive and harmonized data on public and private sector debt for 190 countries with time series extending to the 1950s for advanced economies (Mbaye et al. (2018)). Public sector debt is defined as all debt held by the public sector, including the total gross debt of central, state, and local governments, and social security funds. Public sector debt data is available for more than 40 continuous years for 119 countries and more than 30 years for 142 countries. For countries that do not have aggregate public sector data reported, we use the general government data or central government data. General government debt data is recorded for 88 countries and central government debt data is recorded for a wider sample of 174 countries. We also test the model using the sample of countries with only the central government data, as well as government debt data compiled by the World Bank (Kose et al. (2022)) and the Global Macro Database (Müller et al. (2025)), and find qualitatively similar results (fig. S2). For GDP data we use GDP per capita in constant 2015 USD from the World Development Indicators as in Burke et al. (2015) (World Bank (2025)).

4.2 Constructing counterfactual scenarios

We construct counterfactual scenarios by sequentially removing the influence of tropical cyclones and long-term temperature changes. For the debt ratio, counterfactual scenarios are generated by setting the occurrence of tropical cyclones to zero in each year. For instance, when constructing counterfactual scenarios beginning in 1990, the impact of all tropical cyclones occurring from 1990 onward are removed sequentially, as shown in the main text (fig. 3). This approach also allows us to selectively remove individual hurricane seasons to assess their specific impact.

Let $\mathcal{C}$ denote the set of countries i and $\mathcal{Y} = \{1990, 1991, \ldots, n\}$ the study period. In the main text we restrict the sample to $n = 2019$. Although year fixed effects absorb economic impacts of global shocks such as the COVID-19 pandemic that are common across all countries, they may not capture any idiosyncratic country-specific impacts. Nonetheless, we find that extending the study period to 2022 does not change our main empirical result.

For each country i, we construct a matrix $\mathbf{V}_i \in \mathbb{R}^{(n+1)\times T}$, where each column $\mathbf{v}_{i,y}$ represents a year-specific counterfactual vector capturing the dynamic effect of a shock occurring in year y. Each row corresponds to a calendar year $k \in \{1990, \ldots, n\}$. Each vector $\mathbf{v}_{i,y}$ is constructed as:

$$v_{i,y}[k] = \begin{cases} \sum_{c=1}^{3} \beta^{h}_{c,l} \cdot \mathrm{ws}_{c,i,y}, & \text{if } k = y + h \\ 0, & \text{if } k < y \end{cases}$$

where $\beta^{h}_{c,l}$ denotes the estimated impulse response coefficient at horizon h for wind category c, and $\mathrm{ws}_{c,i,y}$ denotes the share of land area in country i exposed to wind category c in year y.

To compute the total dynamic impact of shocks over the entire study period, we sum the columns of $\mathbf{V}_i$ to obtain a single cumulative counterfactual vector:

$$\mathbf{v}_i^{\text{total}} = \mathbf{V}_i \cdot \mathbf{1}_T$$

where $\mathbf{1}_T \in \mathbb{R}^{T\times 1}$ is a column vector of ones and $T = |\mathcal{Y}|$. For each $i \in \mathcal{C}$, the resulting vector $\mathbf{v}_i^{\text{total}} \in \mathbb{R}^{n+1}$ represents the cumulative impact of all shocks experienced by country i over the study period. In the final step, to construct the counterfactual outcomes for each country, we remove the cumulative impact of shocks from the observed values:

$$y_{it}^{\text{cf}} = \frac{y_{it}^{\text{obs}}}{1 + \mathbf{v}_i^{\text{total}}[t]}$$

where $\mathbf{v}_i^{\text{total}}[t]$ denotes the cumulative percentage change in the outcome due to all tropical cyclone shocks affecting country i up to year t.

4.3 Prediction model

We estimate the implications of these macroeconomic impacts in terms of countries' credit ratings today and their cost of borrowing. In short, we test the hypothesis that due to the long-run economic impacts from tropical cyclones and warming temperatures, the ratings agencies may be assigning ratings to countries that are lower than they would have been absent those shocks.

4.3.1 Credit rating data

Credit rating data from the "Big Three" rating agencies (Moody's, S&P, Fitch) are obtained from Bloomberg Finance L.P. and complemented by additional observations from Trading Economics (Bloomberg L.P. (2023), Trading Economics (2024)). The data include rating changes as well as outlook announcements, which are both known to influence market perceptions and sovereign bond yields (Cantor and Packer (1996), Kenourgios et al. (2020)). Following existing literature, the ratings are converted into a descending linear scale, with the highest rated bonds (AAA) ranked 21 and the lowest rated bonds (C) ranked 1 (e.g. Afonso et al. (2012) Kenourgios et al. (2020)). We add further variation by including the outlook change announcements as 0.5 changes in the rating, as in Eichengreen et al. (2007). For example, an AA rating (rank 19) that receives a negative outlook is ranked as 18.5. The full conversion table is available in table 2. Many countries received their first rating starting in the late 1990s (fig. S10) and 46 countries that have never received a credit rating from the "Big Three" agencies are by definition not included in the data.

4.3.2 Sovereign bond data

Sovereign bond data are from Bloomberg and Refinitiv (now part of London Stock Exchange Group (LSEG)). Bloomberg provides yield data for 69 advanced and emerging market economies.

Historic yield data are available for this limited set of countries because their market size, trading volume and liquid currencies makes it possible to construct yield data from the secondary market. For most countries, however, bond issuance is infrequent and these bonds are not actively traded in the secondary market. Thus, to include a larger set of countries in our analysis, we focus on predicting the annual coupon rates of bonds issued in the primary market, or at the date of issuance.

Sovereign bond data from Bloomberg and Refinitiv are available at the individual issuance level. Combined, we recover 48,000 sovereign bond issuances from 132 countries (27,861 excluding bonds issued by China and Japan), which we use to derive the credit rating and coupon rate relationship for 10-year maturity bonds during the relatively low interest rate period from 2011-2019 (see section 4.3.4). In our study, data have been filtered to include only bonds with fixed coupon rates, bullet maturities, and non-zero-coupon bonds. Private placement bonds are excluded. The dataset includes information on issuance currency, maturity, and issuance size.

4.3.3 Types of prediction models

We compare three different models for prediction: ordered response models (probit), ordered random forest, and two types of gradient boosted decision-tree models (XGBoost) (table 3). Each model has strengths and weaknesses in terms of performing the task at hand.

The ordered probit model is used to predict the probability of an observation being assigned to a category that is ordinal, conditional on a set of predictor variables. Because sovereign credit credit ratings follow an ordinal logic, and the spacing between the categories are not equal (i.e. category thresholds are unequally spaced on the latent scale), ordered probit models have been commonly employed to understand the determinants of ratings (Blanchard (2022), Ardagna (2018)). However, the ordered probit model requires the parallel regression assumption, which means that the marginal effect of predictor variables are consistent across all categories of the outcome variable. This assumption is often violated in practice: for instance, an increase in GDP will not have the same effect on the likelihood of a rating upgrade for a country with a BB rating versus an AA rating. Therefore, we also test Ordered Forest models, a modified form of random forest models, which allows for nonlinear combinations of variables.

Extreme gradient boosting (XGBoost) offers a more powerful way to train a prediction model, where decision trees are used to sequentially minimize a loss function. Even though using XGBoost does not explicitly recognize the ordinal nature of the dependent variables at the outset, we find that it is nonetheless able to learn that the rating categories are ordinal during the training process. On average, our XGBoost model achieves above 70% accuracy and >90% accuracy with tolerance (± 2) in held out test samples (fig. S13).

One might assume that a practical way to implement XGBoost for ordinal outcomes is to treat the ordered categories as continuous variables in a regression task. Intuitively, this mimics the behavior of an ordered probit model that estimates a latent variable to be classified into different categories based on different thresholds. In ordered probit models, the distance between category thresholds can vary flexibly to account for unequal distances between categories on a latent scale (e.g. moving from B to BB is easier compared to moving from BBB to A). However, because XGBoost regression assumes equal spacing between categories based on the provided inputs, it cannot replicate the uneven spacing across categories.

Therefore, we implement XGBoost as a classification task, which has the added benefit of providing a probability distribution across all possible ratings. While we cannot impose the ordinal nature of rating variables in this implementation, we nonetheless find that the model is able to recover the ordinal nature of the ratings (fig. S13).

We additionally test XGBOrdinal, a new package that transforms the ordinal classification task into a series of binary classification tasks using XGBoost (Kahl et al. (2025), Frank and Hall 2001). While inefficient (the time to train the model increases exponentially with the number of boosting iterations added), XGBOrdinal is better able to capture the ordered nature of the outcomes compared to the basic XGBoost Classification. However, the embedded assumptions in XGBOrdinal, on rare occasions, lead to a violation of the Kolmogorov probability axioms (e.g. avoiding negative probabilities and ensuring all probabilities sum to one) and spurious predictions. We therefore use XGBoost Classification as our main model.

After training on forty years of macroeconomic indicators and other variables referenced by rating agencies (e.g. S&P's rating methodology considers variables across five 'pillars': institutional, economic, external, fiscal, and monetary). We predict what each country's rating would have been in 2019 using the counterfactual debt-to-GDP ratios and GDP values estimated if countries had not been exposed to climate shocks. The list of variables used in our prediction model are shown in table 4.

4.3.4 Translating to borrowing costs

Rating changes are translated into borrowing costs, measured as the basis point change in the coupon rate for a fixed 10-year bond. The change in borrowing costs are calculated using the difference in the probability distribution of predicted credit ratings using observed versus counterfactual data. The observed values are from a range of monetary, fiscal, and institutional variables in 2019 (table 4). For the counterfactual data, we replace the debt-to-GDP ratio and GDP per capita data with the counterfactual estimates derived from our empirical model, which removes the effect of all land-falling TCs from 1990 onwards and country-specific warming.

We use the observed and counterfactual probability distributions of credit ratings to calculate the change in expected value of borrowing costs, using a generalized relationship between credit rating and coupon rates for sovereign bonds. This relationship is derived using Bloomberg and Refinitiv data of 9,253 sovereign bonds issued between 2011-2019 by 124 countries (17,261 including bonds issued by China and Japan) (fig. S11, fig. S12). This relationship holds across different time periods, maturities, and interest rate environments. JPY-denominated bonds are excluded from the sample as rates have been kept artificially low by the central bank. Utilizing this relationship allows us to generate predictions for both countries with sparse sovereign bond issuances as well as countries that do not have a credit rating (Extended Data Fig. 2). We run the XGB model with 500 random seeds, each time holding out a random 20% of countries, to derive 500 probability distributions of credit ratings for both observed and counterfactual scenarios.

We additionally consider the change in borrowing costs for bonds denominated in dominant currencies versus local currencies. Among sovereign bonds, countries issuing in their local home currency have faced coupon rates higher than those issued in a dominant currency (USD, EUR, GBP, CHF, CAD). Between 2011-2019, bonds denominated in local currency have paid coupon rates that are on average 170 basis points, or 1.7% higher than bonds denominated in a dominant or liquid currency (fig. S12).

