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]

May 26, 2026
draft

Abstract

Addressing climate change through mitigation and adaptation is anticipated to require more than $6 trillion in global investment annually by 2035. However, many countries face significant barriers to accessing this finance, due to low or absent credit ratings, large debt burdens, and high borrowing costs. Climate change may further amplify these barriers, creating a "vicious cycle" in which mounting economic losses reduce 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 both by their exposure to baseline naturally occurring tropical cyclones (TCs) and by anthropogenic warming. Our empirical estimates suggest that, on average across TC-exposed countries, about 20% of debt-to-GDP ratios are attributable to TCs from 1980 to 2019. Across all countries, GDP levels are on average 12% lower due to the combined impacts of TCs and warming temperatures. In a separate machine-learning analysis, we estimate that these macroeconomic impacts are associated with an increased likelihood of hotter countries receiving credit ratings below investment grade (<BBB–), as well as persistent credit risk premiums of at least 1 basis point in 64 countries and 5 basis points in highly exposed countries. We provide estimates for 181 countries, including many TC-affected and/or hot countries that do not have bond yield data. Future increases in temperature and TC activity may further worsen sovereign credit conditions, 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, 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 (fig. S1).

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), Almeida et al. (2017); Reinhart (2002)). These constraints are compounded by high sovereign debt levels which are projected to reach 100% of global GDP by 2030 (International Monetary Fund (2024)). In our data, 62 countries exposed to TC winds $\geq$18m/s (excluding the U.S., China, and countries in extratropical latitudes) collectively accounted for 20% of world GDP in 2025, with total debt representing 15% of world GDP and 73% of their aggregate GDP. 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. S2, 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); Zenios (2024)). 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). 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. S16). 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)).

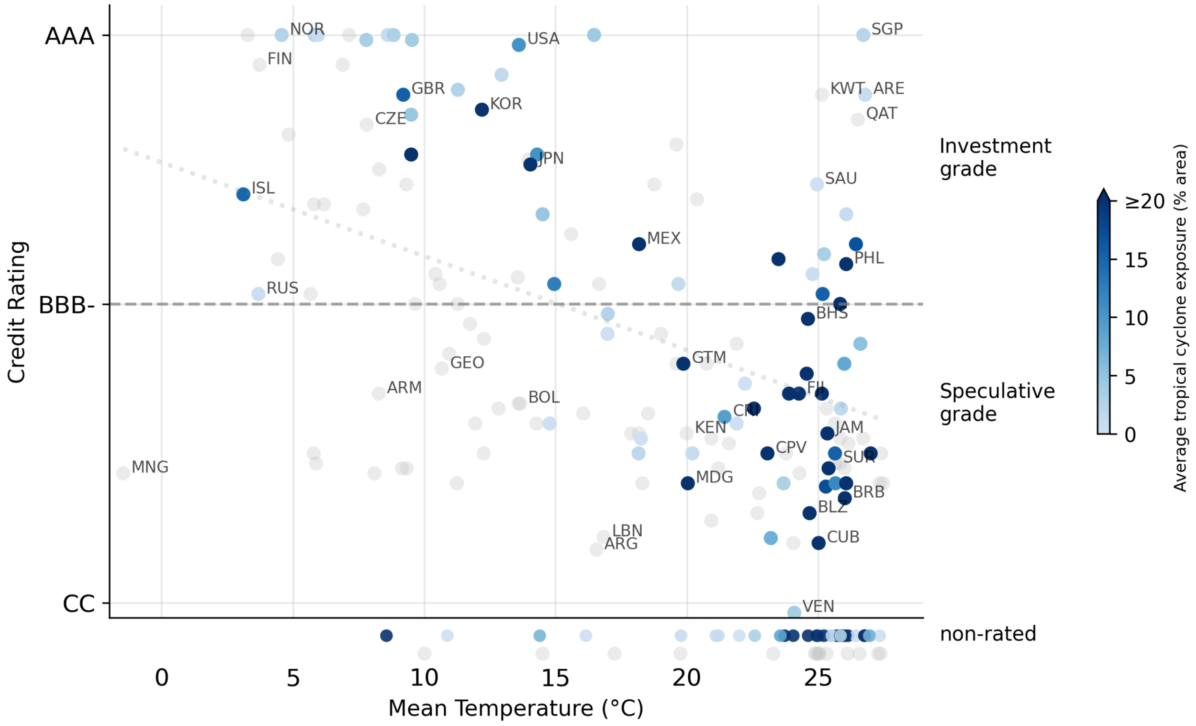


Figure 1. Scatter plot of country mean temperatures, average tropical cyclone exposure, and sovereign credit ratings in 2019. Mean temperatures are on the x-axis, and credit ratings on the y-axis are the average of ratings from the "Big Three" agencies (S&P, Moody's, Fitch). Colors indicate the average 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. Largely focused on the temperature-GDP impact channel or the association between ratings and aggregate indicators of climate risk vulnerability, these studies find that countries facing high climate risk and increasing debt may face rating downgrades ranging between 0.1 and 1 notch (the equivalent of dropping from BBB to BBB-) by 2030 (Cevik and Jalles (2020), Bolton et al. (2023), Klusak et al. (2021), Beirne et al. (2021), Dryden and Volz (2025); Kling et al. (2025)). Other studies investigate the dynamic effect of various local and global shocks on bond yields and estimate effects ranging from 4 to 82 basis points (Anyfantaki et al. (2025); Huesler (2025); Gilchrist et al. (2022); Gande and Parsley (2005); Eichengreen and Mody (1998); Arora and Cerisola (2001)), or that risk premiums are greater than 100 basis points for TC-prone countries and other climate vulnerable countries (Mallucci (2022); Kling et al. (2025)). (See (fig. S3 and fig. S4) for summary.) Yet other studies investigate the fiscal impact of disasters in general (Fisera et al. (2023), Deryugina (2022)) or 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)).

One limitation of studies that measure borrowing cost impacts using bond yields as the outcome is that they are constrained to a set of 10 to 50 advanced and emerging market economies with high volumes of bond issuance that are actively traded in the market (Anyfantaki et al. (2025); Huesler (2025); Gilchrist et al. (2022); Gande and Parsley (2005); Eichengreen and Mody (1998); Arora and Cerisola (2001), see fig. S4). Countries with speculative grade ratings that infrequently issue bonds on the international market are less likely to be affected by the dynamic market pricing effects identified in these studies. Furthermore, the most TC-affected and hottest countries either hold speculative grade ratings or have never received a rating (fig. 1, table S1, table S2). Borrowing costs for these countries depend first and foremost on assessments of their underlying credit risk, which is shaped by macroeconomic, political and institutional factors as identified in numerous studies that attempt to reproduce sovereign credit ratings (Afonso et al. (2011); Klusak et al. (2021); Cantor and Packer (1996); Cevik and Jalles (2020); Ramírez-Rondán et al. (2023); Reinhart et al. (2003)).

This study provides the first global assessment of how historical exposure to baseline naturally-occurring TCs and long-term country-level warming may have shaped countries' debt, and how this in turn may have shaped the cost and availability of capital by altering credit risk. By focusing on the macroeconomic factors that affect underlying credit risk instead of bond yields, we provide estimates on the persistent risk premium faced by a much broader set of TC-affected and hotter countries than are currently represented in the literature. This is distinct from the dynamic market-based risk premium driven by investor perceptions following a shock. Persistent borrowing costs may compound countries' debt burdens and limit their capacity to respond to climate change. We emphasize that the first part of the study leverages exogenous climate variation for causal identification, while the second part faces more difficult identification challenges and is based on machine learning predictions that translate how our empirical findings about debt and GDP impacts may be affecting countries' access to finance from the international capital market.

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); Cevik and Jalles (2020); Kling et al. (2018), see also our own estimates in table S5, table S6). 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). To our knowledge, this study is the first to apply local projections to relate a physical metric of TCs to debt ratios as the outcome, making it distinct from a related study Hsiang and Jina (2014) that uses a distributed lag model with average wind speed intensity as the TC exposure metric. We additionally demonstrate an application of the LP Difference-in-Difference method (Dube et al. (2025)), which to our knowledge is the first application of this method to the macroeconomic impact of TCs and warming.

Next, to understand how the macroeconomic impacts from TCs and temperature change may shape 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. A number of studies have recently applied machine-learning methods to both predict and project credit ratings into the future (Klusak et al. (2021); Burke et al. (2026)), building on rapidly evolving literature that applies machine-learning in economics (Athey and Imbens (2019)). We combine these models with our causal estimates of debt and GDP impacts to predict the persistent credit risk premium faced by 181 countries that are differentially exposed to TCs and long-term warming.

2 Results

We find clear evidence that exposure to TCs impacts 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 category of 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. S16). 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. S6). We additionally show robustness using Local Projections Difference-in-Difference (Dube et al. (2025)), which estimates the effect of each intensity category separately under various clean control conditions (fig. S9, fig. S10, fig. S11).

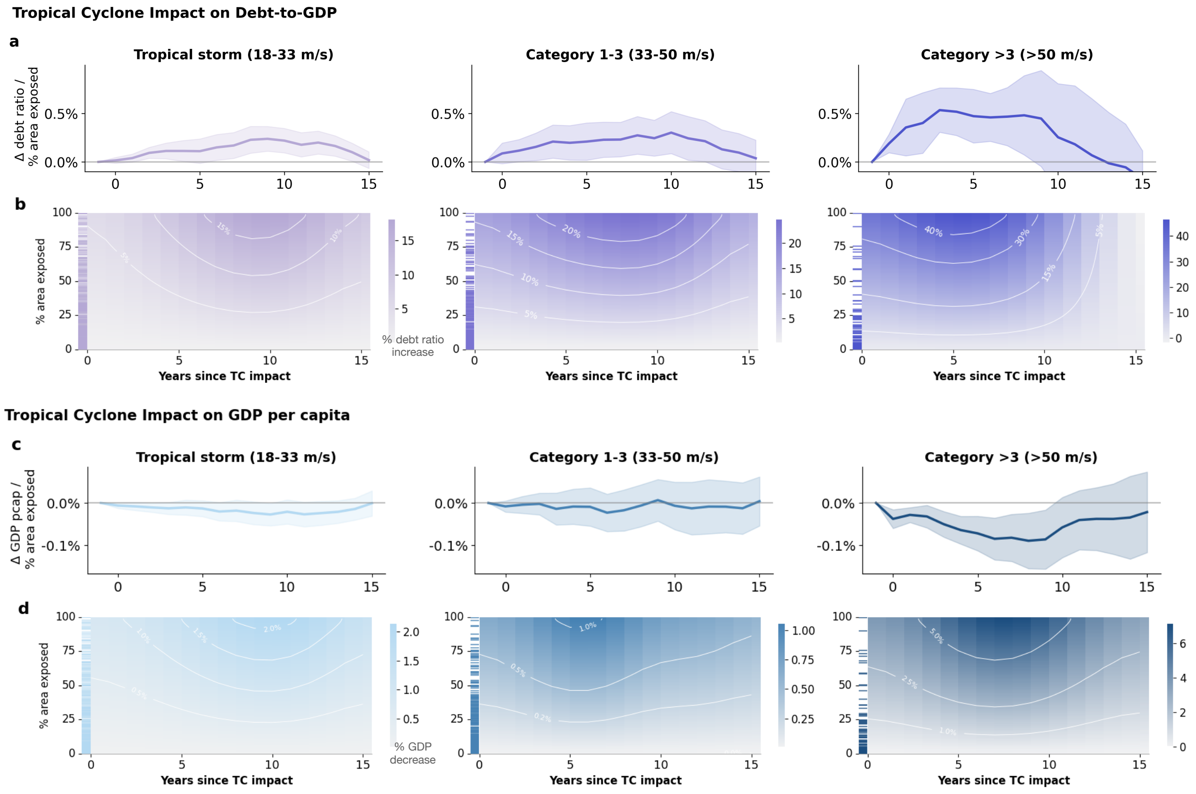


Figure 2. Impact of tropical cyclones on debt-to-GDP ratios and GDP. Panel a plots the response of the debt ratio to 1% of land area exposed to wind speeds of increasing intensity. **Panel b** scales each response estimate by the land area exposed to each wind speed category, from 0 to 100%. The distribution 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 TCs (>50 m/s) reduces GDP by 1% at its peak before returning to trend. For moderately severe TCs (33-50 m/s) we do not detect any significant impact, indicating that economic activity may be recovering quickly in impacted regions as suggested by other studies (Deryugina et al. (2018); del Valle et al. (2020); Groen et al. (2020)). 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. S7). 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. S7).

We also test for differences in the treatment effect along three dimensions: countries' baseline naturally-occurring TC exposure, debt-carrying capacity, and exposure to prior severe storms (SI appendix). The debt-ratio response of countries impacted by a severe TC season in the previous five years is more muted in the short-term relative to countries without recent exposure, but the difference is insignificant after four years. The interaction term is not significant at the 5% significance level for most horizons for the other two dimensions (fig. S13, fig. S14). Restricting the sample to countries without any prior TC exposure yields larger but noisier estimates following a severe TC year, reflecting the substantially smaller clean-control sample at each horizon (fig. S9).

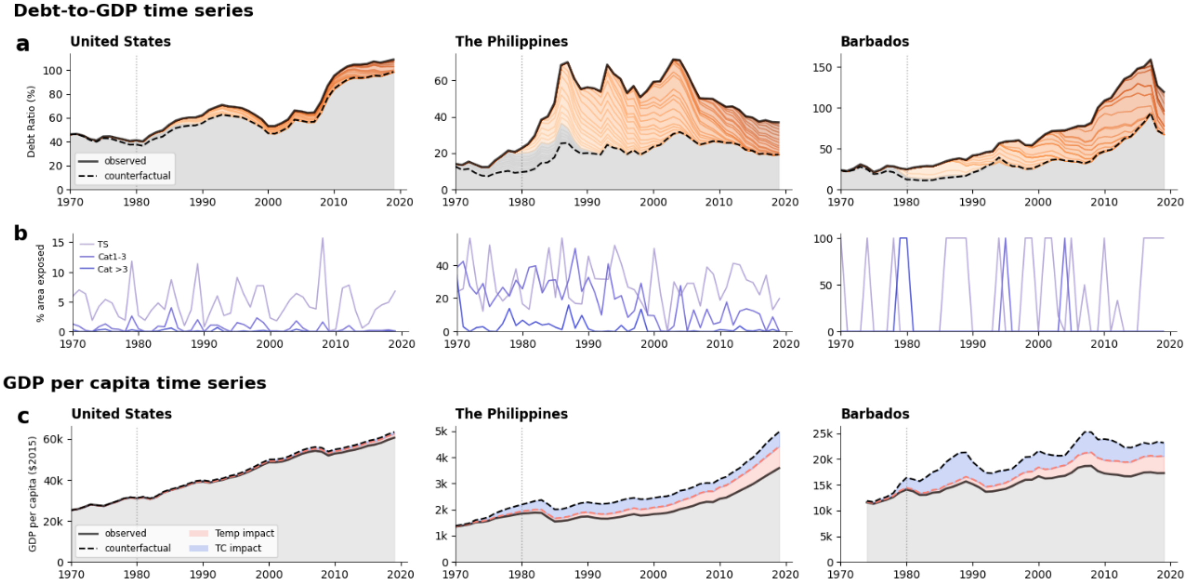


Figure 3. Panel a (observed vs counterfactual debt ratio time series) plots the time series of the observed debt ratio (black line) and counterfactual debt ratios (colored bars) for three countries with varying exposures. Each shaded bar represents the impact of one tropical cyclone season. The black dotted line represents the counterfactual time series representing the impact of TCs in the previous 15 years, and the vertical line in 1980 indicates the start of our model estimates. **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 under the hypothetical scenario that observed warming and TC landfalls did not occur. Given the recovery observed 15 years after a TC, the total counterfactual TC impact in any given year includes the effect of TCs in the previous 15 years. We find that, on average across TC-exposed tropical countries (within latitudes ±23.5°), about 20% of debt ratios from 1980 to 2019 are attributable to TCs, and GDP levels are approximately 12% lower due to the combined impacts of TCs and country-level warming across all countries (fig. 3, fig. S22, fig. S21). Among small island sovereign states, on average 32% of the public debt burden from 1980 to 2019 is attributable to TCs, and GDP levels are 21% lower due to the combined impact of TCs and country-level warming. Based on these estimates, TC-attributable debt in 2019 was approximately $450 billion, representing 0.5 pp of the world debt ratio, or 10 pp of the debt ratio among TC-exposed sovereigns and 18 pp of the debt ratio among SIDS. A map showing the global distribution of debt ratio impacts is shown in fig. 4 (GDP impacts are shown in fig. S15), and the country-specific range of estimates across the 1980-2019 period are shown in fig. S22 (summarized in table S12). In terms of GDP impacts, country-level warming accounts for a larger share of impacts than TCs (fig. 3, panel c, see country-specific estimates in fig. S21, summarized in table S13). In an alternate hypothetical scenario, we conduct a sensitivity test assuming all TCs had 10% less intense wind speeds during 1980-2019, 10% being a global upper bound estimate on the influence of global warming on TC intensity (Knutson et al. (2020); Bloemendaal et al. (2022); Emanuel (2008)). In this scenario, debt ratio impacts would have decreased by 17-40% (P25–P75). We also quantify the impact attributable to the most intense TC seasons experienced by each country rather than all TCs, and find that >60% of debt ratio impacts are attributable to the top 10 TC seasons and >23% of impacts are attributable to the top 5 TC seasons (fig. 3, panel f; fig. S23).