References

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., and Topalova, P. (2020). The effects of weather shocks on economic activity: What are the channels of impact? *Journal of Macroeconomics*, 65:103207.

Afonso, A., Furceri, D., and Gomes, P. (2012). Sovereign credit ratings and financial markets linkages: Application to european data. *Journal of International Money and Finance*, 31(3):606–638. Special Issue: Financial Stress in the Eurozone.

Afonso, A., Gomes, P., and Rother, P. (2011). Short- and long-run determinants of sovereign debt credit ratings. *International Journal of Finance & Economics*, 16(1):1–15.

Almeida, H., Cunha, I., Ferreira, M. A., and Restrepo, F. (2017). The real effects of credit ratings: The sovereign ceiling channel. *The Journal of Finance*, 72(1):249–290.

Ardagna, S. (2018). Rating sovereigns: More upgrades on the horizon. Economics research report, Goldman Sachs Economics Research.

Asonuma, T., Li, M. X., Papaioannou, M. G., Thomas, S., and Togo, E. (2018). Sovereign debt restructurings in grenada: Causes, processes, outcomes, and lessons learned. *Journal of Banking and Financial Economics*, 2018(10):67–105.

Bakkensen, L. A. and Barrage, L. (2025). Climate shocks, cyclones, and economic growth: bridging the micro-macro gap. *The Economic Journal*, page ueaf050.

Bakkensen, L. A. and Mendelsohn, R. O. (2016). Risk and adaptation: Evidence from global hurricane damages and fatalities. *Journal of the Association of Environmental and Resource Economists*, 3(3):555–587.

Bakkensen, L. A., Park, D.-S. R., and Sarkar, R. S. R. (2018). Climate costs of tropical cyclone losses also depend on rain. *Environmental Research Letters*, 13(7):074034.

Beers, D., Jones, E., and Walsh, J. F. (2021). Boc–boe sovereign default database. Database documentation, Bank of Canada and Bank of England. John Fraser Walsh, CFA.

Beirne, J., Renzhi, N., and Volz, U. (2021). Feeling the heat: Climate risks and the cost of sovereign borrowing. *International Review of Economics Finance*, 76:920–936.

Bevacqua, E., Maraun, D., Vousdoukas, M. I., Voukouvalas, E., Vrac, M., Mentaschi, L., and Widmann, M. (2019). Higher probability of compound flooding from precipitation and storm surge in europe under anthropogenic climate change. *Science advances*, 5(9):eaaw5531.

Bevacqua, E., Schleussner, C.-F., and Zscheischler, J. (2025). A year above 1.5 °c signals that earth is most probably within the 20-year period that will reach the paris agreement limit. *Nature Climate Change*, 15(3):262–265.

Bhatia, K., Baker, A., Yang, W., Vecchi, G., Knutson, T., Murakami, H., Kossin, J., Hodges, K., Dixon, K., Bronselaer, B., and Whitlock, C. (2022). A potential explanation for the global increase in tropical cyclone rapid intensification. *Nature Communications*, 13(1):6626.

Bhattacharya, A., Songwe, V., Soubeyran, E., and Stern, N. (2024). Raising ambition and accelerating delivery of climate finance.

Bilal, A. and Känzig, D. R. (2024). The macroeconomic impact of climate change: Global vs. local temperature. (32450). DOI: 10.3386/w32450.

Blanchard, O. J. (2022). Debt sustainability. In *Fiscal Policy under Low Interest Rates*. MIT Press. Open-access MIT Press monograph.

Bloomberg L.P. (2023). sovereign credit ratings. Retrieved November 2023, from Bloomberg Terminal.

Bolton, P., Buchheit, L., Gulati, M., Panizza, U., di Mauro, B. W., and Zettelmeyer, J. (2023). On debt and climate. *Oxford Open Economics*, 2:odad005.

Botzen, W. J. W., Deschenes, O., and Sanders, M. (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*.

Brownbridge, M. and Canagarajah, S. (2024). Climate change vulnerability, adaptation and public debt sustainability in small island developing states. Technical Report 10787, World Bank. Climate Change Group, World Bank.

Burke, M., Alampay Davis, W. M., and Diffenbaugh, N. S. (2018). Large potential reduction in economic damages under un mitigation targets. *Nature*, 557(7706):549–553. © 2018 Macmillan Publishers Ltd., part of Springer Nature.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(75777577):235–239.

Cabezon, E., Hunter, L., Tumbarello, P., Washimi, K., and Wu, Y. (2015). Enhancing macroeconomic resilience to natural disasters and climate change in the small states of the pacific. IMF Working Paper 125, International Monetary Fund.

Cantor, R. and Packer, F. (1996). Determinants and impact of sovereign credit ratings. *Economic Policy Review*, 2(2):37–53.

Cappiello, L., Ferrucci, G., Maddaloni, A., and Veggente, V. (2025). Creditworthy: do climate change risks matter for sovereign credit ratings? *Working Paper Series*, (3042).

Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *The Review of Economics and Statistics*, 95(5):1549–1561.

Cevik, S. and Jalles, J. T. (2020). *Feeling the Heat: Climate Shocks and Credit Ratings*. Number No. 2020/286 in Working Paper. Washington D.C.

Chavas, D. R., Lin, N., and Emanuel, K. A. (2015). A model for the complete radial structure of the tropical cyclone wind field. part i: Comparison with observed structure. *Journal of the Atmospheric Sciences*, 72(9):3647–3662.

Chen, J., Gao, K., Harris, L., Marchok, T., Zhou, L., and Morin, M. (2023). A new framework for evaluating model simulated inland tropical cyclone wind fields. *Geophysical Research Letters*, 50(16):e2023GL104587.

Climate Policy Initiative (2025). Global landscape of climate finance 2025: Emde spotlight. Report, Climate Policy Initiative.

Deryugina, T. (2022). The fiscal consequences of natural disasters. In *Handbook on the Economics of Disasters*. Edward Elgar Publishing.

Diffenbaugh, N. S. and Barnes, E. A. (2023). Data-driven predictions of the time remaining until critical global warming thresholds are reached. *Proceedings of the National Academy of Sciences*, 120(6):e2207183120.

Eichengreen, B., Hausmann, R., and Panizza, U. (2007). Currency mismatches, debt intolerance, and the original sin: Why they are not the same and why it matters. In *Capital Controls and Capital Flows in Emerging Economies: Policies, Practices, and Consequences*, pages 121–170. University of Chicago Press.

Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature*, 436(7051):686–688.

Emanuel, K. (2011). Global warming effects on us hurricane damage. *AMS*. Accepted: 2012-12-03T17:58:22Z.

Fisera, B., Horvath, R., and Melecky, M. (2023). Natural disasters and debt financing costs. *Climate Change Economics*, 14(3):2350015.

G20 Independent Expert Group (2023). Strengthening multilateral development banks: The triple agenda. Technical report, G20 India Presidency. Report of the Independent Expert Group appointed under the India G20 Presidency.

Glavovic, B. C., Dawson, R., Chow, W., Garschagen, M., Haasnoot, M., Singh, C., and Thomas, A. (2022). Cross-chapter paper 2: Cities and settlements by the sea. In Pörtner, H.-O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., and Rama, B., editors, *Climate Change 2022: Impacts, Adaptation and Vulnerability*, pages 2163–2194. Cambridge University Press, Cambridge, UK and New York, NY, USA.

Government of Barbados (2023). Bridgetown initiative: Reform of the international development and climate finance architecture – version 3. `https://www.bridgetown-initiative.org/bridgetown-initiative-3-0/`. Accessed: 2025-06-26.

Government of Barbados (2024). The bridgetown initiative 3.0. Technical report, Government of Barbados, Prime Minister's Office, Bridgetown, Barbados.

Hallegatte, S., Vogt-Schilb, A., Bangalore, M., and Rozenberg, J. (2016). Avoiding disasters: Well-being losses can be mitigated by reducing asset losses. In *Unbreakable: Building the Resilience of the Poor in the Face of Natural Disasters*, Climate Change and Development, pages 111–134. The World Bank.

Hochrainer-Stigler, S., Mechler, R., and Mochizuki, J. (2015). A risk management tool for tackling country-wide contingent disasters: A case study on madagascar. *Environmental Modelling & Software*, 72:44–55.

Horn, S., Reinhart, C. M., and Trebesch, C. (2021). China's overseas lending. *Journal of International Economics*, 133:103539.

Hsiang, S. M. and Jina, A. S. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Working Paper 20352, National Bureau of Economic Research. NBER Working Paper No. 20352.

International Monetary Fund (2014). Debt, growth, and natural disasters: A caribbean trilogy. Imf working paper, International Monetary Fund.

International Monetary Fund (2024). Fiscal monitor: Putting a lid on public debt. Technical report, International Monetary Fund. October 2024.

Jing, R., Heft-Neal, S., Chavas, D. R., Griswold, M., Wang, Z., Clark-Ginsberg, A., Guha-Sapir, D., Bendavid, E., and Wagner, Z. (2024). Global population profile of tropical cyclone exposure from 2002 to 2019. *Nature*, 626(7999):549–554.

Jorda, O. and Taylor, A. M. (2025). Local projections. *Journal of Economic Literature*, 63(1):59–110.

Jordà, (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1):161–182.

Jordà, , Schularick, M., and Taylor, A. M. (2016). Sovereigns versus banks: Credit, crises, and consequences. *Journal of the European Economic Association*, 14(1):45–79.

Jubilee Commission (2025). The jubilee report. Technical report, Pontifical Academy of Social Sciences, Vatican City.

Kahl, F., Kahl, I., and Jonas, S. M. (2025). Xgbordinal: An xgboost extension for ordinal data. *Studies in health technology and informatics*, 327:462–466.

Kenourgios, D., Umar, Z., and Lemonidi, P. (2020). On the effect of credit rating announcements on sovereign bonds: International evidence. *International Economics*, 163:58–71.

Kessler, M. (2024). The rising costs of variable interest rate debt for sovereigns.

Khouakhi, A., Villarini, G., and Vecchi, G. A. (2017). Contribution of tropical cyclones to rainfall at the global scale. *Journal of Climate*, 30(1):79–88.

Kling, G., Lo, Y. C., Murinde, V., and Volz, U. (2018). Climate vulnerability and the cost of debt. (3198093).

Klusak, P., Agarwala, M., Burke, M., Kraemer, M., and Mohaddes, K. (2021). Rising temperatures, falling ratings: The effect of climate change on sovereign creditworthiness. (3811958).

Knutson, T., Camargo, S. J., Chan, J. C. L., Emanuel, K., Ho, C.-H., Kossin, J., Mohapatra, M., Satoh, M., Sugi, M., Walsh, K., and Wu, L. (2020). Tropical cyclones and climate change assessment: Part ii: Projected response to anthropogenic warming. *Bulletin of the American Meteorological Society*, 101(3):E303–E322.

Knutson, T. R., Sirutis, J. J., Zhao, M., Tuleya, R. E., Bender, M., Vecchi, G. A., Villarini, G., and Chavas, D. (2015). Global projections of intense tropical cyclone activity for the late twenty-first century from dynamical downscaling of cmip5/rcp4.5 scenarios. *Journal of Climate*, 28(18):7203–7224.

Kose, M. A., Kurlat, S., Ohnsorge, F., and Sugawara, N. (2022). A cross-country database of fiscal space. *Journal of International Money and Finance*, 128:102682.

Kowalewski, O., Luitel, P., and Vanpée, R. (2025). Sovereign credit rating provision and financial development. *Journal of International Financial Markets, Institutions and Money*, 101:102153.

Lang, V., Mihalyi, D., and Presbitero, A. F. (2023). Borrowing costs after sovereign debt relief. *American Economic Journal: Economic Policy*, 15(2):331–358.

Lin, N., Kopp, R. E., Horton, B. P., and Donnelly, J. P. (2016). Hurricane sandy's flood frequency increasing from year 1800 to 2100. *Proceedings of the National Academy of Sciences*, 113(43):12071–12075.

Lucas, R. E. (1990). Why doesn't capital flow from rich to poor countries? *The American Economic Review*, 80(2):92–96.

Mallucci, E. (2022). Natural disasters, climate change, and sovereign risk. *Journal of International Economics*, 139:103672.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M. I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J. B. R., Maycock, T. K., Waterfield, T., Yelekçi, O., Yu, R., and Zhou, B., editors (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Mbaye, S., Moreno-Badia, M., and Chae, K. (2018). Global debt database: Methodology and sources. IMF Working Paper 18/111, International Monetary Fund, Washington, DC.

Melecky, M. and Raddatz, C. E. (2011). How do governments respond after catastrophes? natural-disaster shocks and the fiscal stance. SSRN Scholarly Paper 1759155, Social Science Research Network, Rochester, NY.

Mellios, C. and Paget-Blanc, E. (2006). Which factors determine sovereign credit ratings? *The European Journal of Finance*, 12(4):361–377.

Moftakhari, H. R., Salvadori, G., AghaKouchak, A., Sanders, B. F., and Matthew, R. A. (2017). Compounding effects of sea level rise and fluvial flooding. *Proceedings of the National Academy of Sciences*, 114(37):9785–9790.

Mohan, P. and Strobl, E. (2021). The impact of tropical storms on the accumulation and composition of government debt. *International Tax and Public Finance*, 28(3):483–496.

Montiel Olea, J. L. and Plagborg-Møller, M. (2021). Local projection inference is simpler and more robust than you think. *Econometrica*, 89(4):1789–1823. © 2021 The Econometric Society.

Montiel Olea, J. L., Plagborg-Møller, M., Qian, E., and Wolf, C. K. (2025). Local projections or vars? a primer for macroeconomists. Working Paper 33871, National Bureau of Economic Research. NBER Working Paper No. 33871.

Müller, K., Xu, C., Lehbib, M., and Chen, Z. (2025). The global macro database: A new international macroeconomic dataset. SSRN Scholarly Paper 5121271, Social Science Research Network, Rochester, NY.

Nath, I. B., Ramey, V. A., and Klenow, P. J. (2023). How much will global warming cool global growth?

Nordhaus, W. D. (2010). The economics of hurricanes and implications of global warming. *Climate Change Economics*, 01(01):1–20.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, 88(2):221–231.

Noy, I. and Nualsri, A. (2011). Fiscal storms: Public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics*, 16(1):113–128.

Ouattara, B. and Strobl, E. (2013). The fiscal implications of hurricane strikes in the caribbean. *Ecological Economics*, 85:105–115.

Paris Club and G20 (2020). Common framework for debt treatments beyond the DSSI. Paris Club/G20 Joint Statement.

Phan, T. and Schwartzman, F. (2024). Climate defaults and financial adaptation. *European Economic Review*, 170:104866.

Pielke, R. A. (2007). Future economic damage from tropical cyclones: sensitivities to societal and climate changes. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*.

Rappaport, E. N. (2014). Fatalities in the united states from atlantic tropical cyclones: New data and interpretation. *Bulletin of the American Meteorological Society*, 95(3):341–346.

Romer, C. D. and Romer, D. H. (2019). Fiscal space and the aftermath of financial crises: How it matters and why. Working Paper 25768, National Bureau of Economic Research. NBER Working Paper No. 25768.

Rossi-Hansberg, E. and Zhang, J. (2025). Local gdp estimates around the world. Working Paper 33458, National Bureau of Economic Research.

Schleypen, J. R., Plinke, C., and Geiger, T. (2024). The impacts of multiple tropical cyclone events and associated precipitation on household income and expenditures. *Economics of Disasters and Climate Change*, 8(2):197–233.

Slany, A. (2020). Multiple disasters and debt sustainability in small island developing states. Research Paper No. 55, UNCTAD/SER.RP/2020/14, United Nations Conference on Trade and Development (UNCTAD). UNCTAD Research Paper No. 55.

Sobel, A. H., Camargo, S. J., Hall, T. M., Lee, C.-Y., Tippett, M. K., and Wing, A. A. (2016). Human influence on tropical cyclone intensity. *Science*, 353(6296):242–246.

Sobel, A. H., Lee, C.-Y., Bowen, S. G., Camargo, S. J., Cane, M. A., Clement, A., Fosu, B., Hart, M., Reed, K. A., Seager, R., and Tippett, M. K. (2023). Near-term tropical cyclone risk and coupled earth system model biases. *Proceedings of the National Academy of Sciences*, 120(33):e2209631120.

Southern, R. L. (1979). The global socio-economic impact of tropical cyclones. *Australian Meteorological Magazine*, 27:175–195.

Trading Economics (2024). Sovereign credit ratings by country. Accessed January 2024.

UNCTAD (2023). A world of debt: A growing burden to global prosperity. Un global crisis response group brief, United Nations Conference on Trade and Development, Geneva.

UNCTAD (2024). Sovereign debt vulnerabilities in developing countries. UNCTAD Report UNCTAD/GDS/2024/4, United Nations Conference on Trade and Development, Geneva.

UNEP Finance Initiative, Munich Re (2024). Managing physical climate-related risks in loan portfolios. Technical supplement, UNEP Finance Initiative. Accessed June 2025.

UNFCCC. Conference of the Parties serving as the meeting of the Parties to the Paris Agreement (CMA) (2024). New collective quantified goal on climate finance: Draft decision fccc/pa/cma/2024/l.22. Draft decision, UN Climate Change Conference – Baku, November 2024. UNFCCC Draft Decision FCCC/PA/CMA/2024/L.22; publication date 24 November 2024.

United Nations Development Programme (2025). Reforming the common framework for african countries. Technical report, UNDP.

United Nations, Inter-agency Task Force on Financing for Development (2022). Financing for sustainable development report 2022. Available from: https://developmentfinance.un.org/fsdr2022. Accessed July 2025.

van Oldenborgh, G. J., van der Wiel, K., Sebastian, A., Singh, R., Arrighi, J., Otto, F., Haustein, K., Li, S., Vecchi, G., and Cullen, H. (2017). Attribution of extreme rainfall from hurricane harvey, august 2017. *Environmental Research Letters*, 12(12):124009.

Volz, U., Beirne, J., Ambrosio Preudhomme, N., Fenton, A., Mazzacurati, E., Renzhi, N., and Stampe, J. (2020). Climate change and sovereign risk. Technical report, SOAS University of London and Asian Development Bank Institute and World Wide Fund for Nature Singapore and Four Twenty Seven, London, Tokyo, Singapore, and Berkeley, CA.

Wahl, T., Jain, S., Bender, J., Meyers, S. D., and Luther, M. E. (2015). Increasing risk of compound flooding from storm surge and rainfall for major us cities. *Nature Climate Change*, 5(12):1093–1097.

World Bank (2025). World development indicators. Accessed: 2024-10-05.

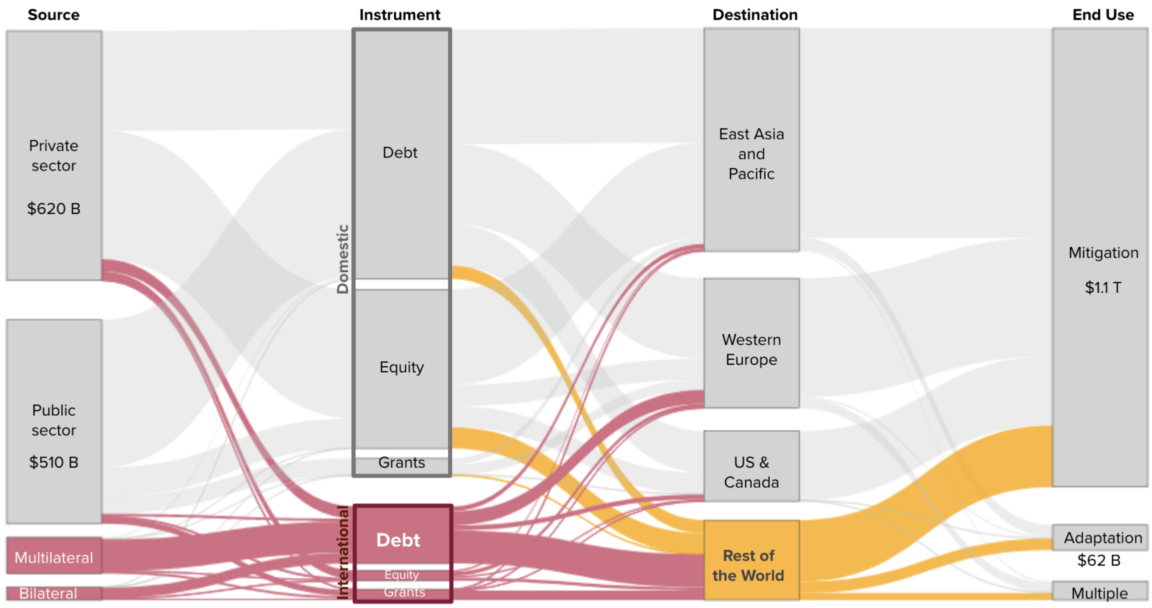
Xi, D., Lin, N., and Gori, A. (2023). Increasing sequential tropical cyclone hazards along the us east and gulf coasts. nat. climate change, 13, 258–265.

Young, R. and Hsiang, S. (2024). Mortality caused by tropical cyclones in the united states. *Nature*, 635(8037):121–128.