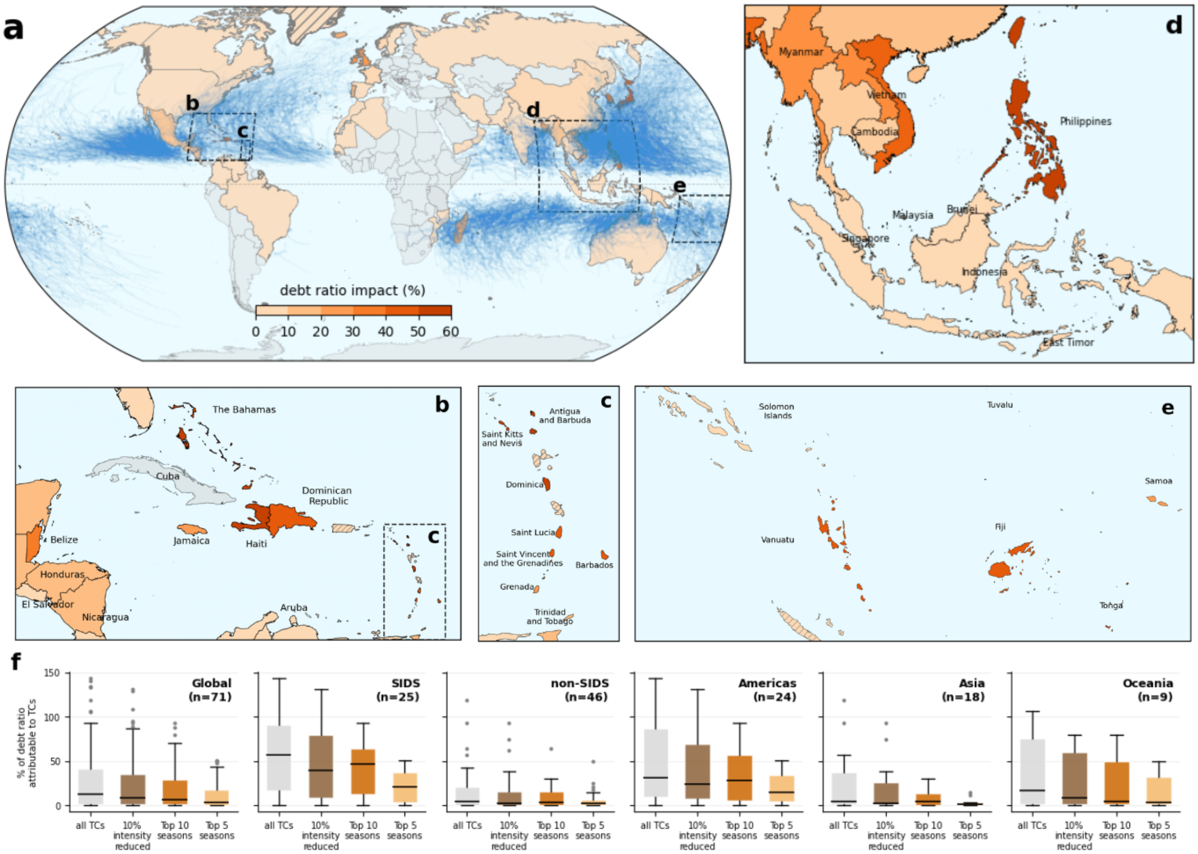


Figure 4. Share of countries' debt ratio in 2019 attributable to tropical cyclone exposure. Panel A shows the global map, where blue lines show tropical cyclone tracks from 1980-2019. **Sub-panels b-e** provide a zoomed-in view of regions that are highly exposed to tropical cyclones. Hatch marks indicate sovereign territories and dependencies without a debt record, and grey indicates countries either without tropical cyclone exposure or debt records. **Panel F** shows the impact of a sensitivity test assuming 10% reduced wind intensity from 1980-2019, and the impact attributable to the top 10 and 5 TC seasons. Each box plot represents the range of country-specific values.

Next, we investigate how the long-run impact on debt ratios and GDP may affect 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 receive below–investment-grade ratings (<BBB-) and 93 countries are less likely to receive a rating up-

grade as a consequence of these macroeconomic impacts (fig. S32). On average, the macroeconomic impacts attributed to TCs and warming are associated with a 0.02 notch downgrade for investment-grade sovereigns, a 0.09 notch downgrade for speculative-grade sovereigns, and a 0.2 notch downgrade for SIDs (fig. S31, table S11). We refer readers to fig. S3 for a comparison with other estimates from literature and we additionally confirm that debt ratio and GDP are important determinants of credit ratings in our own data (table S6, table S5). In addition, using the LP model with credit ratings as the outcome, we confirm that the most severe TC seasons are associated with negative rating actions, although estimates are unstable due to limited time series for the most TC-affected and hottest countries, with 51 countries only receiving their first credit rating after 2000 and 20 Small Island Developing States that are non-rated (fig. S19, table S2).

These rating changes are associated with a change in the borrowing costs of countries, measured here as the basis point difference in the expected coupon rates of sovereign bonds (Methods). Many countries with below investment-grade ratings are likely incurring additional borrowing costs of 1 to 45 basis points due to the persistent credit risk premium associated with the impact of TCs and warming temperatures (fig. 5). We emphasize that the estimates for non-rated countries are out of sample predictions. 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)(fig. S33).

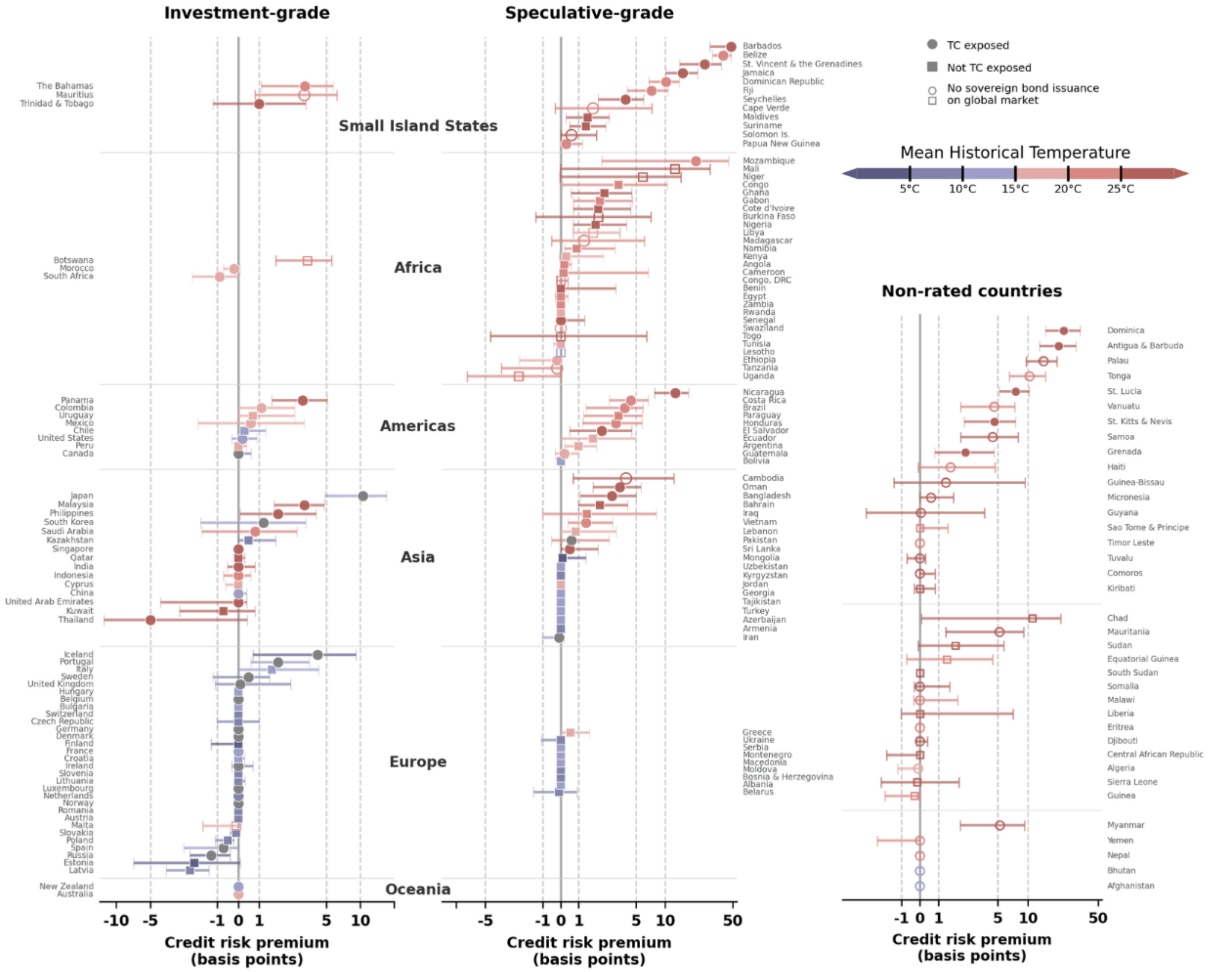


Figure 5. The change in borrowing cost associated with tropical cyclones and warming temperatures. Values are plotted separately for countries with investment-grade (left) and speculative-grade ratings (center), and non-rated countries (right). Colors are based on each country's mean historical temperature. Circle markers indicate countries exposed to TCs (in gray for countries that are outside tropical latitudes ±23.5°) and square markers not exposed to TCs, respectively. Empty markers indicate countries that have not issued sovereign bonds in the international market. 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,fig. S1, Bhattacharya et al. (2024)). Understanding the dynamic impact of baseline 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 baseline 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 high exposure to physical risks (e.g. temperature anomalies and disasters) or transition risks (e.g. dependence on fossil fuel revenues) is 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 thus may not 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. We additionally test average wind speed as the exposure metric in our local projections model and find a peak GDP reduction of 0.10% per m/s, compared with $\sim$0.3% per m/s in Hsiang and Jina (2014). Unlike their finding that income losses persist without recovery over two decades, our main model using % land area exposure finds

GDP impacts that peak within a decade before returning to trend. Furthermore, our % land area metric captures larger effects among SIDS. For the most severe TC years where Cat3+ winds cover at least half a country's land area, peak impacts in SIDS are 1.5× greater on GDP per capita (-8.3% vs -5.4%) and 1.2× greater on the debt ratio (+66% vs +57%) compared to the average wind speed metric (fig. S20).

A major caveat of our analysis is that we do not directly measure the impacts of TC-induced precipitation or storm surge. It is projected that climate change will increase the likelihood of major category TCs and TC-induced precipitation (Sobel et al. (2023), Masson-Delmotte et al. (2021), Knutson et al. (2015), Khouakhi et al. (2017)), 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)). 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 TC winds due to persistent challenges in both satellite and ground-based 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. Disentangling damages attributable to wind, precipitation, and storm surge remains an important avenue for future work.

We also provide a new 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 utilizes 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 baseline 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 turn contributing to a rebound in economic activity (Deryugina et al. (2018); del Valle et al. (2020); Groen et al. (2020)). 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.

We turn to prediction-based models to estimate how these macroeconomic impacts may shape credit risk and borrowing costs. We distinguish between two different types of borrowing cost impacts: the dynamic pricing effect realized through changes in the bond yield following a shock, and the longer-term persistent effect on borrowing costs realized through changes in the underlying sovereign credit risk. Existing studies that focus on bond yields are limited to a narrow set of 10 to 50 advanced and emerging market countries that have large volumes of bond issuance that are frequently traded. By focusing on the macroeconomic factors that are key drivers of underlying credit risk, and utilizing data on credit ratings and coupon rates that are available for a wider sample of countries, we provide borrowing cost estimates for 181 countries, including countries that are most affected by TCs and the warming climate. We show that on average, our estimates are of similar magnitude to the dynamic pricing effect identified by other studies, with greater impacts estimated for speculative grade and non-rated countries (fig. S4). Our estimates can be interpreted as the persistent credit risk premium on top of which additional shock related borrowing costs may accrue.

4 Conclusion

There have been increasing calls for sovereign debt relief in recent years, whether through debt cancelations, 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 disasters (UNEP Finance Initiative, Munich Re (2024)). At the sovereign level, however, no overarching institution exists to coordinate debt relief across official (i.e., 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 that 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.

Our findings show that exposure to baseline TCs and warming temperatures are associated with higher credit risk, which in turn affects the borrowing costs 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. S28). 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:

$$y_{i,t+h} - y_{i,t-1} = \boldsymbol{\beta}_t^h \cdot \mathbf{tc}_{i,t} + \delta_t^h \cdot \boldsymbol{\tau}_{i,t} + \mathbf{x}'_{i,t}\,\boldsymbol{\eta}_h + \alpha_i + \gamma_t + \phi_i(t) + \epsilon_{i,t} \qquad \text{for } h = 0, 1, \ldots, H \quad (1)$$

The model allows us to estimate the impact of tropical cyclone ($\boldsymbol{\beta}_t^h$) and temperature (δ_t^h) shocks occurring in year t on outcomes (y) for country (i) at increasing time horizons ($t+h$). The term $\mathbf{x}'_{i,t}\,\boldsymbol{\eta}_h$ represents the lagged TC and temperature controls with their horizon-specific coefficients:

$$\mathbf{x}'_{i,t}\,\boldsymbol{\eta}_h \;=\; \sum_{l=1}^{n} \boldsymbol{\beta}_l^h \cdot \mathbf{tc}_{i,t-l} \;+\; \sum_{l=1}^{n} \delta_l^h \cdot \boldsymbol{\tau}_{i,t-l}$$

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

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

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

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. S5 and table S3.

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 300-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:

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

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. S8).

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. S7).

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. S5). 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:

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

where $\beta_{c,l}^{h}$ 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 TCs and warming temperatures, the ratings agencies may be assigning ratings to countries that are lower than they would have been absent TCs and warming.

4.3.1 Rationale for the XGB model in our setting

While the first part of the paper exploits exogenous climate variation to identify causal effects of temperature and TCs, the second part uses a prediction-based model (XGBoost) to translate these macroeconomic impacts into higher borrowing costs in terms of a persistent credit risk premium that may be affecting exposed countries. Given the causal identification challenges in this second component, we detail below the rationale for the prediction-based approach in our setting. The different prediction models that were tested are outlined in SI Appendix.

First, countries most exposed to TCs and the greatest warming impacts either do not have rating data or rarely issue bonds, making it challenging to estimate the causal impact on credit ratings or bond yields. More than half of 92 TC-exposed countries in our sample and nearly three-quarters of 109 countries that have experienced >1°C warming are either speculative grade or non-rated. Furthermore, bonds issued by speculative-grade countries are not actively traded in secondary markets and do not have data on bond yields. Due to these data limitations, existing literature on the borrowing cost impact of disasters has been restricted to a relatively smaller number of advanced and emerging market economies with bonds that are actively traded in the market. We collect some of the quantitative estimates from this literature for comparison with our estimates, which also show the number of countries included across each study (fig. S3 and fig. S4).

Second, we are interested in measuring the cost of borrowing as a persistent credit risk premium faced by countries due to the macroeconomic impacts attributed to TCs and warming. This differs from the dominant approach in literature that uses bond yields in two important ways. i) Bond yields capture short-term dynamic effects of the market response to external shocks and are not relevant for countries that infrequently issue bonds in the international capital market. If there was a persistent risk premium faced by these countries, it would be through macroeconomic impacts that affect their credit risk. ii) Measuring borrowing cost impacts based on event shocks tend to be biased towards events that are considered more severe, using disaster exposure metrics that introduce endogeneity concerns (e.g. using EM-DAT disaster damage metrics for severity). Our estimates show that even low-intensity storm years can have a significant effect on debt and GDP if a large area is affected. These low intensity exposures are unlikely to have a dynamic effect on bond yields in the near-term, but affect credit risk in the long-term through their persistent effect on debt and GDP. We confirm that the debt ratio and GDP are significant determinants of credit ratings based on literature and using our own data (table S6, table S5) as described in SI Appendix.

With the XGB approach, we can translate our findings to a broader set of countries with ratings (and non-rated countries) without being limited to a smaller number of countries that have robust bond yield data. Using XGB offers several advantages compared to black-box machine learning models in that it is much more interpretable (because we can investigate each decision tree to see which variables contribute to the predictions; see for example fig. S30), preserves probability distributions across ratings instead of providing a single prediction, and treats missing data as information (instead of dropping an observation entirely). Furthermore, we are able to test the performance of predictions out-of-sample (fig. S29), before applying it to estimate potential impacts to non-rated countries. Our XGBoost model achieves above 70% accuracy and >90% accuracy with tolerance (±2) in held out test samples that leave out 20% of countries (fig. S27, fig. S29).

4.3.2 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 expected value of credit ratings using observed and counterfactual data, using the probability distributions generated by the XGB model. The observed values are from a range of monetary, fiscal, and institutional variables in 2019 (table S10). 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 (fig. S25). This is similar to the approach taken by Burke et al. (2026), which draws from the credit rating and bond spread relationship derived by Aizenman et al. (2013) using credit default swaps for European Union countries. In our context, to derive estimates for countries that have not frequently issued bonds on the international market, we rely on the coupon rates assigned to sovereign bonds at issuance. Unlike bond yields, which fluctuate depending on market perceptions of credit risk in the secondary market, coupon rates represent the fixed costs to the sovereign issuer.

From the broader Bloomberg and Refinitiv sample of approximately 48,000 sovereign bond issuances from 132 countries (1980-2023), we restrict to fixed-coupon, bullet-maturity bonds with non-zero coupons issued in the relatively low-interest-rate period that followed the global financial crisis (2011-2019), yielding 9,253 sovereign bonds from 124 countries (17,261 including bonds issued by China and Japan) (fig. S25, fig. S26). The general quadratic relationship we uncover 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 on the international market as well as countries that do not have a credit rating (fig. 5). 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. S26).

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.

Aizenman, J., Binici, M., and Hutchison, M. (2013). Credit ratings and the pricing of sovereign debt during the euro crisis. *Oxford Review of Economic Policy*, 29(3):582–609.

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.

Anyfantaki, S., Grimaldi, M. B., Madeira, C., Malovana, S., and Papadopoulos, G. (2025). Decoding climate-related risks in sovereign bond pricing: A global perspective. SSRN Scholarly Paper 5337906, Social Science Research Network, Rochester, NY.

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

Arora, V. and Cerisola, M. (2001). How does u.s. monetary policy influence sovereign spreads in emerging markets? *IMF Staff Papers*, 48(3):474–498.

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.

Athey, S. and Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, 11:685–725.

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.

Bloemendaal, N., de Moel, H., Martinez, A. B., Muis, S., Haigh, I. D., van der Wiel, K., Haarsma, R. J., Ward, P. J., Roberts, M. J., Dullaart, J. C. M., and Aerts, J. C. J. H. (2022). A globally consistent local-scale assessment of future tropical cyclone risk. *Science Advances*, 8(17):eabm8438.

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.

Burke, M., Mohaddes, K., and Raissi, M. (2026). The adaptation imperative: Climate change and sovereign credit risk. Working Paper CWPE 2608 / INET Oxford Working Paper No. 2026-03, Cambridge Working Papers in Economics and INET Oxford.

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.

del Valle, A., de Janvry, A., and Sadoulet, E. (2020). Rules for recovery: Impact of indexed disaster funds on shock coping in mexico. *American Economic Journal: Applied Economics*, 12(4):164–195.

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

Deryugina, T., Kawano, L., and Levitt, S. (2018). The economic impact of hurricane katrina on its victims: Evidence from individual tax returns. *American Economic Journal: Applied Economics*, 10(2):202–233.

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.

Dryden, A. and Volz, U. (2025). International capital markets as a means of financing climate action: Smooth sailing or stormy waters? Technical report, Centre for Sustainable Finance, SOAS, University of London, London.

Dube, A., Girardi, D., Jordà, Ò., and Taylor, A. M. (2025). A local projections approach to difference-in-differences. *Journal of Applied Econometrics*, 40(7):741–758.

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.

Eichengreen, B. and Mody, A. (1998). What explains changing spreads on emerging-market debt: Fundamentals or market sentiment? SSRN Scholarly Paper 226156, Social Science Research Network, Rochester, NY.

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

Emanuel, K. (2008). The hurricane–climate connection. *Bulletin of the American Meteorological Society*, 89(5):ES10–ES20.

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.

Gande, A. and Parsley, D. C. (2005). News spillovers in the sovereign debt market. *Journal of Financial Economics*, 75(3):691–734.

Gilchrist, S., Wei, B., Yue, V. Z., and Zakrajšek, E. (2022). Sovereign risk and financial risk. *Journal of International Economics*, 136:103603. NBER International Seminar on Macroeconomics 2021.

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.

Goldsmith-Pinkham, P., Gustafson, M. T., Lewis, R. C., and Schwert, M. (2023). Sea-level rise exposure and municipal bond yields. *The Review of Financial Studies*.

Goldsmith-Pinkham, P., Hull, P., and Kolesár, M. (2024). Contamination bias in linear regressions. *American Economic Review*, 114(12):4015–4051.

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.

Groen, J. A., Kutzbach, M. J., and Polivka, A. E. (2020). Storms and jobs: The effect of hurricanes on individuals' employment and earnings over the long term. *Journal of Labor Economics*, 38(3):653–685.

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.

Huesler, J. (2025). The impact of hurricane strikes on caribbean sovereign bond returns. *Financial History Review*, 32(2):159–196.

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).

Kling, G., Lo, Y. C., Murinde, V., and Volz, U. (2025). Climate vulnerability and the cost of debt. *Oxford Open Economics*, 4:odaf003.

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*.

Ramírez-Rondán, N. R., Rojas-Rojas, R. M., and Villavicencio, J. A. (2023). Political institutions, economic uncertainty and sovereign credit ratings. *Finance Research Letters*, 53:103656.

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.

Reinhart, C. (2002). Default, currency crises and sovereign credit ratings. SSRN Scholarly Paper 298262, Social Science Research Network, Rochester, NY.

Reinhart, C. M., Rogoff, K. S., and Savastano, M. A. (2003). Debt intolerance. *Brookings Papers on Economic Activity*, 2003(1):1–62.

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.

Roth, J. (2026). Interpreting event-studies from recent difference-in-differences methods. *arXiv preprint arXiv:2401.12309*. arXiv:2401.12309 [econ.EM].

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.

Zenios, S. A. (2024). The climate-sovereign debt doom loop: What does the literature suggest? *Current Opinion in Environmental Sustainability*, 67:101414.

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 Methods

Pre-trends and Local Projections Difference-in-Difference

Pre-trends from the standard local projection model with debt-to-GDP ratio as the outcome are visualized in the first row of fig. S9 and fig. S10. While the pretrend coefficients for the tropical storm exposure are small and insignificant, the pre-trends for moderate (category 1-2) and severe (category 3+) wind speed exposures show a non-zero drift in opposite directions. We demonstrate this is likely an artifact arising from contamination bias between the two treatment bins rather than a violation of parallel trends (fig. S12). The contamination bias occurs when there is heterogeneity in within-country correlation across treatment bins, combined with heterogeneity in treatment effects (Goldsmith-Pinkham et al., 2024).

In our setting, TC exposure is heterogeneously correlated especially within the cat 1-2 and cat3+ treatment bins given the way that TC wind fields intersect with countries of varying size. Small island countries are dominantly exposed to cat 3+ winds that are negatively correlated with cat 1-2 exposure, given that direct TC hits often affect up to 100% of countries' land area with either cat1+ or cat3+ winds (e.g. Dominica, Antigua and Barbuda, Barbados). Among larger countries, cat3+ exposure is positively correlated with cat1-2 exposure, as TC wind fields do not entirely cover the countries' land area (e.g. Dominican Republic, Philippines, Belize). This heterogeneity in treatment correlation within countries means that a single pooled regression slope cannot capture both settings, leaving residuals that systematically differ by country type and create the potential for biased estimates. The nonzero within-country slopes in fig. S12 indicate the presence of nonzero contamination weights (Goldsmith-Pinkham et al., 2024). When GDP per capita is the outcome, the presence of contamination weight on its own does not appear as pronounced differences in the pre-trends because heterogeneity in treatment effects do not coincide with differential outcomes in the country groups affected by the contamination weights. We also note that even absent contamination bias, pre-trend tests alone using the standard event study settings may be insufficient for validating the identifying assumption because the pre-treatment coefficients are estimated with different effective samples and weighting structures (Roth 2024).

To further demonstrate that the pretrends in the main model do not constitute evidence of a parallel trends violation, we additionally show results using Local Projections Difference-in-Differences (LP-DiD) (Dube et al., 2025).

For each TC wind-speed bin $c \in \{1,2,3\}$ and each horizon h, we estimate

$$y_{i,t+h} - y_{i,t-1} \;=\; \beta_c^h \, tc_{c,i,t} \;+\; \mathbf{x}_{i,t}' \boldsymbol{\eta}_h \;+\; \alpha_i \;+\; \gamma_{r(i),t} \;+\; \varepsilon_{i,t,h}, \qquad (i,t) \in \mathcal{S}_h^c(K), \tag{3}$$

where $tc_{c,i,t}$ is the share of country i's land area exposed to wind-speed category c in year t, and β_c^h is the bin-specific impulse response at horizon h. The control vector $\mathbf{x}_{i,t}$ carries the same temperature shock terms ($\tau_{i,t}$ and $\tau_{i,t} \cdot \bar{T}_i$) and outcome pre-trend lags as the main specification,

α_i is a country fixed effect, and $\gamma_{r(i),t}$ is a region × year fixed effect (with $r(i)$ assigning each country to one of seven geographic regions, plus a pooled high-income group). Unlike the main LP, equation (3) is estimated separately for each bin c, on the clean-control sample $\mathcal{S}_h^c(K)$ defined as the union of treated observations ($tc_{c,i,t} > 0$) and control observations ($tc_{c,i,t} = 0$) for which no exposure in a designated exclusion set occurs anywhere in the comparison window $[t-K,\ t+h]$. We consider three exclusion rules of increasing restrictions: (i) drop only country-years with any Cat 3+ exposure; (ii) drop those with exposure in the target bin c itself; (iii) drop those with exposure in any bin. The buffer $K \geq 0$ governs whether the clean-control restriction applies symmetrically to both pre- and post-treatment horizons ($K \geq 1$) or only to post-treatment horizons ($K = 0$).

With LP DiD, we estimate separate regressions for each treatment bin and impose clean-control conditions within each bin, thereby eliminating the cross-treatment contamination bias identified above. It also avoids negative weighting bias from already-treated observations entering the control group, and this clean-control restriction may be applied symmetrically to both pre- and post-treatment horizons, addressing the asymmetry concern raised by Roth (2024). We recover similar main estimates with flattened pre-trends under LP-DiD and show how these hold across a variety of clean control conditions (fig. S9). While the effective control group changes with each exclusion rule and exclusion window, estimates remain qualitatively consistent. The most restrictive exclusion rule that removes observations with TC exposure in all bins yields the noisiest estimates and widest confidence intervals, reflecting the substantially smaller clean-control sample at each horizon. With GDP per capita as the outcome, the LP-DiD again recovers estimates qualitatively similar to the standard LP, with the cleanest pretrends for the Cat3+ treatment bin, which is also the treatment bin in which we recover the largest and most precise post-treatment estimates (fig. S10).

Heterogeneous Treatment Effects

We test whether the macroeconomic response to a TC shock depends on country characteristics by augmenting equation (3) with a binary indicator $D_{i,t} \in \{0,1\}$ and its interaction with each contemporaneous TC–bin term. For each horizon h we estimate

$$y_{i,t+h} - y_{i,t-1} \;=\; \sum_{c\in\{1,2,3\}} \left(\beta_c^h\, tc_{c,i,t} + \theta_c^h\, tc_{c,i,t}\cdot D_{i,t}\right) \;+\; \lambda_h\, D_{i,t} \;+\; \mathbf{x}_{i,t}'\,\boldsymbol{\eta}_h \;+\; \alpha_i \;+\; \gamma_{r(i),t} \;+\; \varepsilon_{i,t,h}, \tag{4}$$

on the same LP-DiD clean-control sample as in equation (3) with the one-sided window ($K = 0$) and the Cat 3+ exclusion rule. The interaction coefficient θ_c^h identifies the state-dependent shift in the impulse response between countries with $D_{i,t} = 1$ and $D_{i,t} = 0$; standard errors are clustered by country.

We test three definitions of $D_{i,t}$, each capturing a different mechanism through which prior characteristics may modulate the TC response:

1. **TC frequency.** D_i^{freq} is a country-level dummy equal to one if country i's number of Cat 1+ exposure years over 1980–2019 exceeds the cross-country median (among countries with any Cat 1+ exposure).

2. **Debt-carrying capacity.** D_i^{cap} is a country-level dummy equal to one if country i is classified as high-capacity using the Country Policy and Institutional Assessment (CPIA) Index, used by the IMF to assess countries' debt carrying-capacities.

3. **Compounding (prior severe exposure).** $D_{i,t}^{\text{prior}} = \mathbf{1}\{\sum_{k=1}^{5} tc_{3,i,t-k} > 0\}$ is a time-varying dummy equal to one whenever country i experienced any Cat 3+ exposure in the preceding five years.

The first two indicators are time-invariant and the level term $\lambda_h \, D_{i,t}$ is absorbed by the country fixed effect α_i; the third is time-varying so λ_h is separately identified. Results for both outcomes (debt ratio and GDP per capita) are reported in fig. S13 and fig. S14.

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, 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 S4. Many countries received their first rating starting in the late 1990s (fig. S24) and 46 countries that have never received a credit rating from the "Big Three" agencies are by definition not included in the data.

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.

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 S9). 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. S27).

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. S27).

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 S10.

Determinants of credit ratings

We estimate two complementary panel specifications relating sovereign credit ratings to macroeconomic, institutional, and climate-exposure indicators. Let $R_{i,t}$ denote the average rating of country i in year t, and let $\mathbf{Z}_{i,t}$ collect the macro and institutional regressors (public debt/GDP, log GDP per capita, GDP growth, primary balance, current account/GDP, inflation, unemployment, current and 5-year-lagged sovereign default flags, and the WGI Regulatory Quality, Rule of Law, and Political Stability indices).

The first specification (table S5) includes country and year fixed effects and is estimated separately for the full sample and five subsets (investment grade, speculative grade, SIDS, TC-exposed >Cat 1, TC-exposed >Cat 3):

$$R_{i,t} \;=\; \boldsymbol{\zeta}' \, \mathbf{Z}_{i,t} \;+\; \alpha_i \;+\; \gamma_t \;+\; \epsilon_{i,t}. \tag{5}$$

The second specification (table S6) drops country fixed effects and instead introduces a subgroup dummy D_i (e.g., below-IG, SIDS, TC-exposed) so that the dummy coefficient is identified from cross-country variation:

$$R_{i,t} \;=\; \boldsymbol{\zeta}'\,\mathbf{Z}_{i,t} \;+\; \theta\,D_i \;+\; \gamma_t \;+\; \epsilon_{i,t}. \tag{6}$$

Standard errors are clustered by country in both specifications.

Public debt and GDP per capita are highly significant determinants of ratings across all subsets: a 1 pp increase in public debt/GDP is associated with roughly a 0.04 notch lower rating, and a 1 log-unit increase in GDP per capita with roughly a 2.4 notch higher rating. Countries exposed to >Cat 3 winds carry on average a 0.9 notch lower rating ($p < 0.10$), and SIDS carry a 1.8 notch lower rating ($p < 0.01$), even after controlling for macro fundamentals, institutional quality, and default history.

Determinants of coupon rates

We additionally confirm that credit ratings are a significant determinant of coupon rates in our data with Panel OLS (table S7, table S8). The estimation sample is further restricted to 10-year-maturity bonds and country-years with complete macro, institutional, and rating data, yielding $\sim$5,800 bond issuances from 81 countries. Let $C_{i,j,t}$ denote the coupon rate of sovereign bond j issued by country i in year t, and let $R_{i,t}$ be the sovereign credit rating. The first specification (table S7) uses year and currency fixed effects:

$$C_{i,j,t} \;=\; \boldsymbol{\zeta}'\,\mathbf{Z}_{i,t} \;+\; \kappa\,R_{i,t} \;+\; \theta\,D_i \;+\; \gamma_t \;+\; \rho_j \;+\; \epsilon_{i,j,t}, \tag{7}$$

where ρ_j is a currency-of-denomination fixed effect and D_i is a sub-group dummy (below-IG, TC-exposed, or their interaction). The second specification (table S8) replaces year fixed effects with two global financial-conditions proxies: the US 10-year Treasury yield r_t^{US10} and the CBOE Volatility Index (VIX) v_t:

$$C_{i,j,t} \;=\; \boldsymbol{\zeta}'\,\mathbf{Z}_{i,t} \;+\; \kappa\,R_{i,t} \;+\; \theta\,D_i \;+\; \pi_1\,r_t^{\mathrm{US10}} \;+\; \pi_2\,v_t \;+\; \rho_j \;+\; \epsilon_{i,j,t}, \tag{8}$$

with standard errors clustered by country in both specifications.

Sovereign credit ratings are a significant determinant of coupon rates: a 1-notch lower rating is associated with roughly 12–19 bps higher coupon rates ($p < 0.01$). A 1 pp increase in public debt/GDP raises the coupon by an additional $\sim$0.4 bps even after controlling for the credit rating, indicating that debt level carries information for borrowing costs beyond what is summarised in the rating. Below-IG countries pay a $\sim$56 bps premium and TC-exposed countries a $\sim$28 bps premium relative to otherwise-similar issuers, with the joint below-IG $\times$ TC-exposed interaction adding a further $\sim$70–90 bps. The two global financial-conditions proxies also have the expected sign: a 1 pp rise in the US 10-year yield raises coupon rates by $\sim$84 bps, and a 1-unit rise in VIX by $\sim$3 bps.

Supplementary Figures

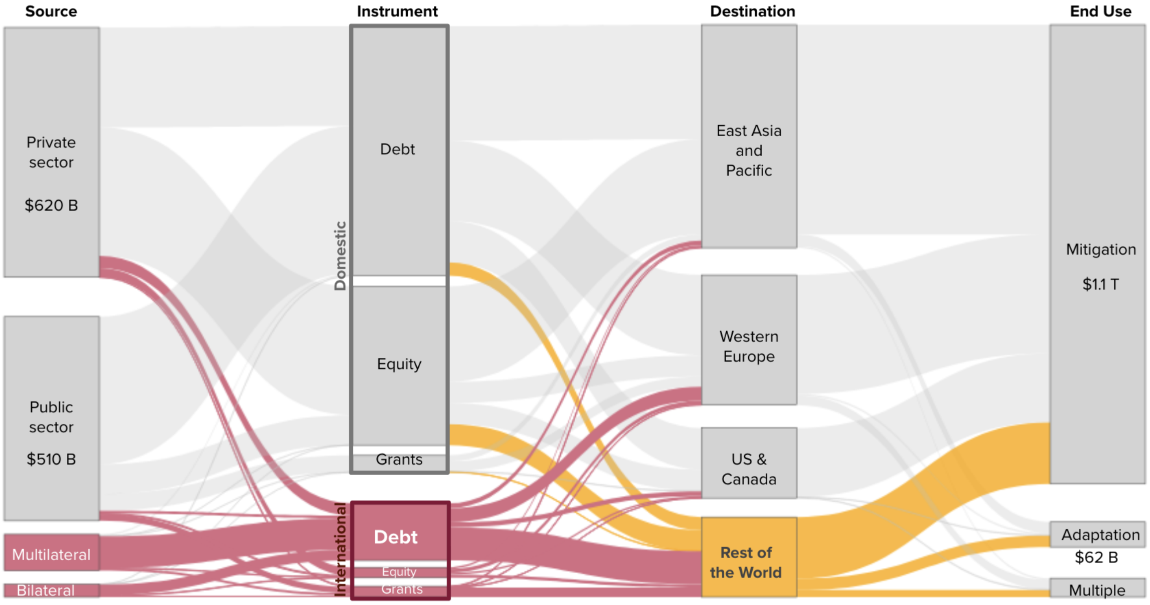


Figure S1. Global climate finance flows in 2022/2023. Data from Climate Policy Initiative.