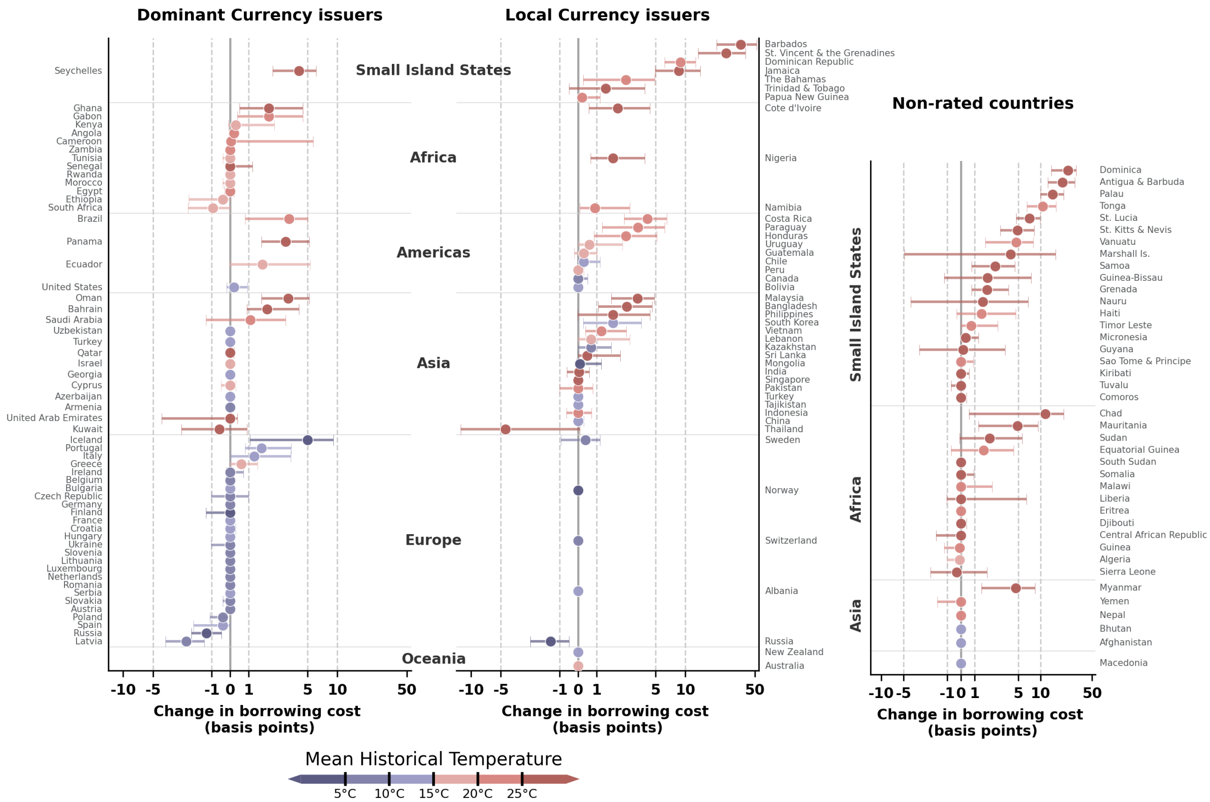
Zhang, L. W. and Chang, C.-P. (2020). Do natural disasters increase financial risks? an empirical analysis. *Buletin Ekonomi Moneter dan Perbankan*, 23:61–86.

Contents

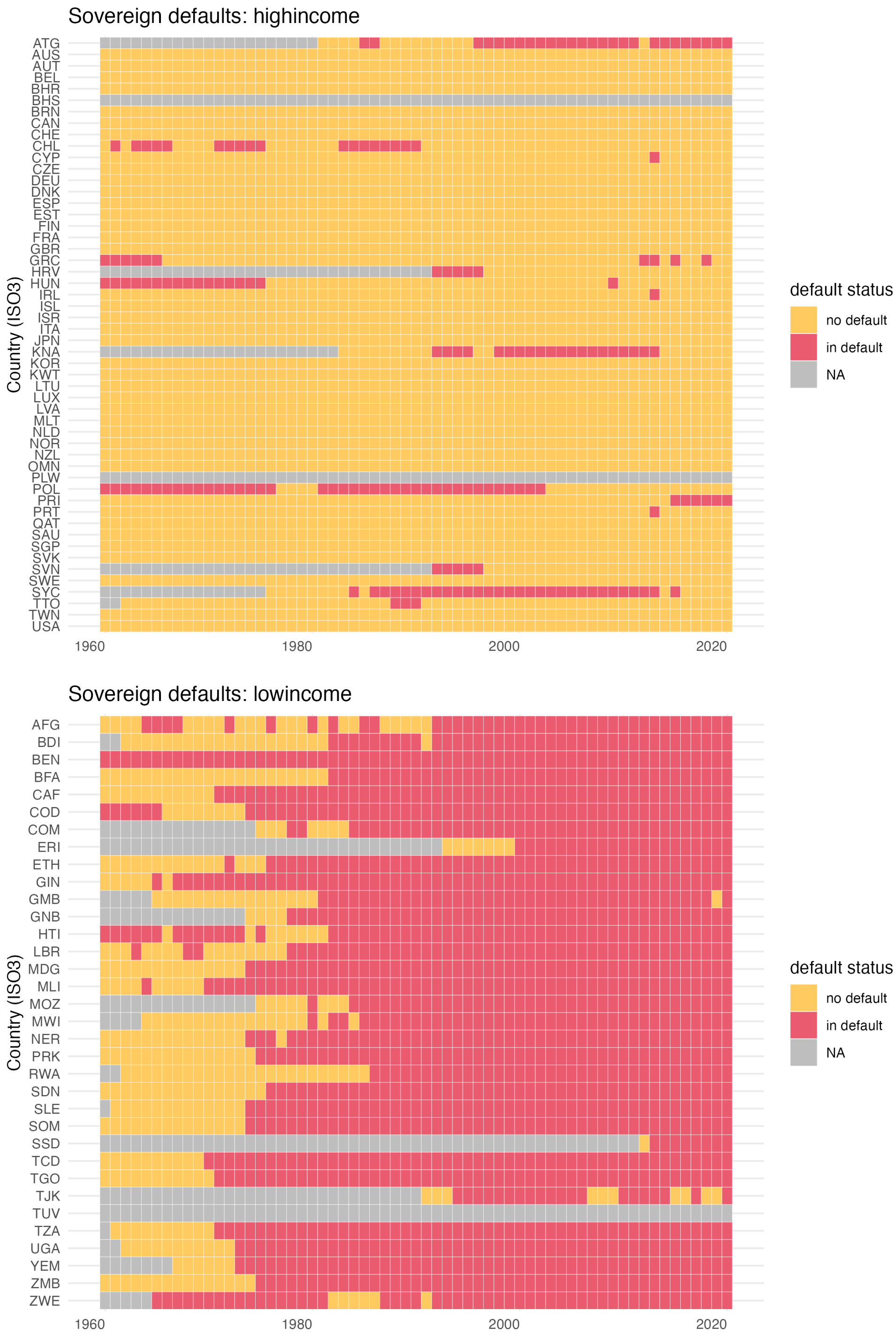
Supplementary Figures



Extended Data Fig. 1. Global climate finance flows in 2022/2023. Data from Climate Policy Initiative.



Extended Data Fig. 2. The change in borrowing cost attributed to historical tropical cyclones and climate change. Values are plotted separately for countries with that issue predominantly in a dominant currency, local currency, and estimates for non-rated countries. Colors are based on each country's mean historical temperature. Error bars show the inter-quartile range of predictions derived from 500 randomized training samples in the rating prediction model, with each sample holding out 20% of countries.



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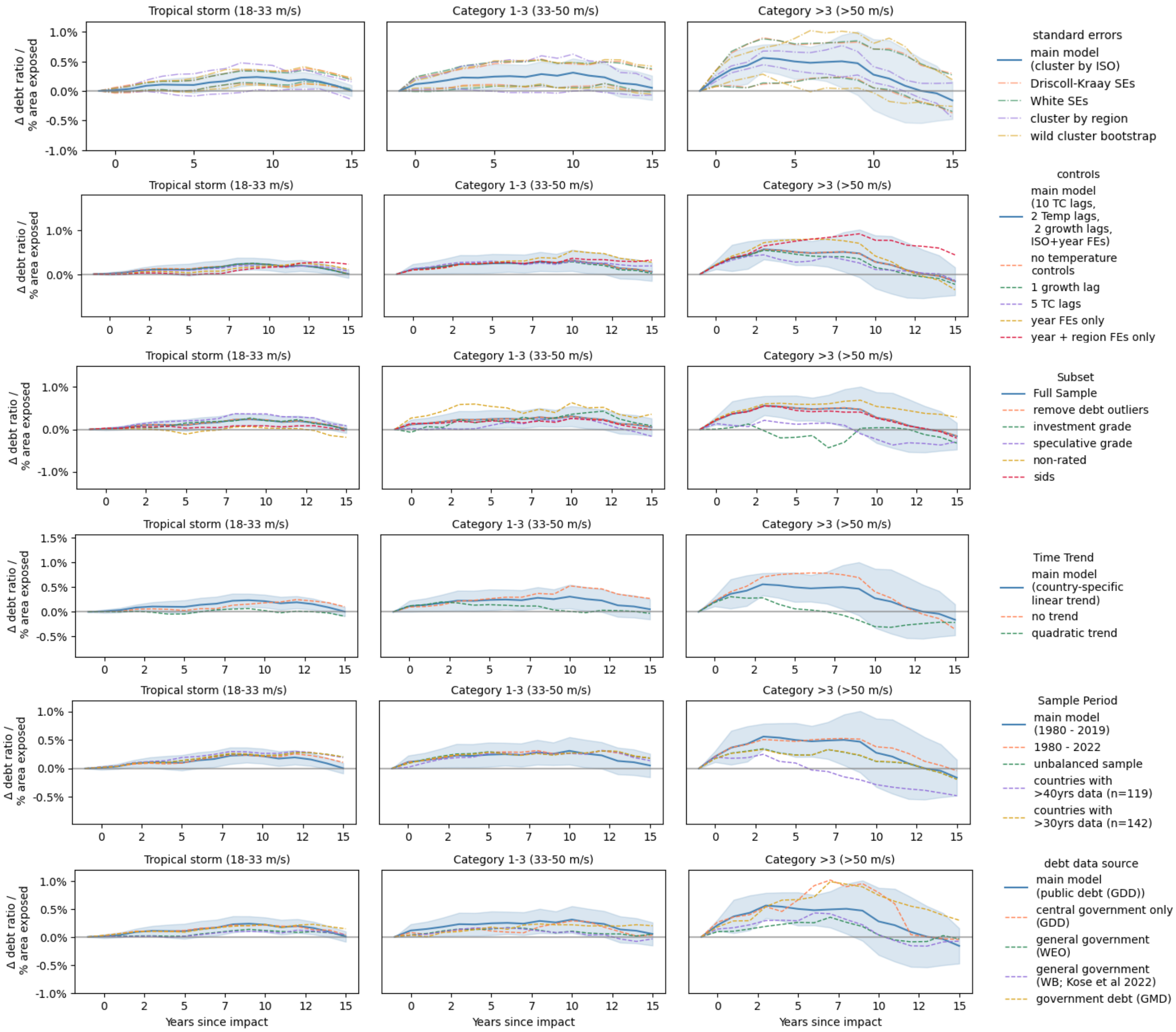
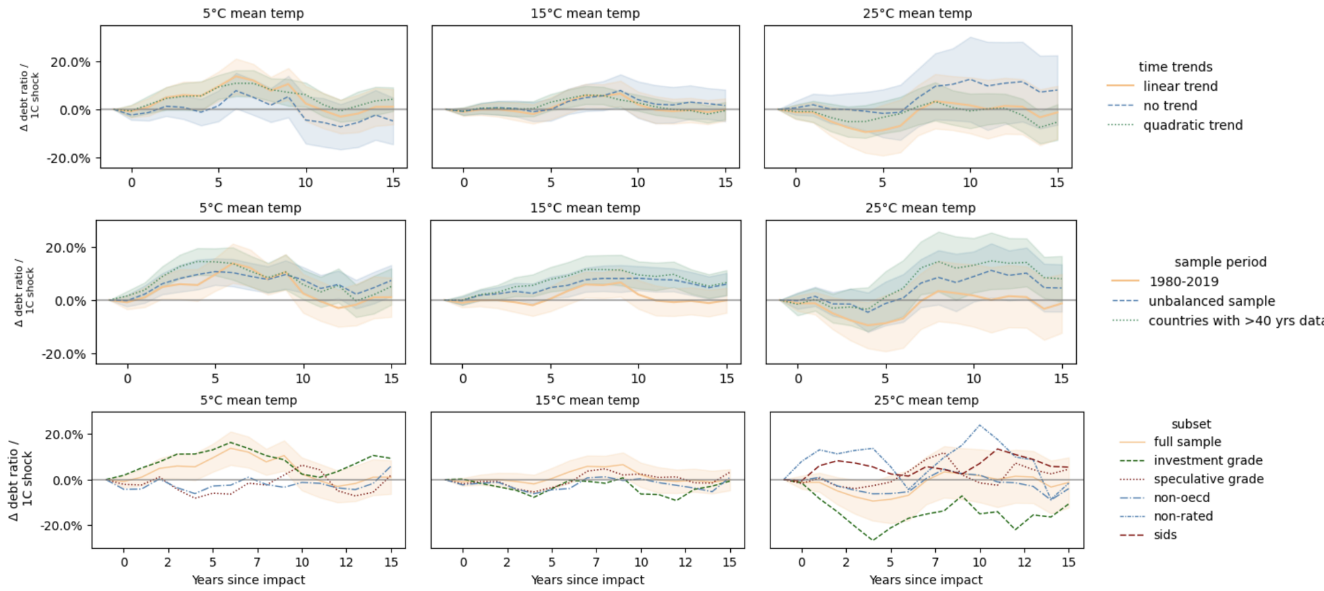


Figure S2. Tropical cyclone impacts on debt ratio. Columns plot the impulse response functions following 1% land area affected by increasing wind speed intensities. Rows are based on robustness checks, by standard error, inclusion of different controls, subsets, time trend, sample period, and the debt data source.



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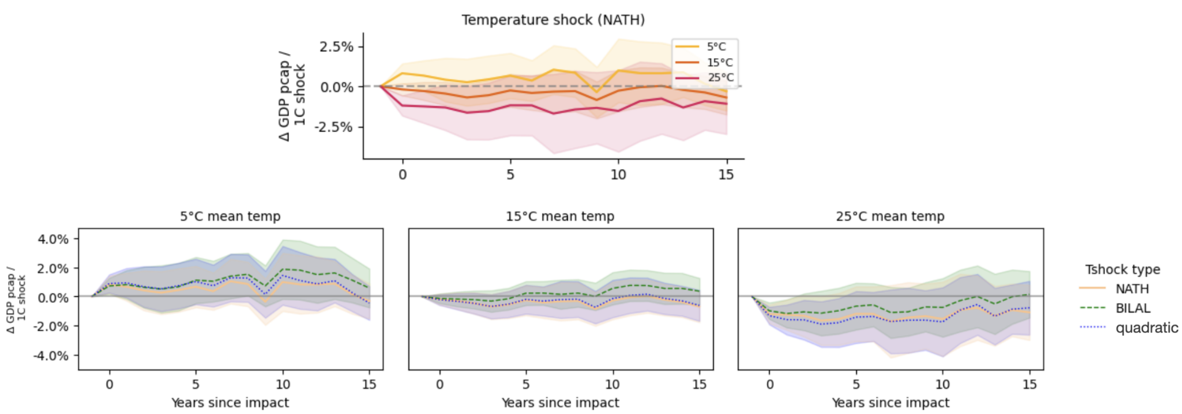

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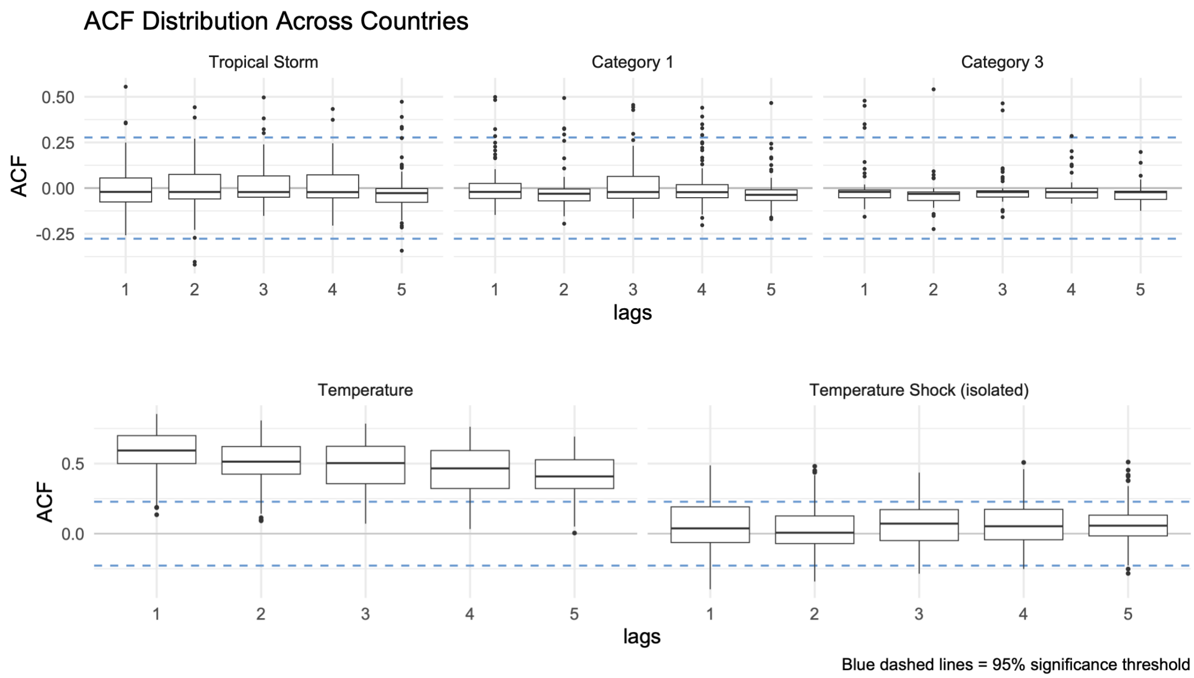

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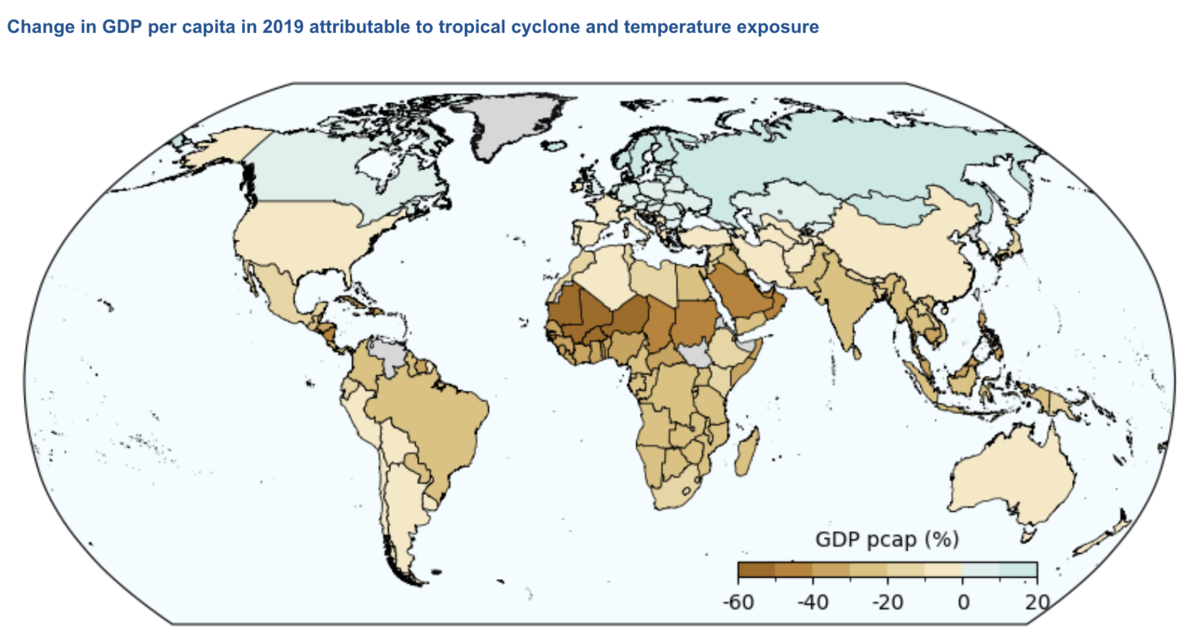