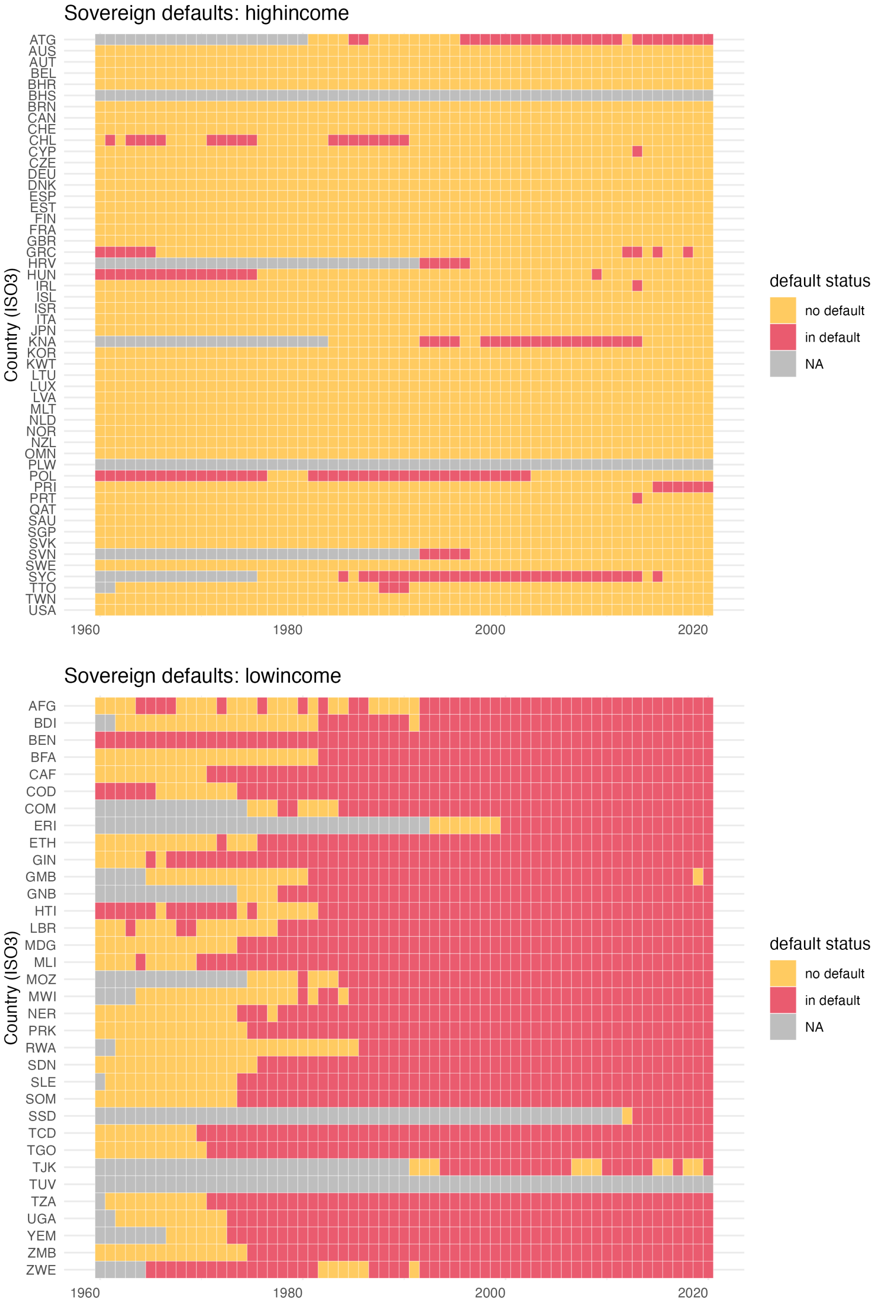


Figure S2. Sovereign default status of high-income (Panel A) and low-income (Panel B) countries over time. Default episodes include any missed payments on loans or bonds falling outside the grace period, owed to both official and private creditors. Data from Bank of Canada and Bank of England (Beers et al., 2021).

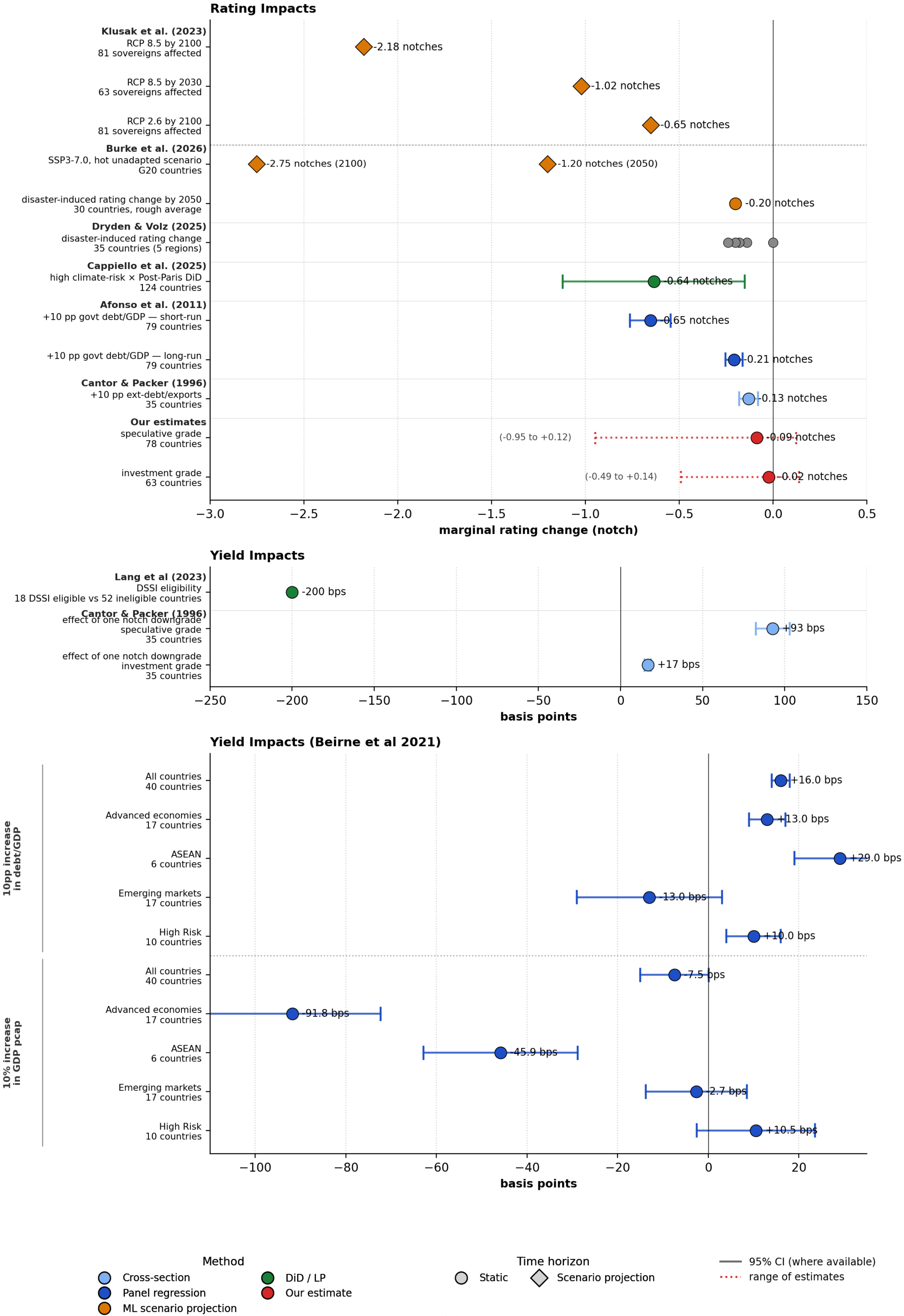


Figure S3. Compilation of estimates from selected studies on macroeconomic factor impacts on sovereign credit ratings and comparison with our estimates.

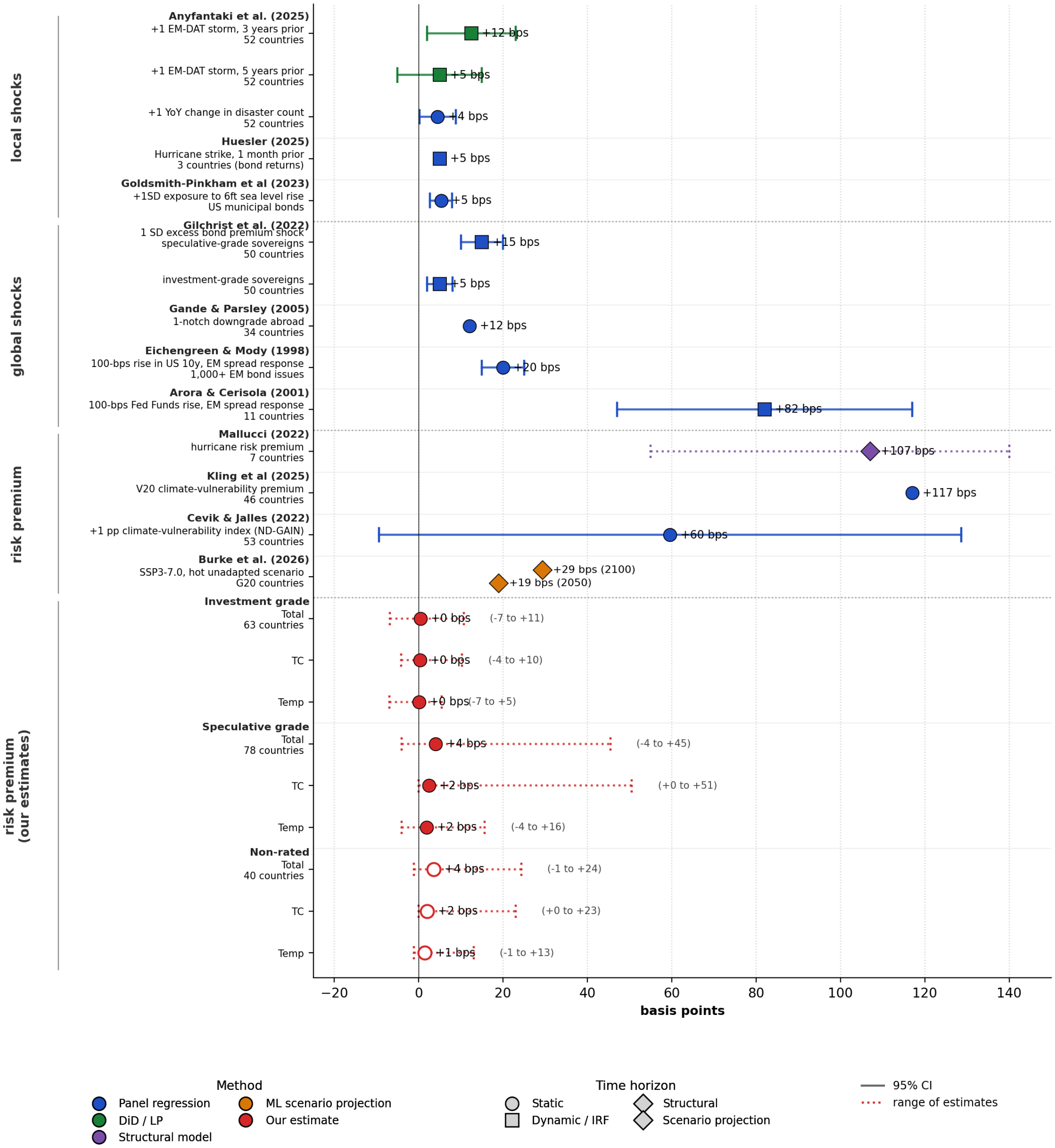


Figure S4. Compilation of estimates from selected studies on the impact of various local and global shocks on bond yields, risk premiums, and comparison with our own estimates.

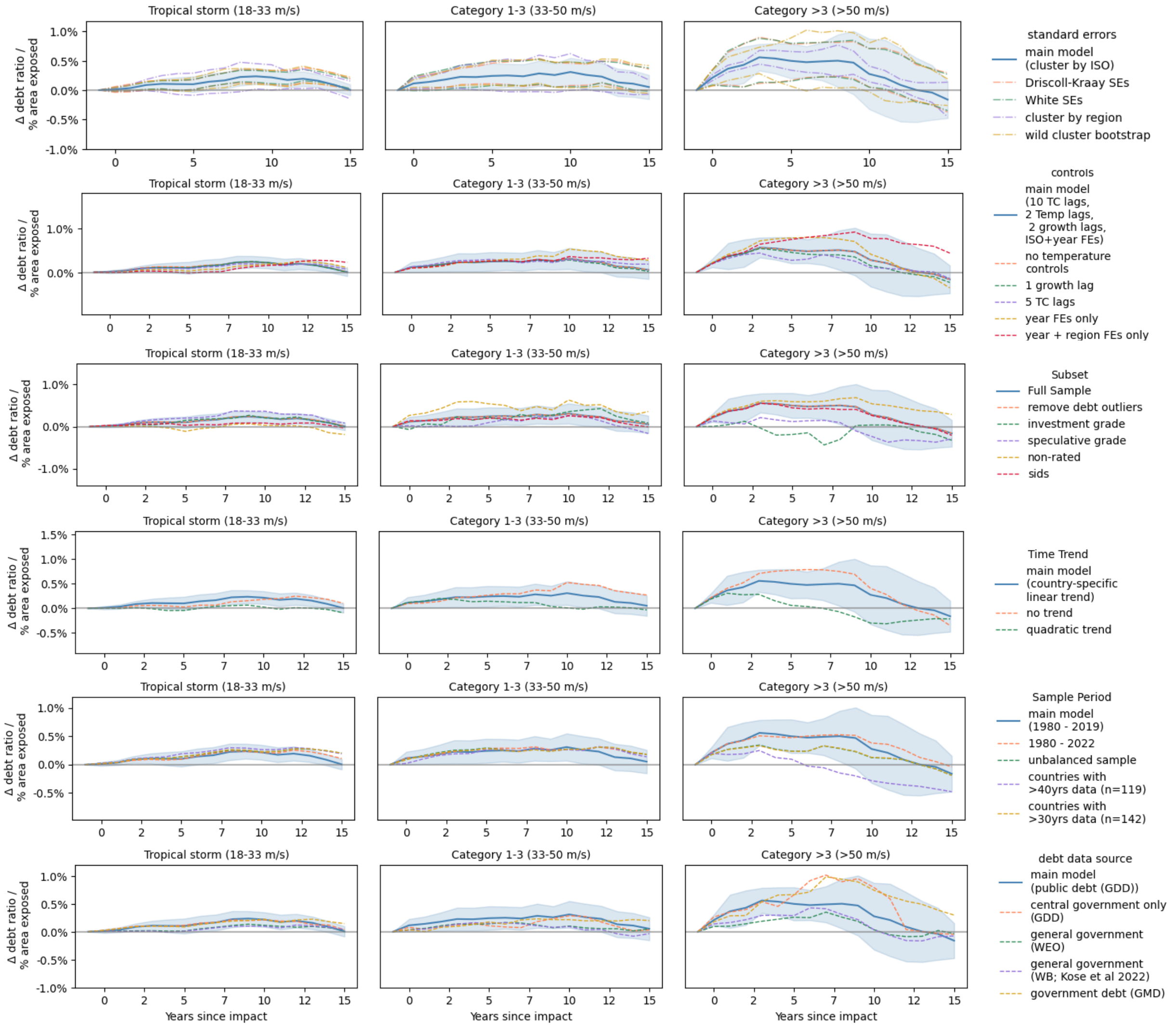


Figure S5. Tropical cyclone impacts on debt ratio. Columns plot the impulse response functions following 1% land area affected by increasing wind speed intensities. Rows are based on robustness checks, by standard error, inclusion of different controls, subsets, time trend, sample period, and the debt data source.

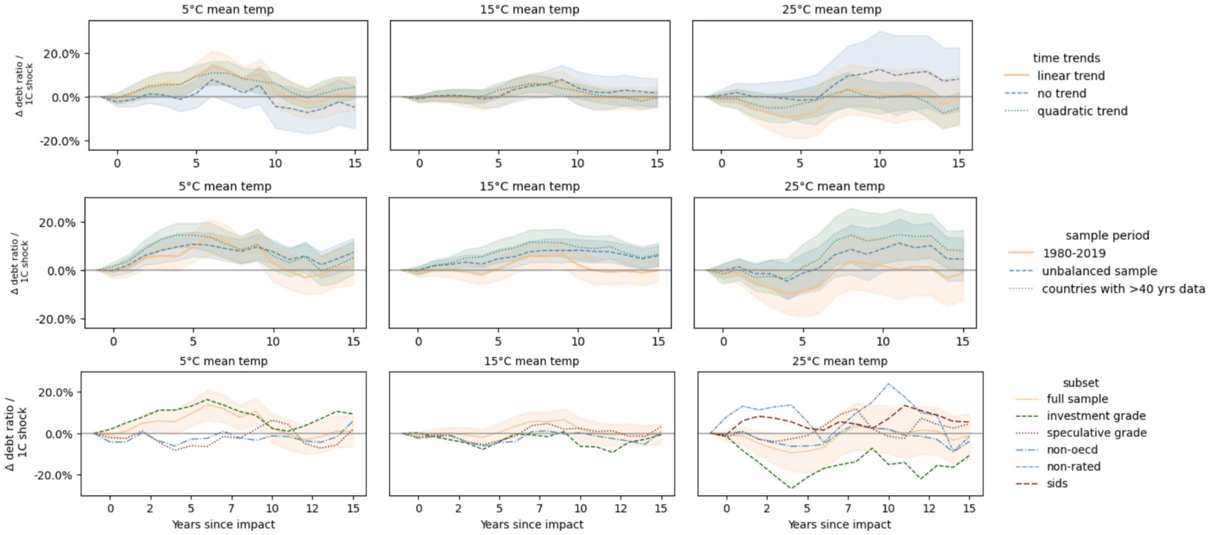


Figure S6. Temperature impacts on debt ratio. Columns plot the impulse response functions following 1°C hotter year, conditional on the countries' historical average temperature (selectively constructed for 5°C, 15°C, 25°C). Rows show sensitivity to time trends, sample period, and subset of countries. The distribution of countries' annual mean temperature is shown in fig. S17.