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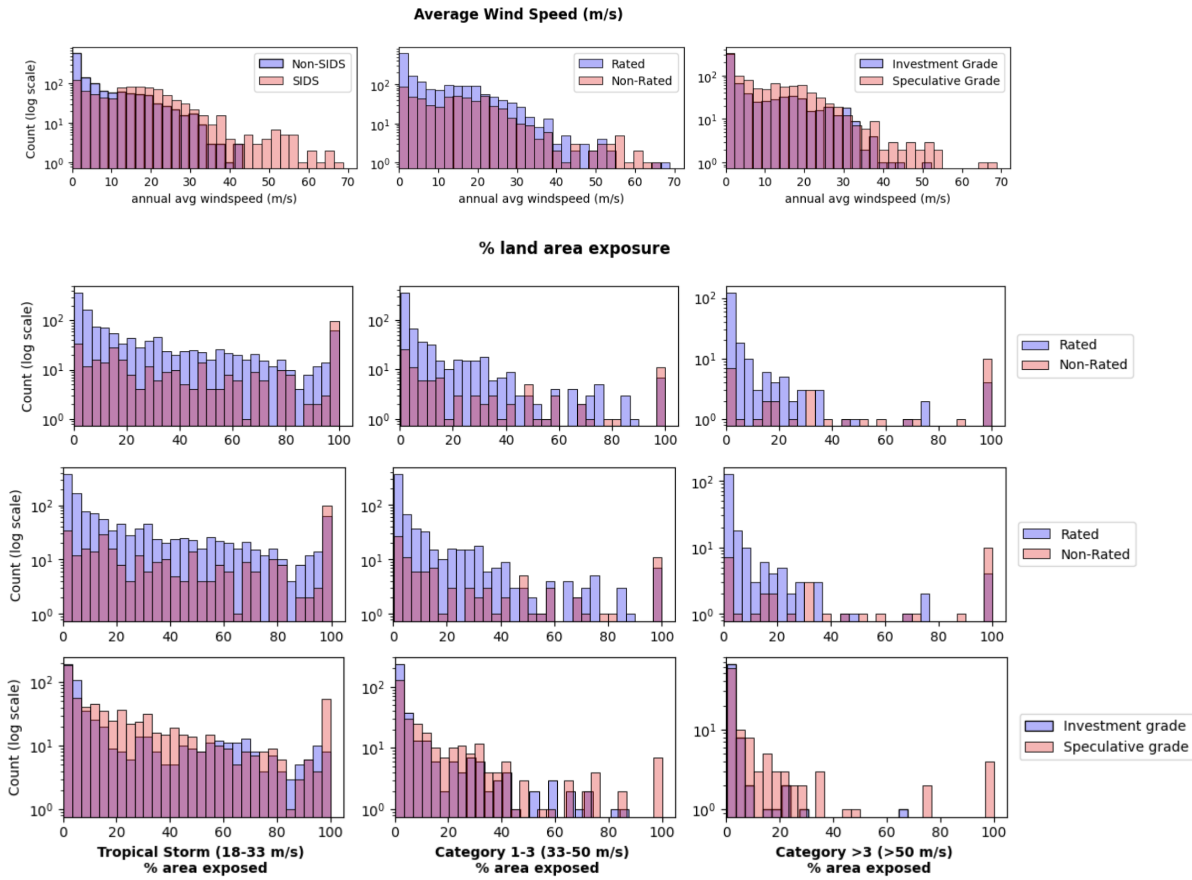

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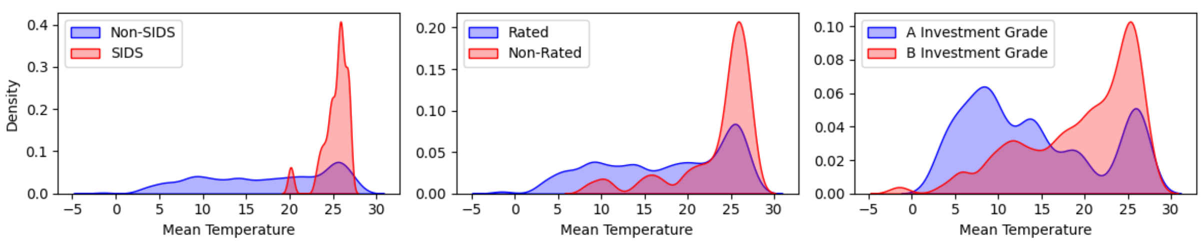

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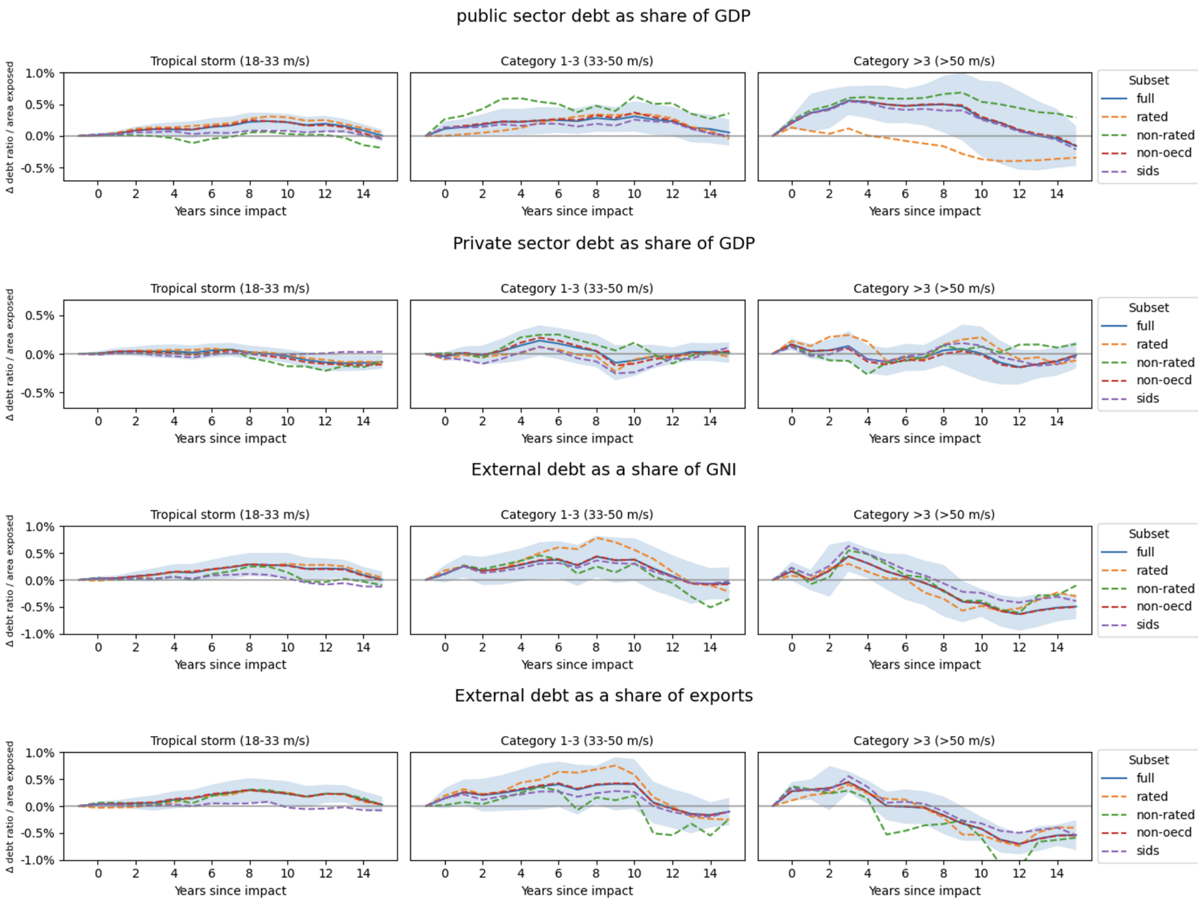

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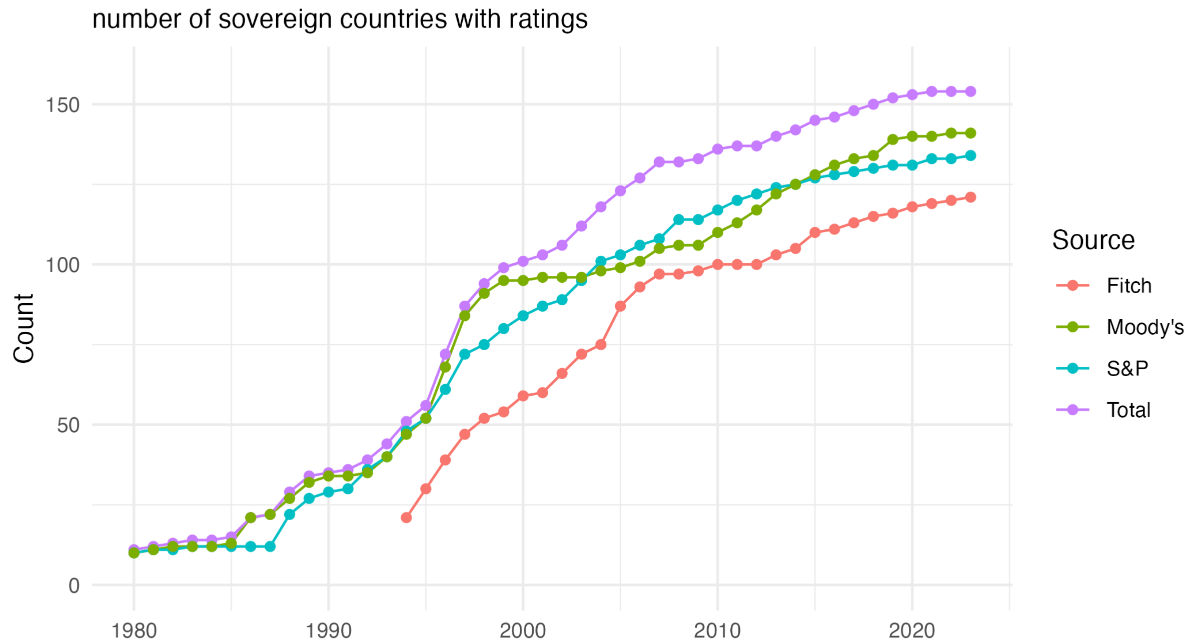

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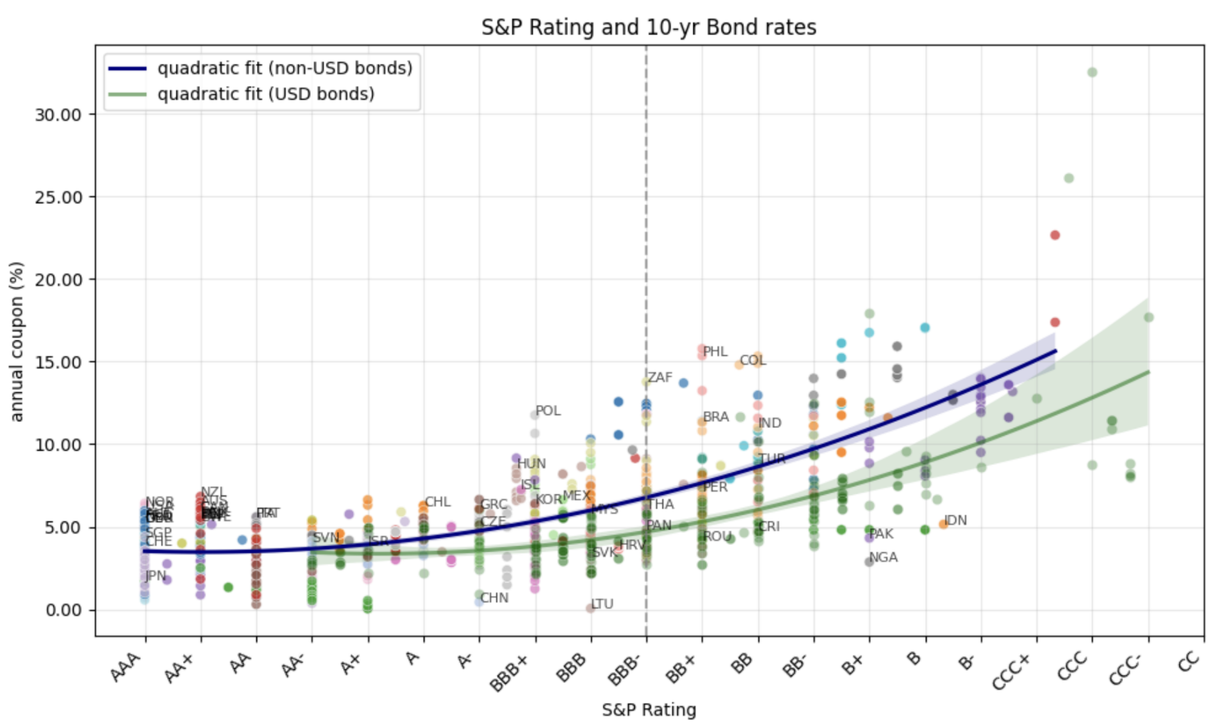

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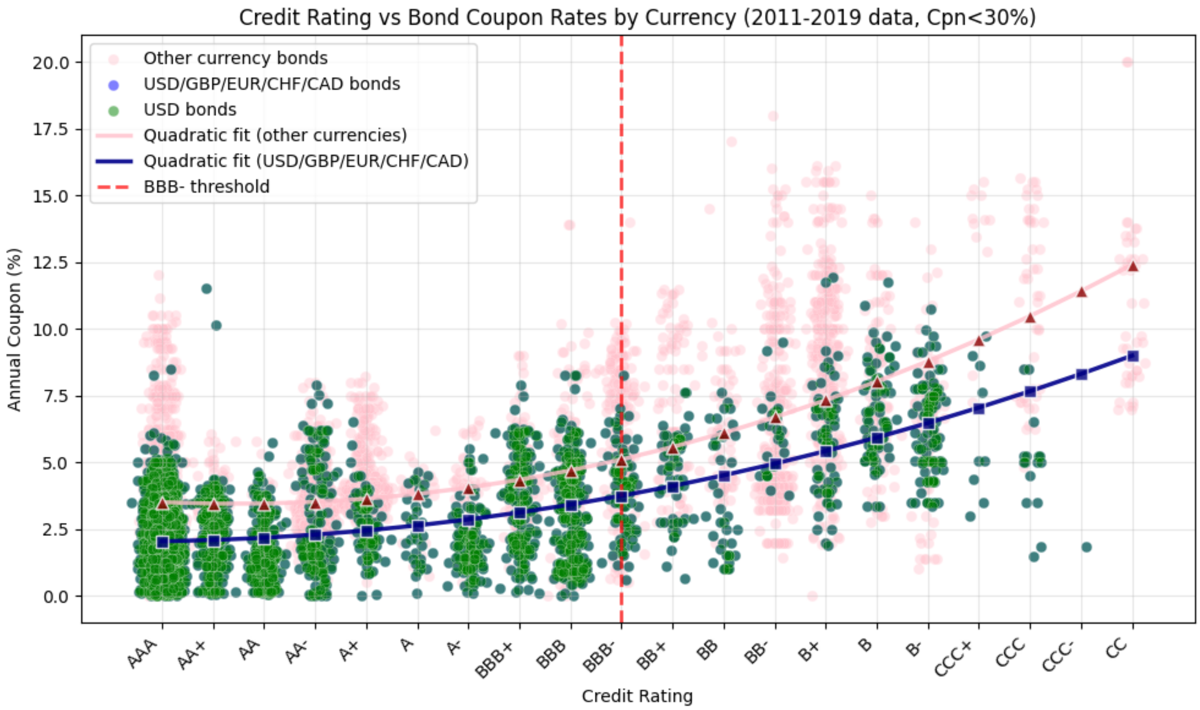

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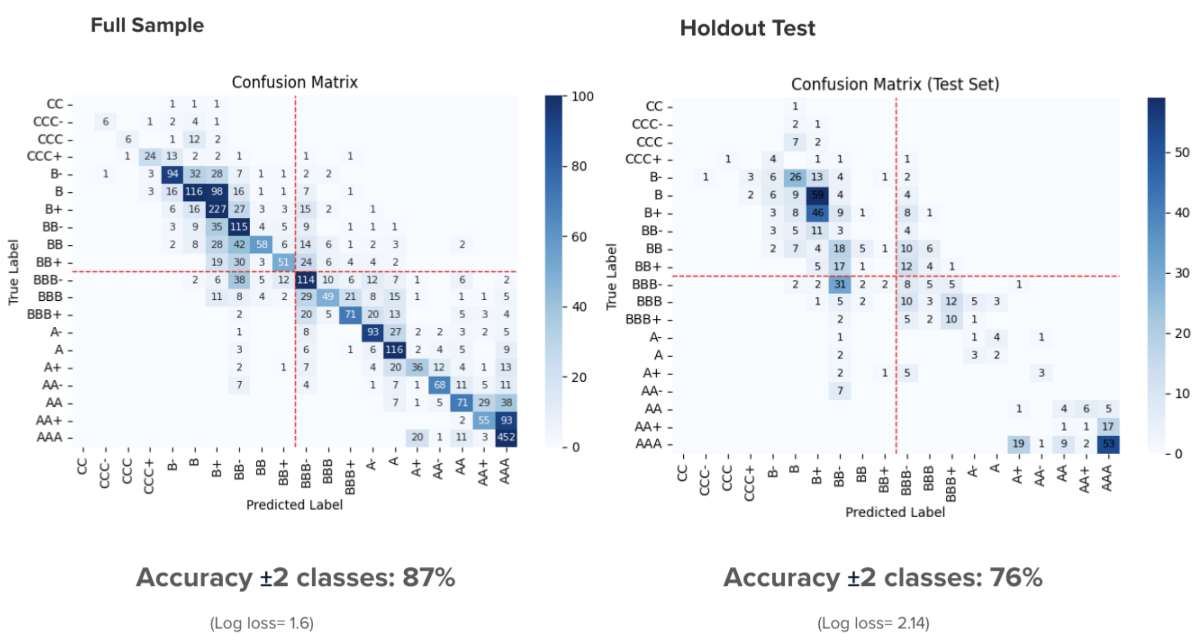

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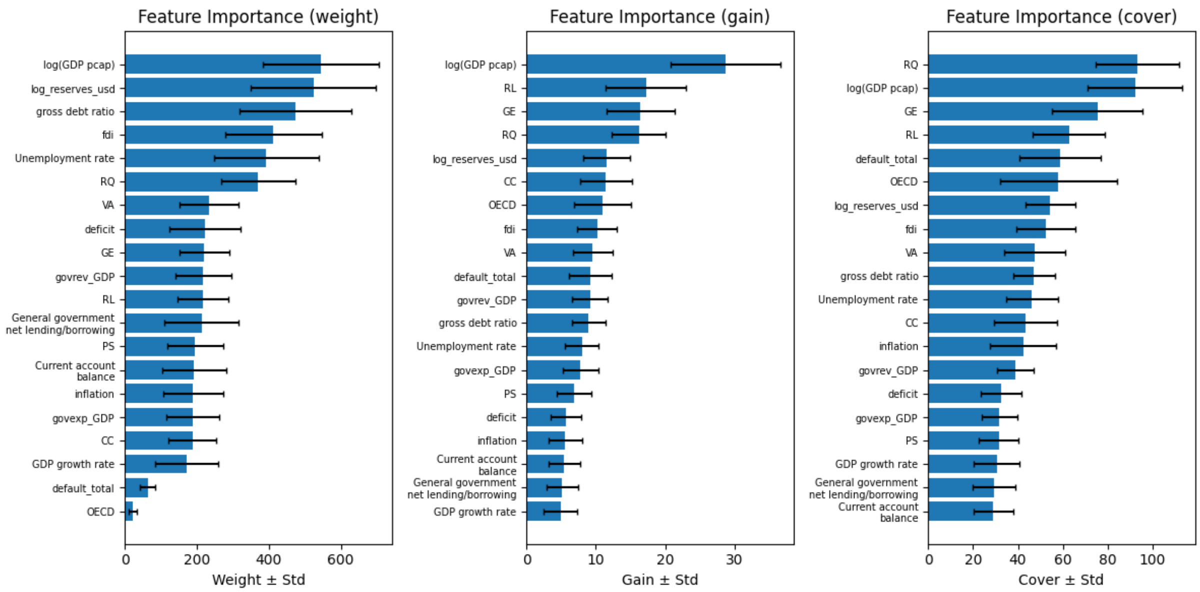

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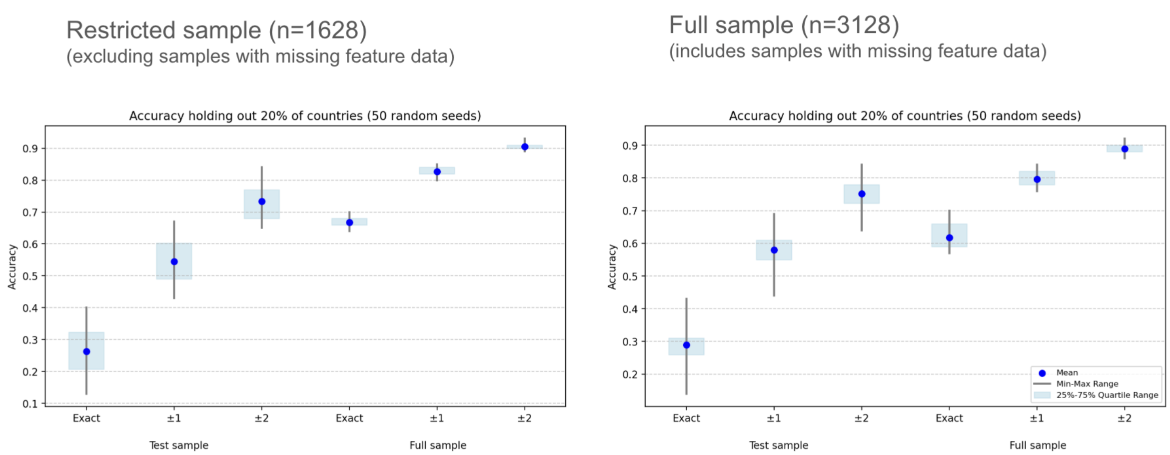