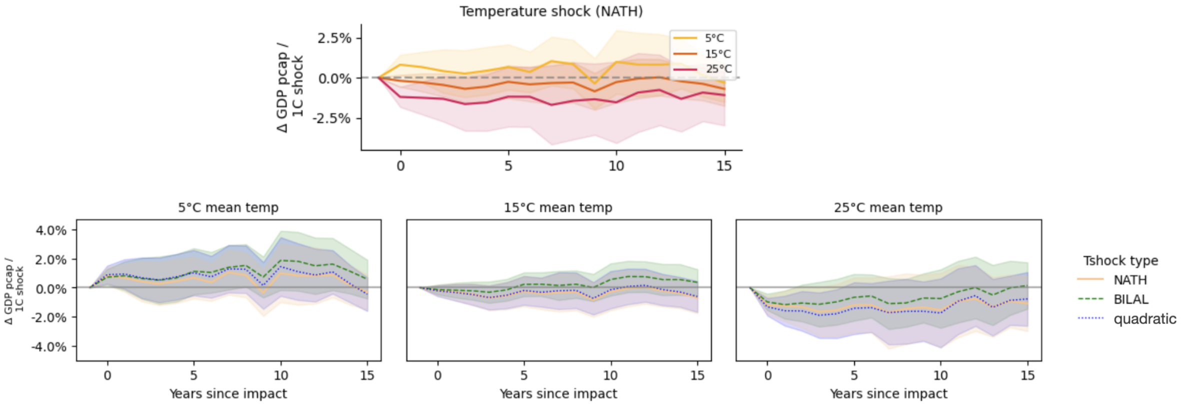


Figure S7. Temperature impacts on GDP. Top panel shows the GDP IRF following a 1°C hotter year, with temperature shocks isolated using method from Nath et al 2024. Bottom panel plots the IRFs (selectively constructed for 5°C, 15°C, 25°C), comparing three different methods of isolating the temperature shock.

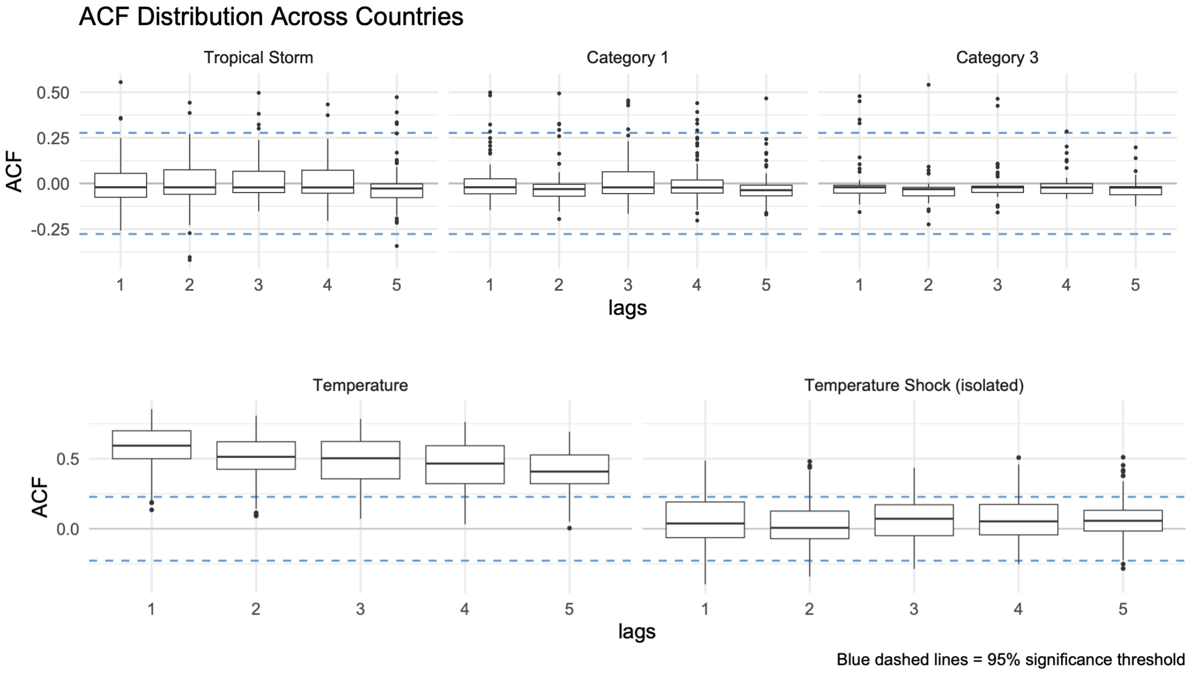


Figure S8. Distribution of autocorrelation function (ACF) plots across countries, up to 5 lags. Top panel shows the ACF plots for each of the TC exposure metric (% land area exposed to different wind intensities). Bottom panel shows the ACF plots for annual temperature, where the temperature shock is not isolated (left) and isolated as in Nath et al 2024 (right).

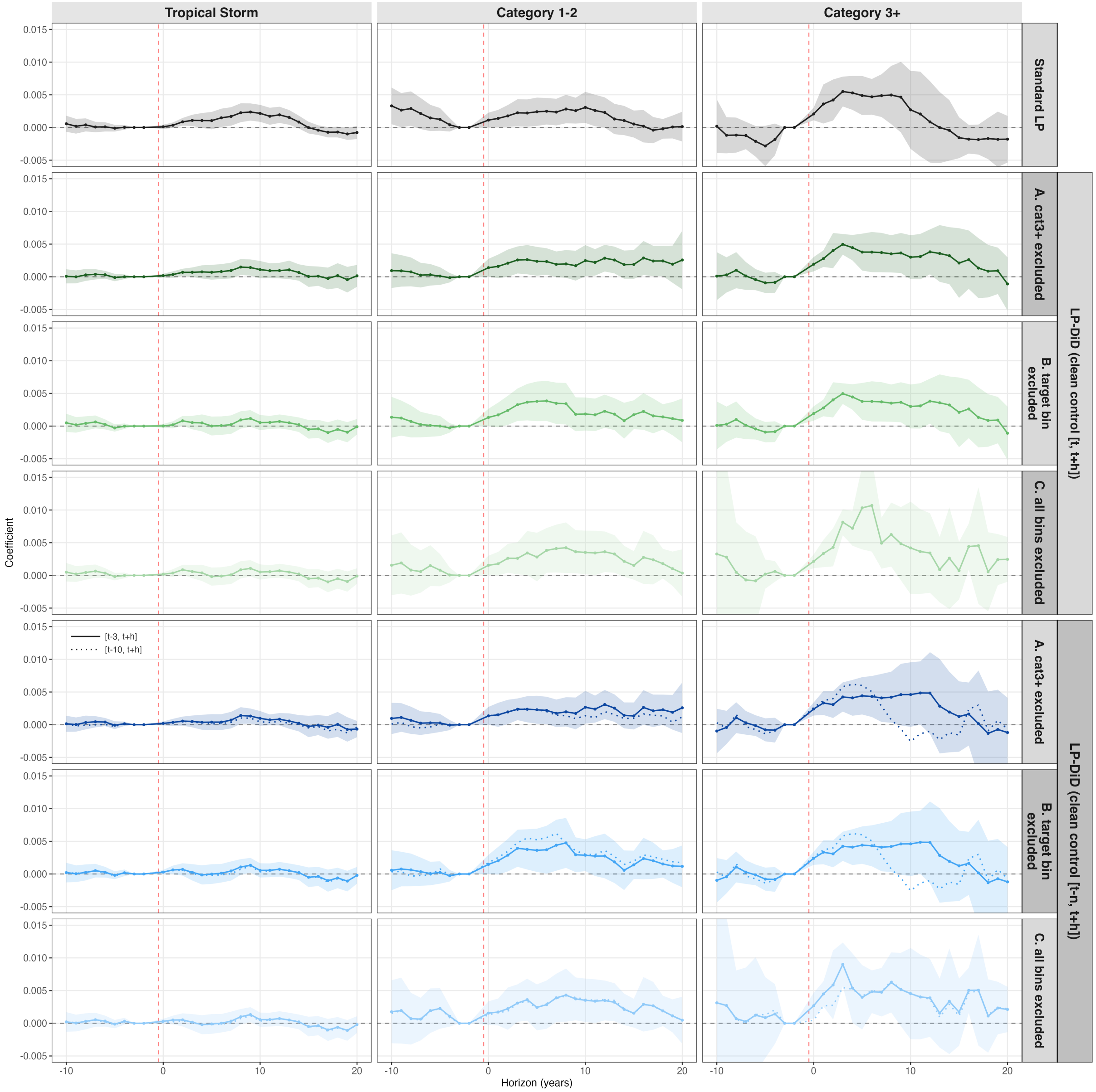


Figure S9. LP Difference-in-Difference estimates with various clean control conditions (debt ratio outcome)

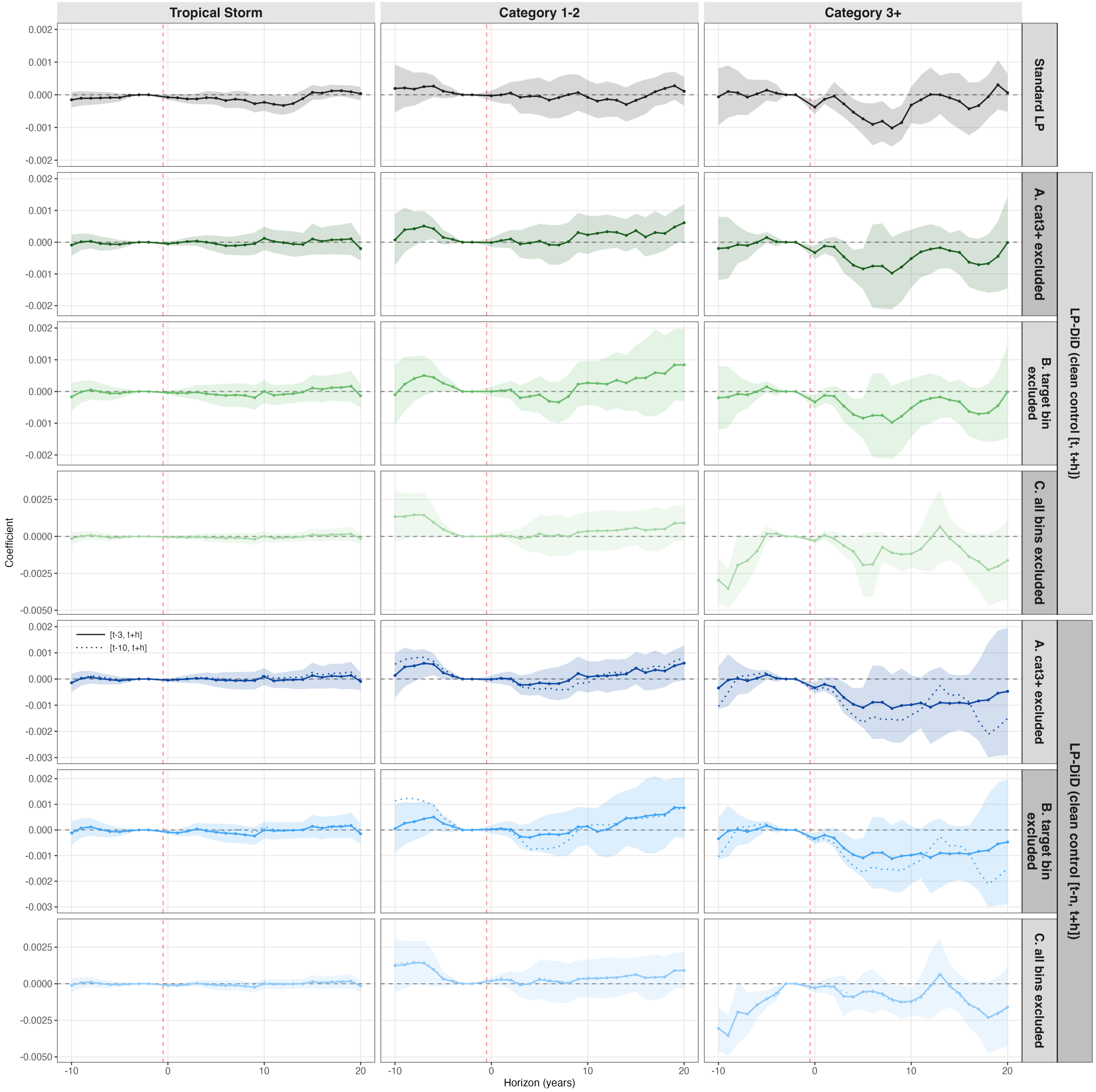


Figure S10. LP Difference-in-Difference estimates with various clean control conditions (GDP per capita outcome)

a: Exclude observations with a Cat3+ event in the one-sided window [t, t+h].
b: Exclude observations with a TARGET-BIN event in the one-sided window [t, t+h].
c: Exclude observations with a Cat3+ event in the two-sided window [t-3, t+h].
d: Exclude observations with a TARGET-BIN event in the two-sided window [t-3, t+h].

Figure S11. Illustration of 4 different clean-control conditions applied to 3 TC target bins, using Jamaica as an example (at h=3; or three years following a TC year). The top panel shows Jamaica's annual TC exposure (% of country land area) from 1980-2019. The three sub-panels below show, for each TC target bin (TS, Cat 1-2, Cat 3+), four variants of the clean-control exclusion window. Each cell (representing one year) is classified as treated (target-bin color), clean control (green), or excluded (grey). The right-hand annotation gives the number of clean-control years under each clean control condition.

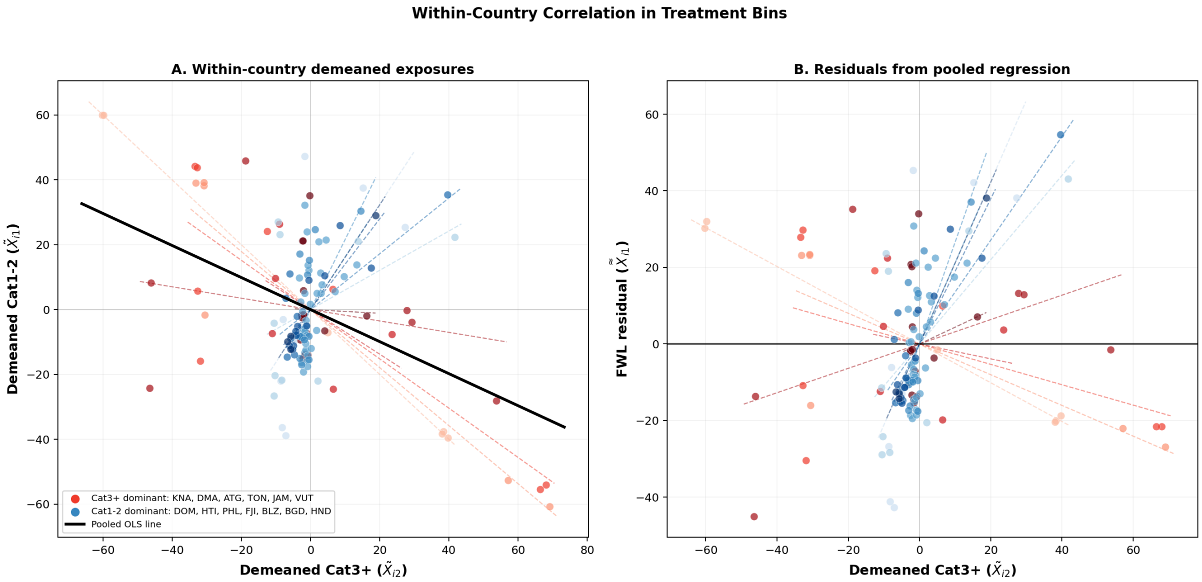


Figure S12. Panel A shows within-country demeaned Cat1-2 vs Cat3+ exposures. Dashed lines are within-country fitted lines; the black line is the pooled OLS slope averaging over all within-country lines. Smaller countries with dominant Cat3+ exposures show negative within-country correlation, while larger countries (blue) show positive correlation. Panel B shows the residuals from the pooled regression line in Panel A. Nonzero within-country slopes indicate the presence of nonzero contamination weights (Goldsmith-Pinkham et al. 2024)

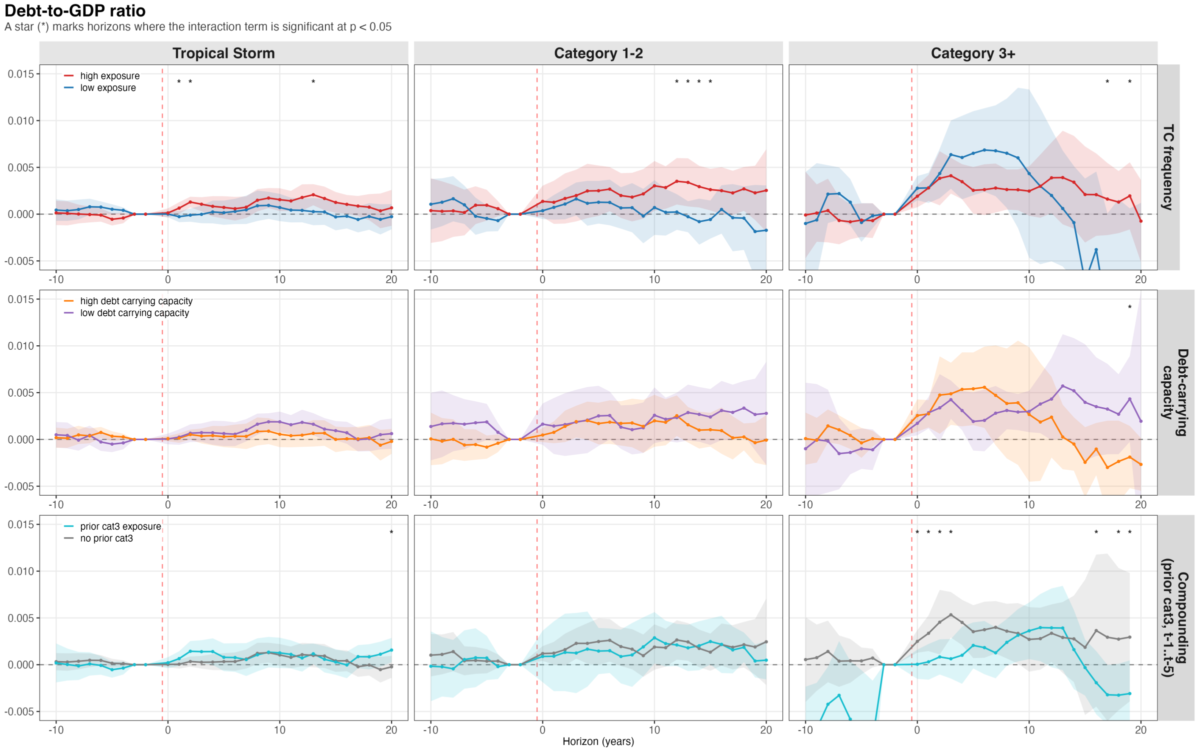


Figure S13. LP DiD interactions (debt ratio)

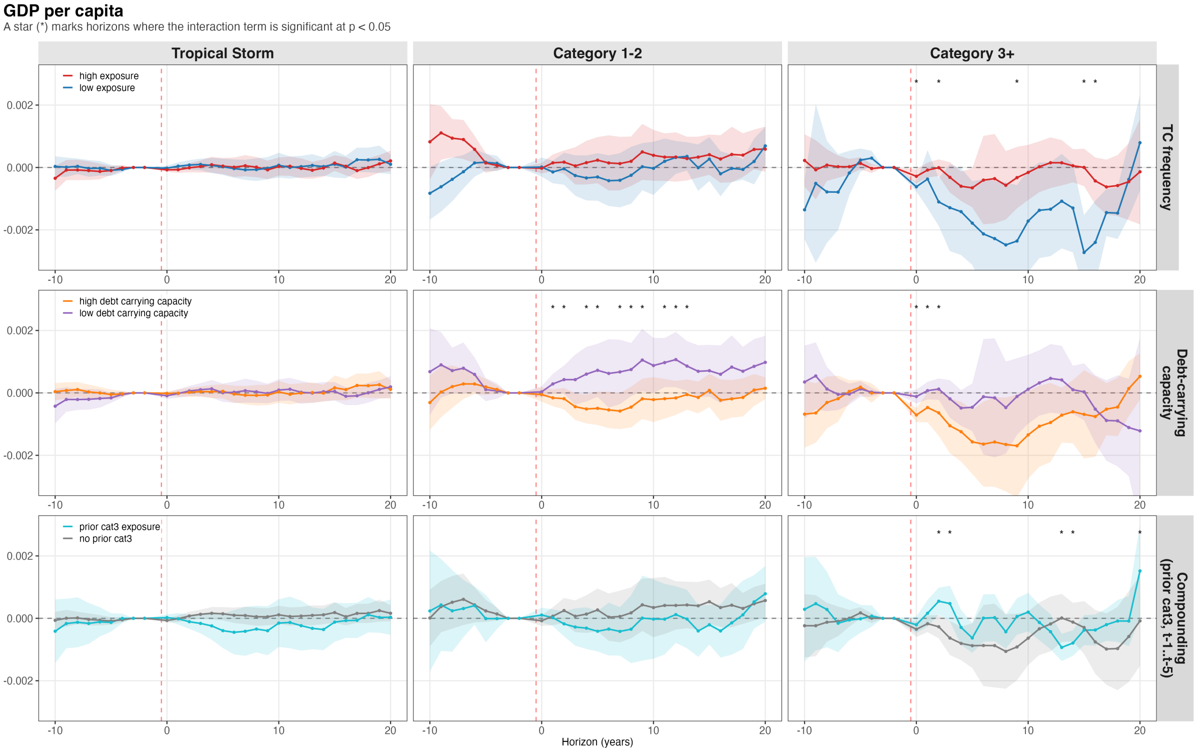


Figure S14. LP DiD interactions (GDP per capita)

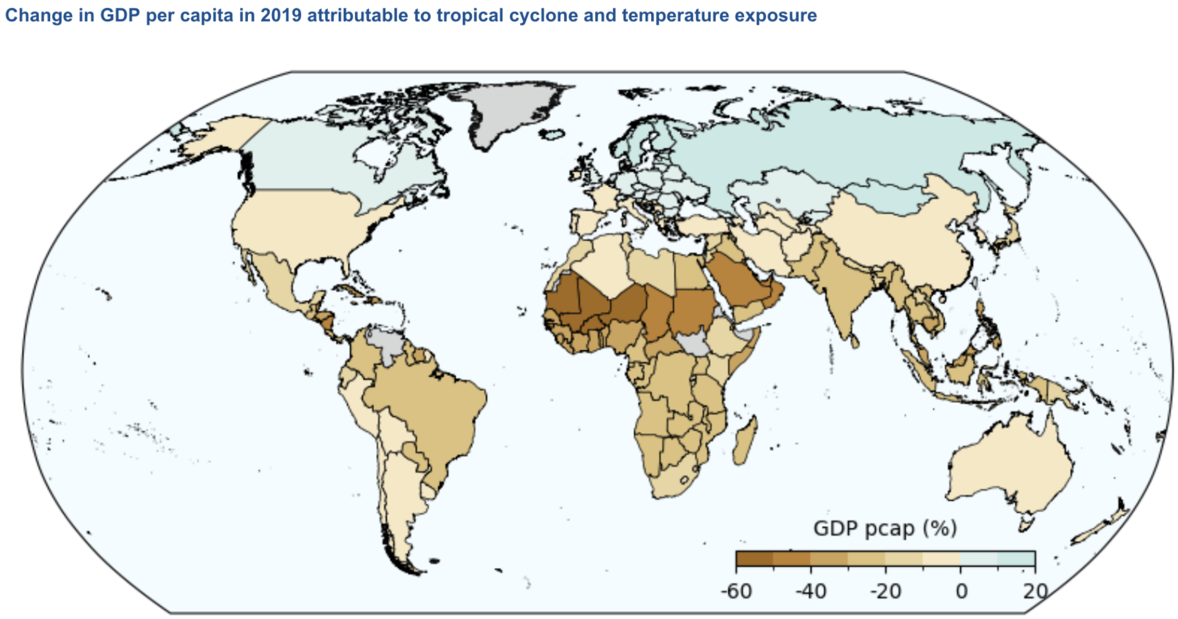


Figure S15. Global map of the share of countries' GDP in 2019 attributable to tropical cyclones and temperature shocks from 1990 onward.

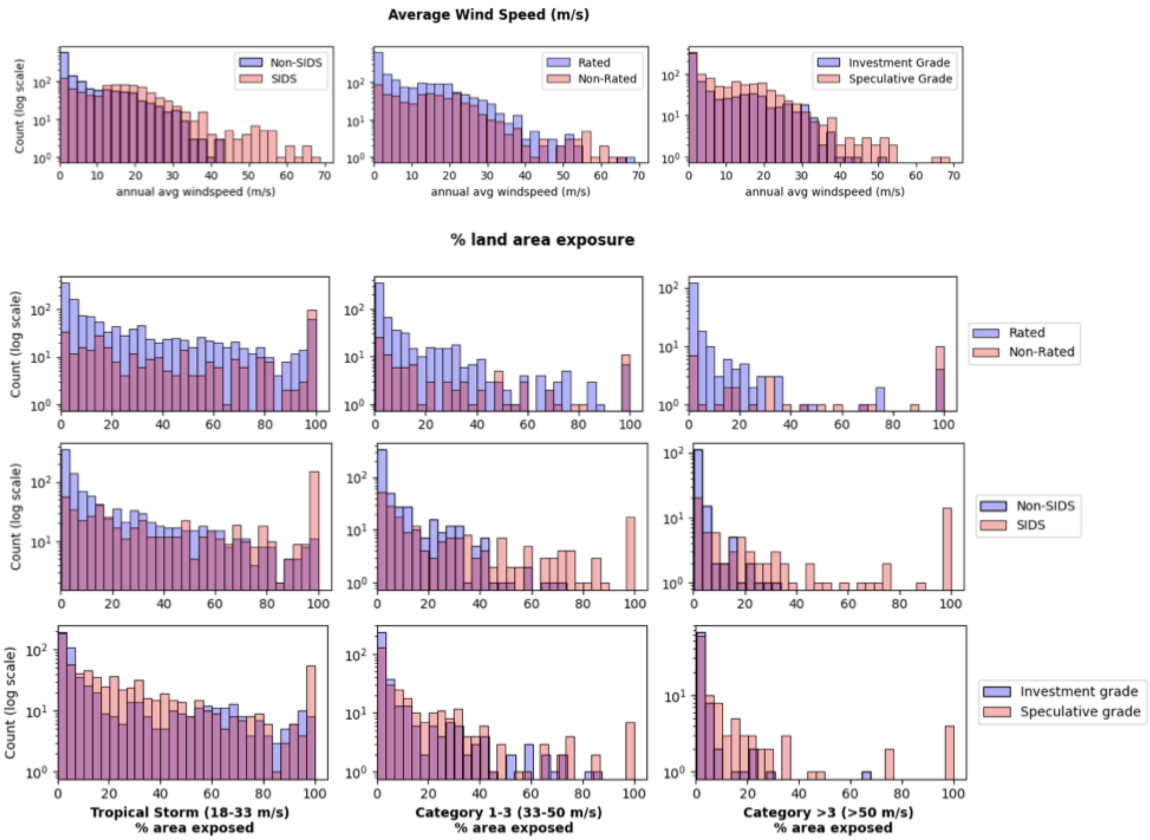


Figure S16. Distribution of annual wind speed exposure by country subsets (Small Island Developing States (SIDS) vs non-SIDS, rating vs non-rated countries, investment grade vs speculative grade countries).

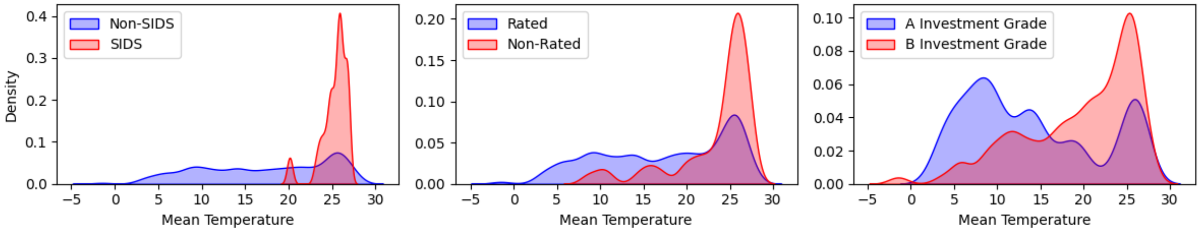


Figure S17. Distribution of annual average temperatures by country subsets (Small Island Developing States (SIDS) vs non-SIDS, rating vs non-rated countries, investment grade vs speculative grade countries).

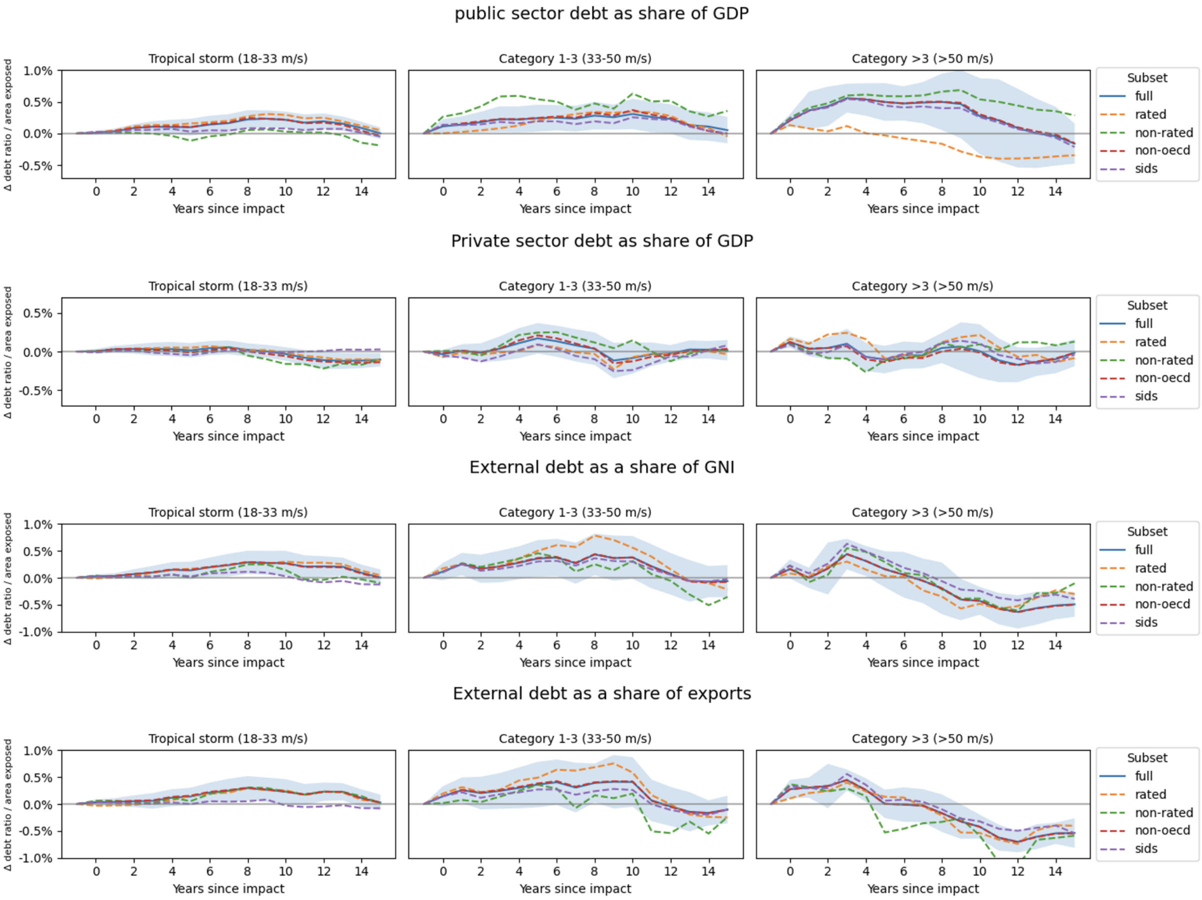


Figure S18. Impulse response functions for alternative debt metrics.