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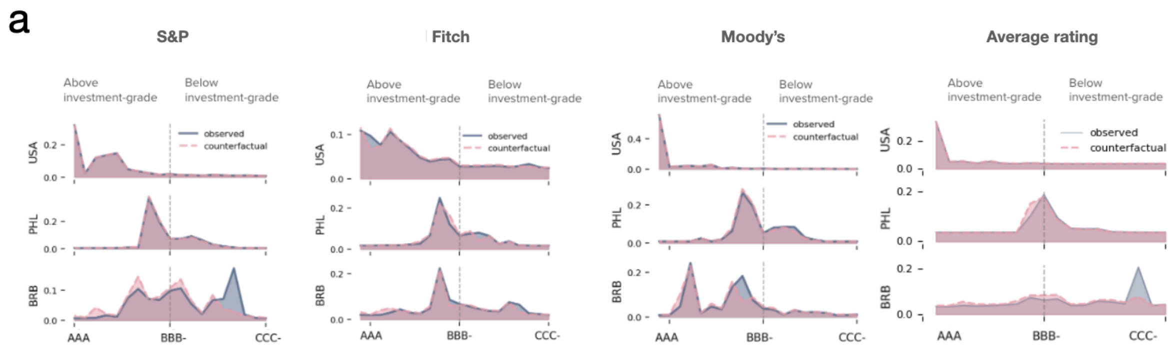
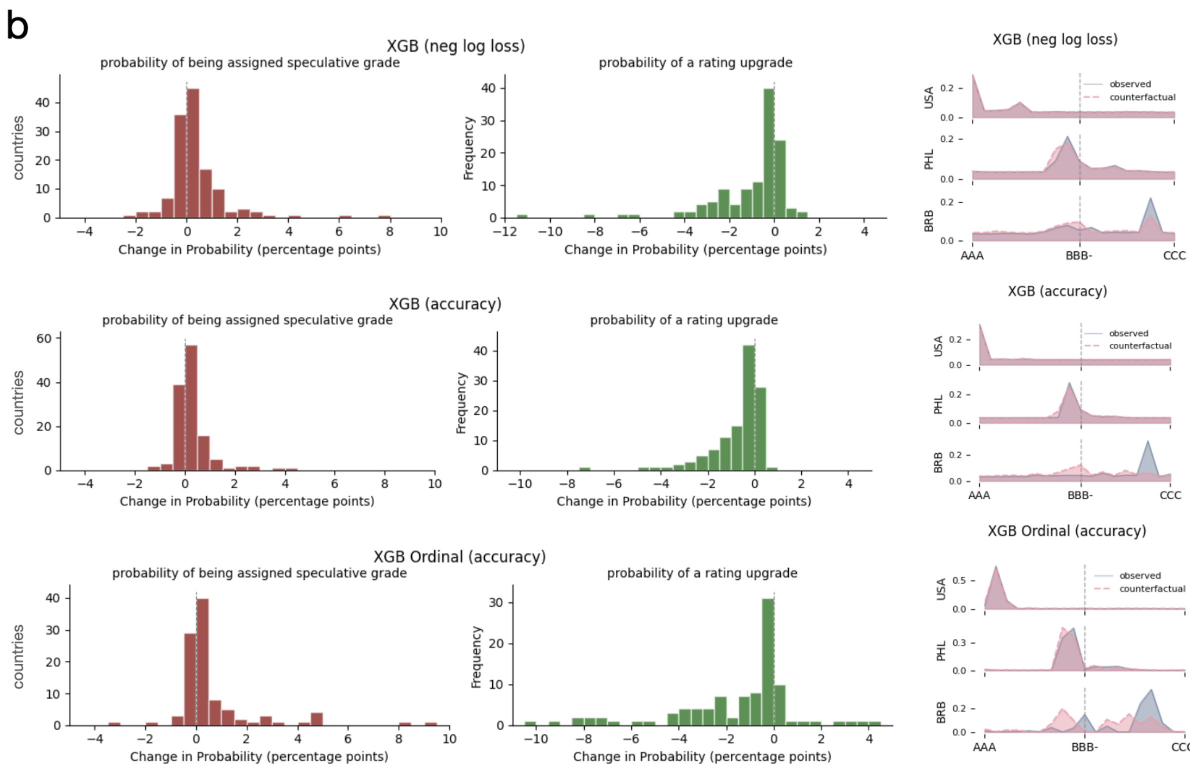


(a)



(b)

Figure S16. Counterfactual credit ratings. Panel a shows the probability distribution of sovereign credit ratings for three selected countries (The United States, The Philippines, Barbados) using observed vs counterfactual debt-to-GDP ratio and GDP in 2019, based on rating data from S&P, Fitch, and Moody's. Our main model uses the average score across three rating agencies. Panel b plots the distribution of how much more likely countries are to be assigned a below–investment-grade rating (left) or the probability of receiving a rating upgrade (right) in the counterfactual scenario. Results from different training models are shown, for XGB classification using log loss as the scoring method (our main model), using accuracy as the scoring method, and XGB Ordinal.

Tables

Table 1. Robustness Checks

Category	**Specification**
Model specifications	• Testing TCs and temperature shocks separately • Testing each of the TC metrics separately • Time trends (no trend, linear, quadratic) • Alternative metric of TC exposure (using average wind speed, as in Hsiang 2014)
Time period	• Sample from 1980–2019 (removing COVID years; main model) • Sample from 1990–2022 (longest period preserving balanced sample, with exposure shocks starting in 1980)
Testing subsets + removing outliers	• Removing large TC-impacted economies (China, US) • Removing debt ratio outliers (Venezuela, Argentina) • Testing subsets of countries (rated vs. non-rated countries)
Selecting control variables	• Lags of country GDP growth • Without temperature controls • Lags of TC, temperature shocks
Standard error treatments	• Wild bootstrap (jittering the residuals) • Empirical bootstrap (country block) • Driscoll-Kraay standard errors (adjust for both serial correlation over time and cross-sectional dependence across units)
Different GDP debt datasets	• Global Debt Database (main model; based on IMF data, Mbaye et al. 2018) • World Economic Outlook / World Bank (Kose et al. 2022) • Global Macro Database (Müller et al. 2025)

category	ordinal scale	Moody's	S&P	Fitch
	21.0	Aaa	AAA	AAA
	20.5	Aaa*/Aa1**	AAA*/AA+**	AAA*/AA+**
	20.0	Aa1	AA+	AA+
	19.5	Aa1*/Aa2**	AA+*/AA**	AA+*/AA**
	19.0	Aa2	AA	AA
	18.5	Aa2*/Aa3**	AA*/AA-**	AA*/AA-**
	18.0	Aa3	AA-	AA-
	17.5	Aa3*/A1**	AA-*/A+**	AA-*/A+**
	17.0	A1	A+	A+
investment-grade	16.5	A1*/A2**	A+*/A**	A+*/A**
	16.0	A2	A	A
	15.5	A2*/A3**	A*/A-**	A*/A-**
	15.0	A3	A-	A-
	14.5	A3*/Baa1**	A-*/BBB+**	A-*/BBB+**
	14.0	Baa1	BBB+	BBB+
	13.5	Baa1*/Baa2**	BBB+*/BBB**	BBB+*/BBB**
	13.0	Baa2	BBB	BBB
	12.5	Baa2*/Baa3**	BBB*/BBB-**	BBB*/BBB-**
	12.0	Baa3	BBB-	BBB-
	11.5	Baa3*/Ba1**	BBB-*/BB+**	BBB-*/BB+**
	11.0	Ba1	BB+	BB+
	10.5	Ba1*/a2**	BB+*/BB**	BB+*/BB**
	10.0	Ba2	BB	BB
	9.5	Ba2*/Ba3**	BB*/BB-**	BB*/BB-**
	9.0	Ba3	BB-	BB-
	8.5	Ba3*/B1**	BB-*/B+**	BB-*/B+**
	8.0	B1	B+	B+
	7.5	B1*/B2**	B+*/B**	B+*/B**
	7.0	B2	B	B
	6.5	B2*/B3**	B*/B-**	B*/B-**
speculative-grade	6.0	B3	B-	B-
	5.5	B3*/Caa1**	B-*/CCC+**	B-*/CCC+**
	5.0	Caa1	CCC+	CCC+
	4.5	Caa1*/Caa2**	CCC+*/CCC**	CCC+*/CCC**
	4.0	Caa2	CCC	CCC
	3.5	Caa2*/Caa3**	CCC*/CCC-**	CCC*/CCC-**
	3.0	Caa3	CCC-	CCC-
	2.5	Caa3*/Ca**	CCC-*/CC**	CCC-*/CC**
	2.0	Ca	CC	CC
	1.5	Ca*	CC*	CC*
	1.0	C	C	C

Table 2. Conversion table of ratings from Moody's, S&P, Fitch to a descending linear ordinal scale. Ratings greater than BBB-/Baa3 are considered investment-grade ratings.

	Ordered Probit	Ordered Forest	XGB Classification	XGBoost Ordinal
What	Maximum likelihood estimation (MLE) to find parameter values that best fit the observed data	Random forest bagging + imposing ordinal nature of outcome variables	Gradient boosted decision trees; trees are built sequentially to minimize loss	Gradient boosted decision trees; trees are built sequentially to minimize loss
Pros	Naturally preserves ordinal nature of outcome variables	Account for nonlinear combinations of predictors.	Account for nonlinear combinations of predictors, and missing data also counts as information. Model is able to learn the ordered nature of outcome variables.	Ordinal nature of outcomes are preserved through a series of binary predictions.
Cons	Requires parallel regression assumption	Performs poorly in replicating the ordinal nature of outcomes 'Probabilities' for predictions are assigned based on the 'voting' behavior of trees	Need to be careful with overfitting.	Need to be careful with overfitting. On rare occasions, violates the Kolmogorov axioms of probability

Table 3. Table listing different rating prediction models that were tested in this study, their pros and cons.

Variable	Definition	Source
Current account balance	The difference between a country's savings and investments, reflecting net trade in goods and services plus net income and transfers (% of GDP)	World Economic Outlook
General government net lending/borrowing	Government fiscal balance; surplus or deficit as a percentage of GDP	World Economic Outlook
Gross debt ratio	Total government debt as a percentage of GDP	World Economic Outlook
log(GDP pcap)	Log of GDP per capita	World Economic Outlook
GDP growth rate	Annual percentage change in real GDP	World Economic Outlook
Deficit	Government budget deficit, typically expenses minus revenues (% of GDP)	World Economic Outlook
log_reserves_usd	Natural logarithm of foreign exchange reserves in USD; indicates external liquidity buffer	World Economic Outlook
Foreign Direct Investment (FDI)	Cross-border investment flows into a country (% of GDP)	World Economic Outlook
Inflation	Annual percentage change in consumer price level	World Economic Outlook
Unemployment rate	Percentage of the labor force without jobs but actively seeking work	World Economic Outlook
default_total	Indicator of whether a country is in some form of sovereign debt default in a given year	BoC–BoE Sovereign Default Database
govexp_GDP	Government expenditure as a percentage of GDP	World Economic Outlook
govrev_GDP	Government revenue as a percentage of GDP	World Economic Outlook
Voice and Accountability (VA)	Captures perceptions of citizens' ability to participate in government selection and freedom of expression	World Governance Indicators
Regulatory Quality (RQ)	Captures perceptions of the government's ability to formulate and implement sound policies that promote private sector development	World Governance Indicators
Government Effectiveness (GE)	Captures perceptions of public service quality and policy implementation credibility	World Governance Indicators
Rule of Law (RL)	Captures perceptions of contract enforcement, property rights, police, and court quality	World Governance Indicators
Control of Corruption (CC)	Captures perceptions of the extent to which public power is exercised for private gain	World Governance Indicators

Table 4. Table listing the prediction variables, definitions, and data source used in the XGB model.