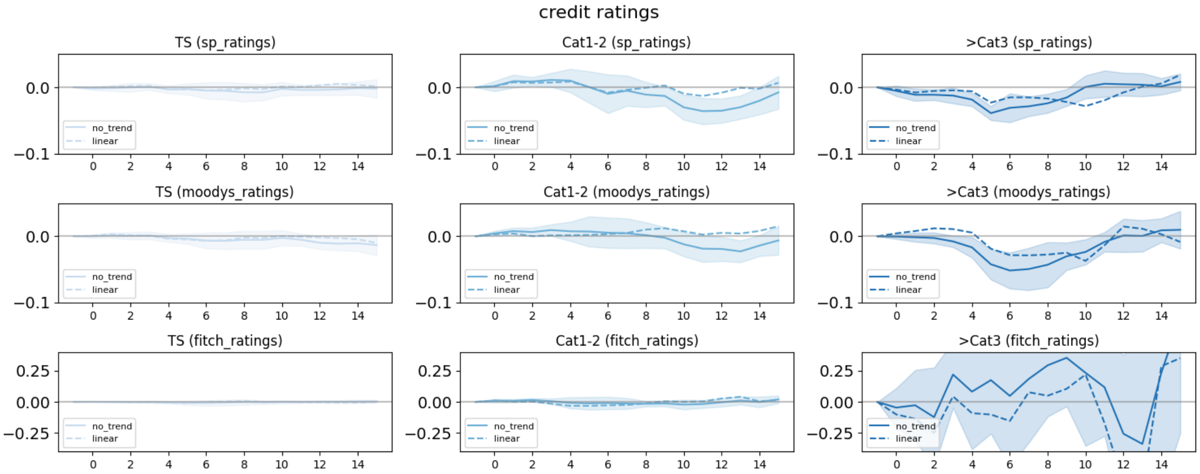


Figure S19. LP Model using credit ratings as outcome

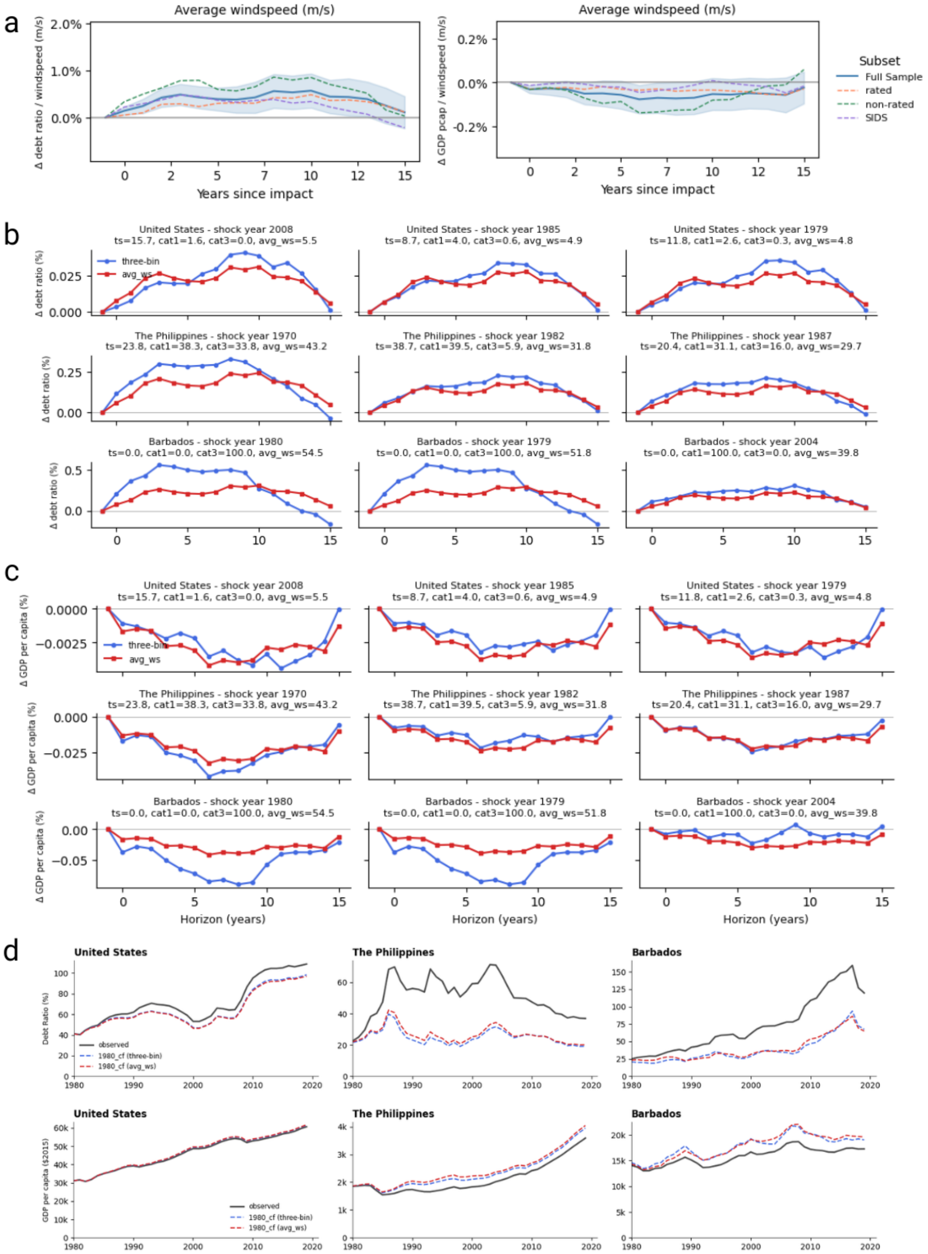


Figure S20. IRF robustness using average windspeed (`avg_ws`) as a continuous TC-exposure metric, instead of the baseline three-bin (TS / Cat 1-2 / Cat 3+) land area classification. **(a)** Average impulse response per +1 m/s of `avg_ws` on the debt-to-GDP ratio (left) and log GDP per capita (right) across the full sample and three subsets. **(b, c)** Per-shock-year IRF comparisons for debt ratio (b) and GDP per capita (c), for three illustrative countries and three shock years. Blue solid lines show the baseline three-bin response; red dashed lines show the `avg_ws` response. **(d)** Aggregate counterfactual debt-ratio (top) and GDP-per-capita (bottom) trajectories for the same three countries.

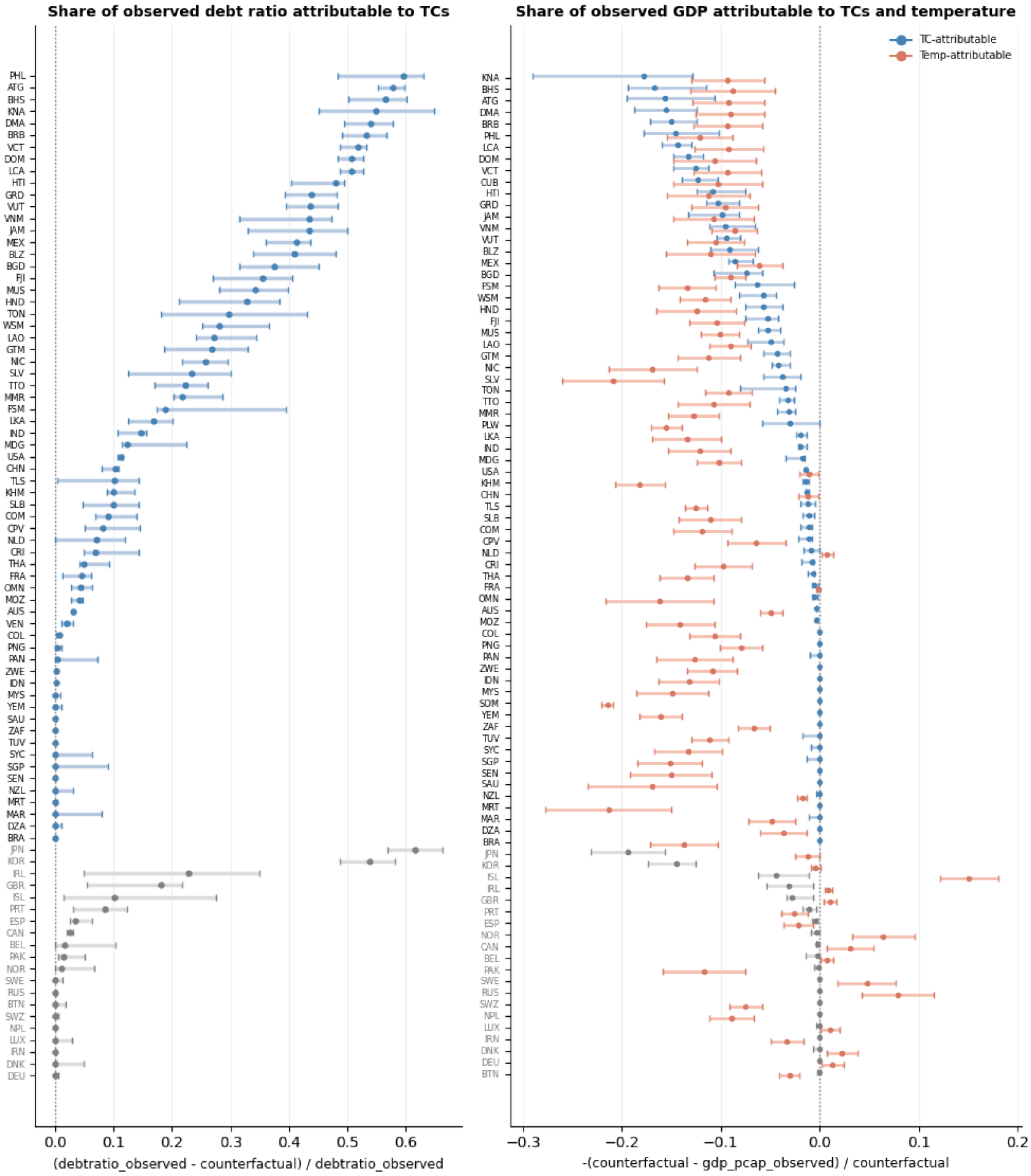


Figure S21. Country-level debt-to-GDP and GDP-per-capita impacts (inter-quartile range) attributable to TCs (blue) and temperature (orange), among sovereigns with at least one TC season with >18m/s wind speeds, 1980–2019. TC impact estimates for extra-tropical countries (latitudes ±23.5) are shown in gray as the wind field model-estimated exposures are less reliable at extra-tropical latitudes.

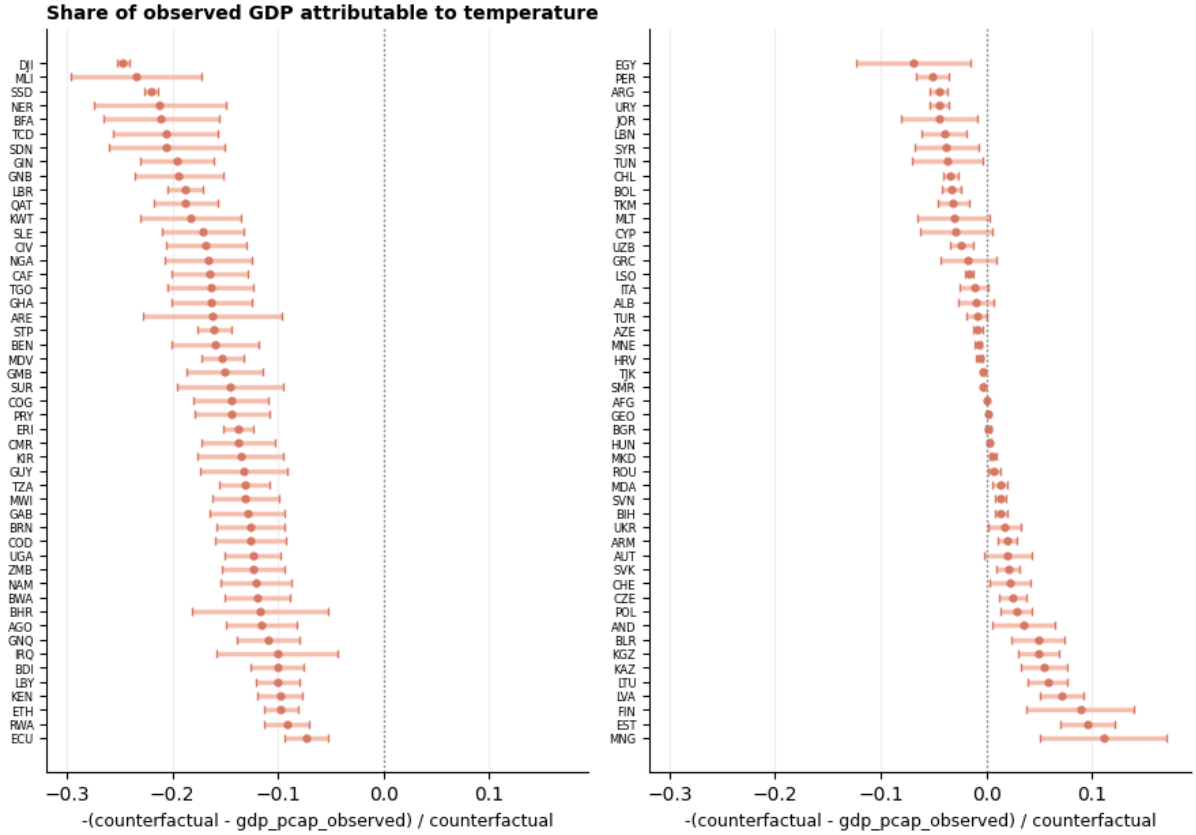


Figure S22. Country-level GDP-per-capita impacts (inter-quartile range) attributable to temperature among sovereigns with no recorded TC exposure (1980–2019)

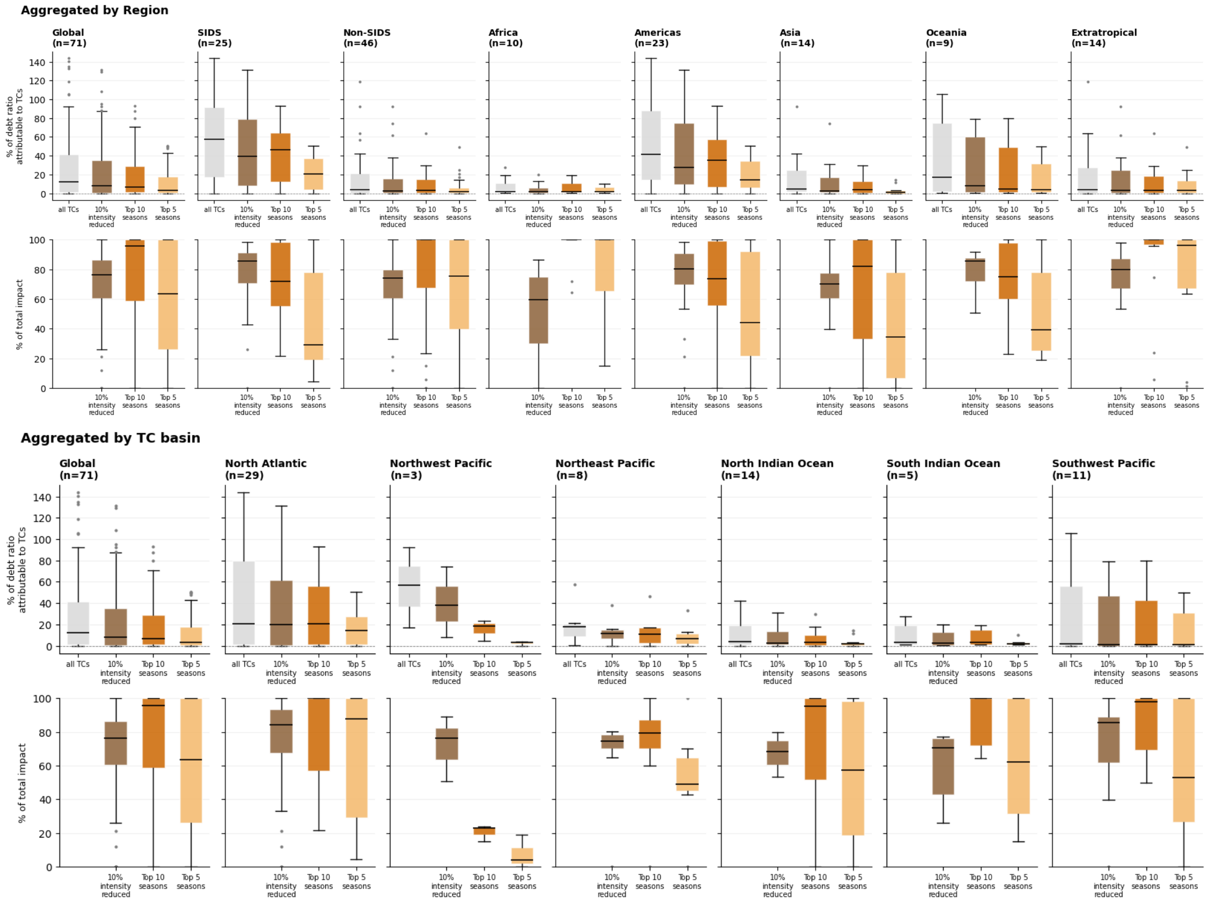


Figure S23. TC-attributable debt-ratio impacts under alternative counterfactual scenarios, aggregated by region (top) and TC basin (bottom). Scenarios include the impact of all TCs, a sensitivity test assuming all TCs with 10% reduced wind speeds, and the impact of the top 10 and top 5 TC seasons for each country. The top row shows the country-level rate of debt ratios attributable to TCs; the bottom row shows the corresponding share of total impact attributed to all TCs.

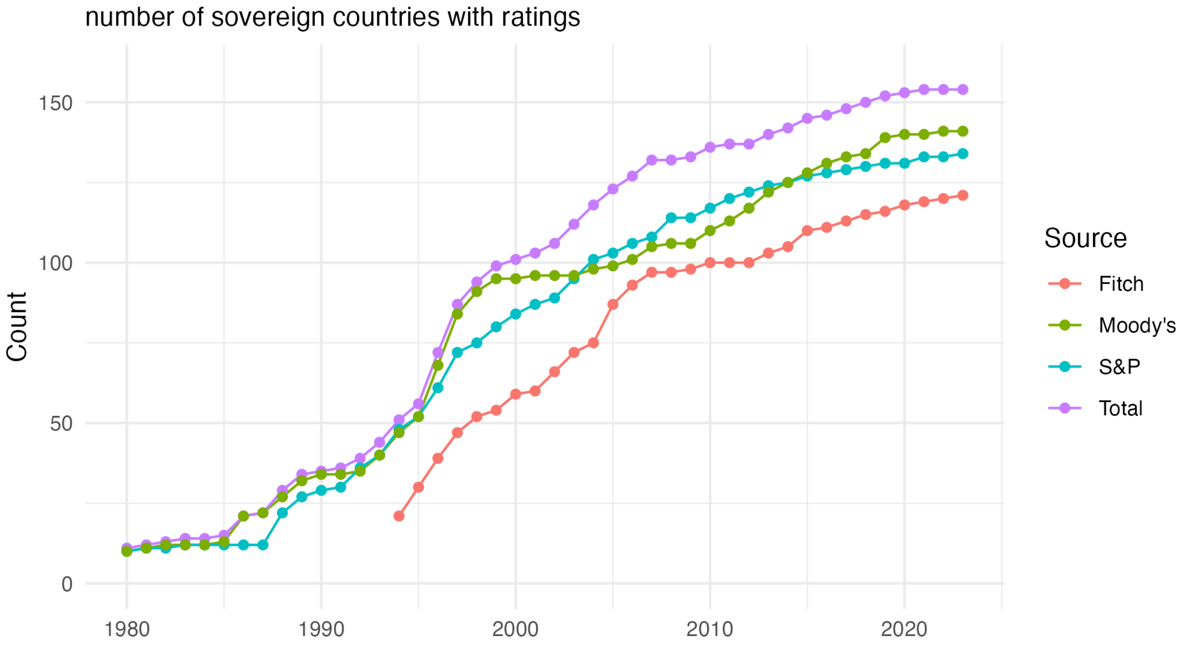


Figure S24. The number of unique sovereign countries with a rating from the three major credit rating agencies. The total number of countries with an assigned rating is plotted separately, as some countries do not have ratings from all agencies.

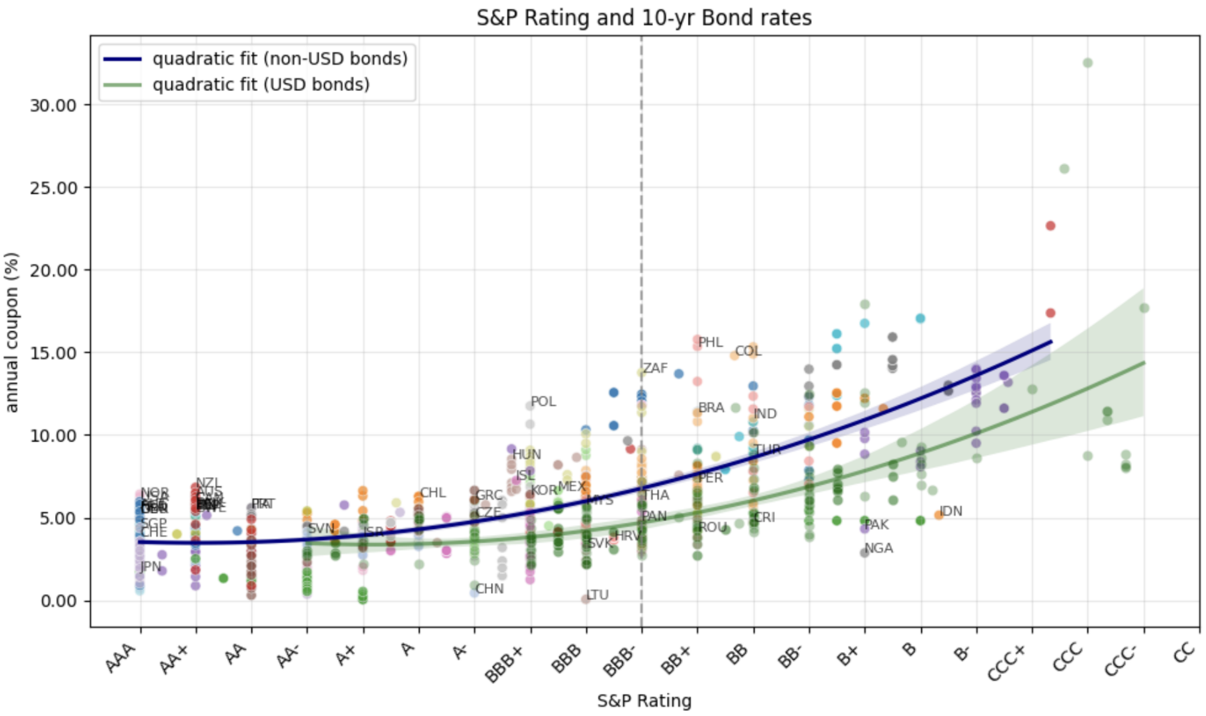


Figure S25. Scatter plot of sovereign credit ratings and annual coupon rates associated with 10-yr maturity bond issuances. Data from Bloomberg available for 53 developed and emerging market countries.

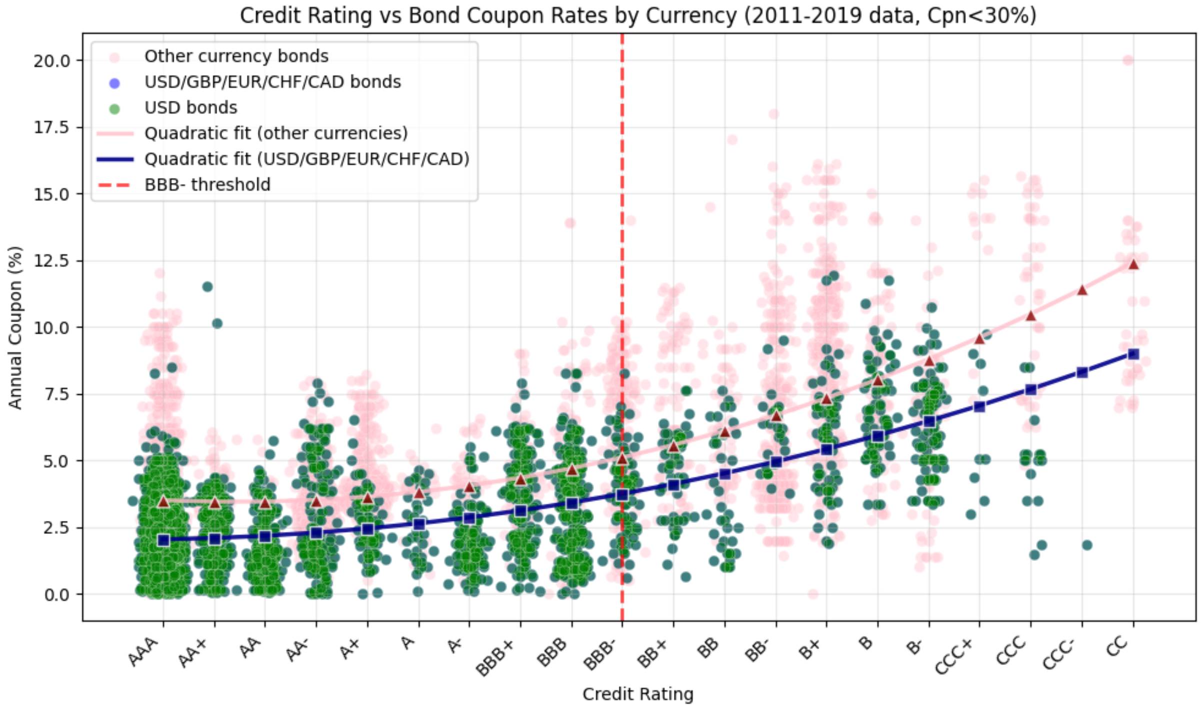


Figure S26. Fitted relationship between sovereign credit ratings and coupon rates, by currency of denomination. Dominant currency are bonds denominated in USD, EUR, GBP, CHF or CAD and local currency are bonds denominated in any other currency. Data from London Stock Exchange Group available for 124 countries with bond issuances between 2011-2019.

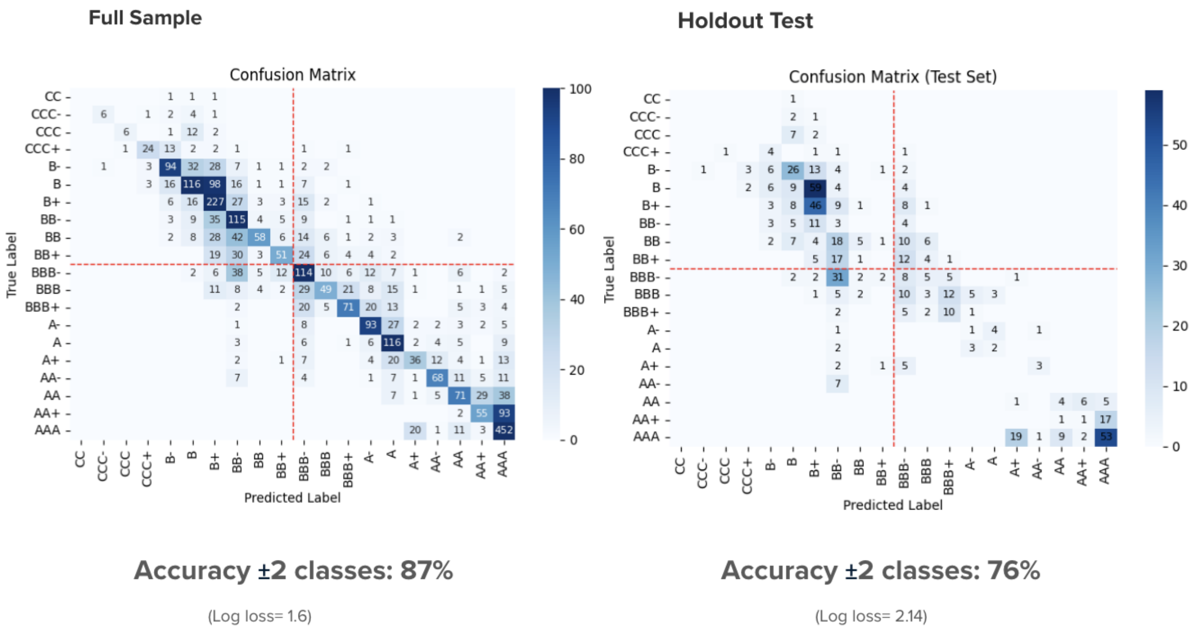


Figure S27. Confusion matrix for the sovereign credit rating prediction model using XGBoost for one random seed. Left panel is for the full sample of countries, right panel is for 20% of held out countries.

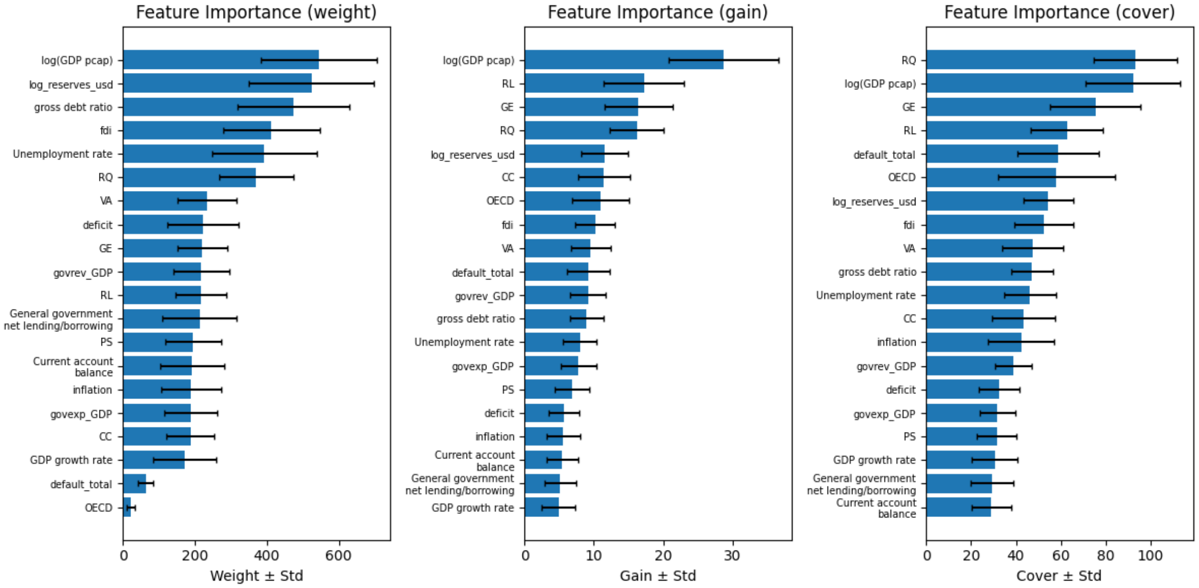


Figure S28. Feature importance rankings from the XGBoost credit rating prediction model. "Weight" describes how often a feature is used; "Gain" describes how useful a feature is in minimizing loss; "Cover" describes how much a feature reduces uncertainty. The error bars show the range of 500 random seeds.

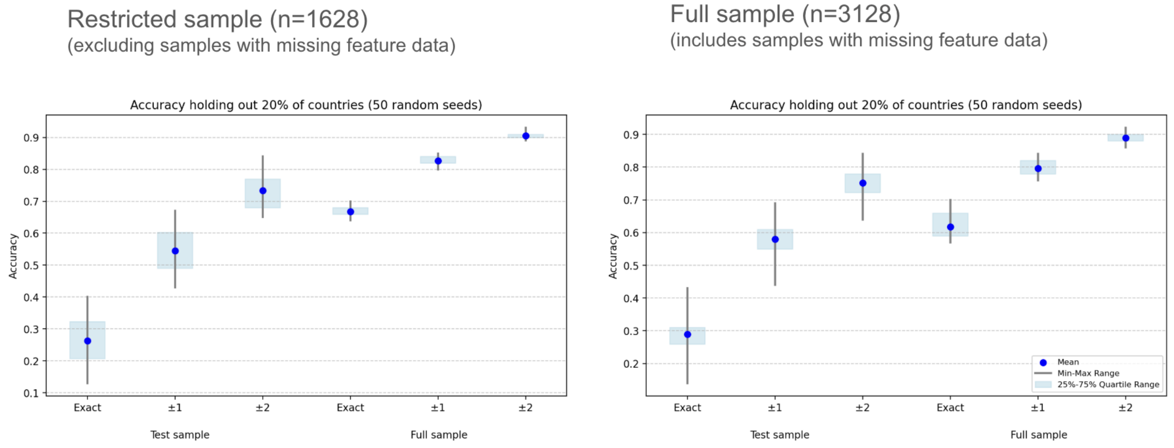


Figure S29. Accuracy of the XGBoost credit rating prediction model for held out test samples and the full sample. The shaded area of the box plots show the inter-quartile range of accuracy after randomly assigning out 20% of countries for the held out test sample. Left panel shows the results for a restricted sample where observations with missing feature data are excluded. Right panel shows the results where observations with missing feature data are included (XGBoost treats the missing data as information, which allows us to take advantage of greater volume of training data).

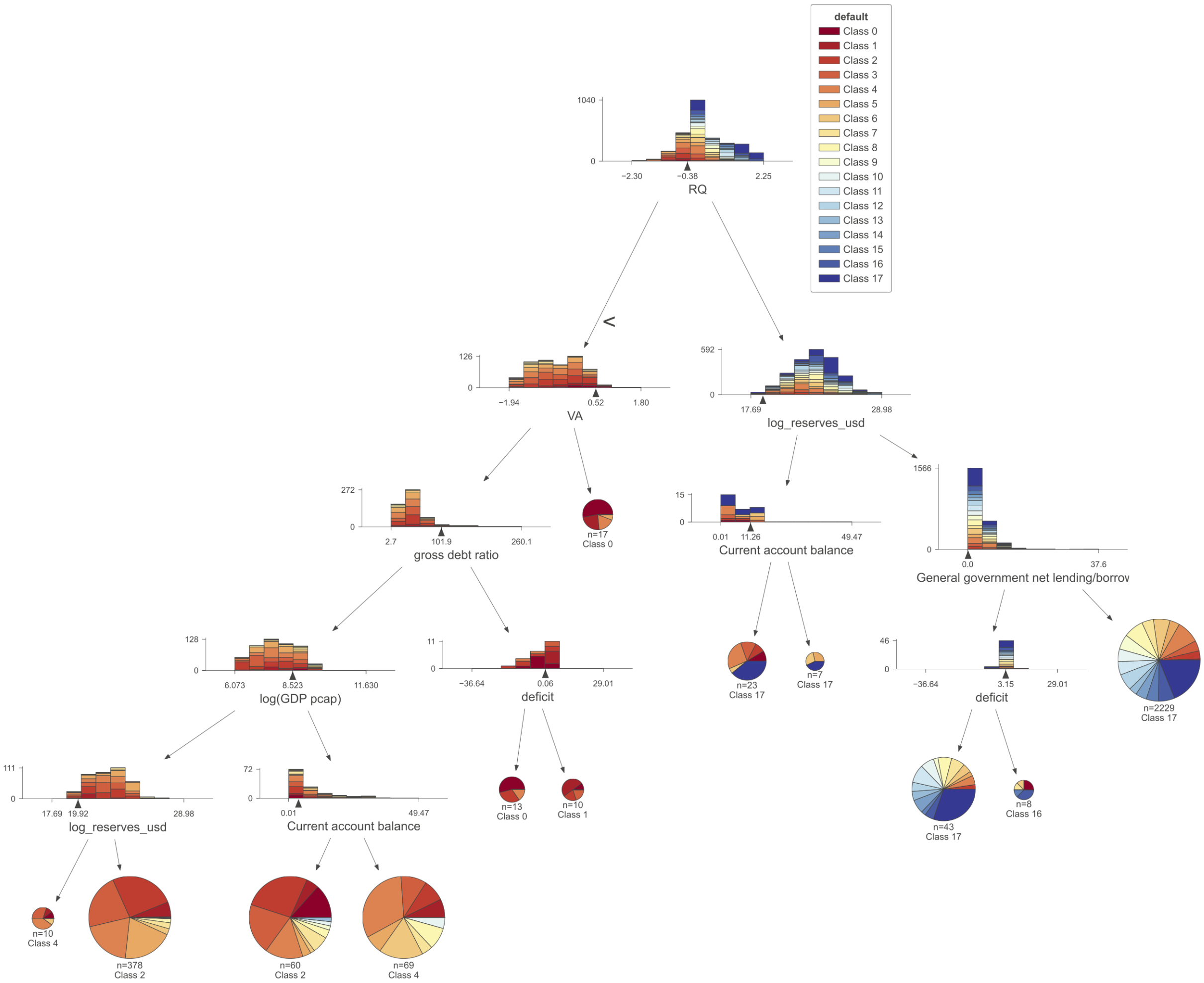


Figure S30. Example decision-tree showing how combination of variables yield final class predictions.

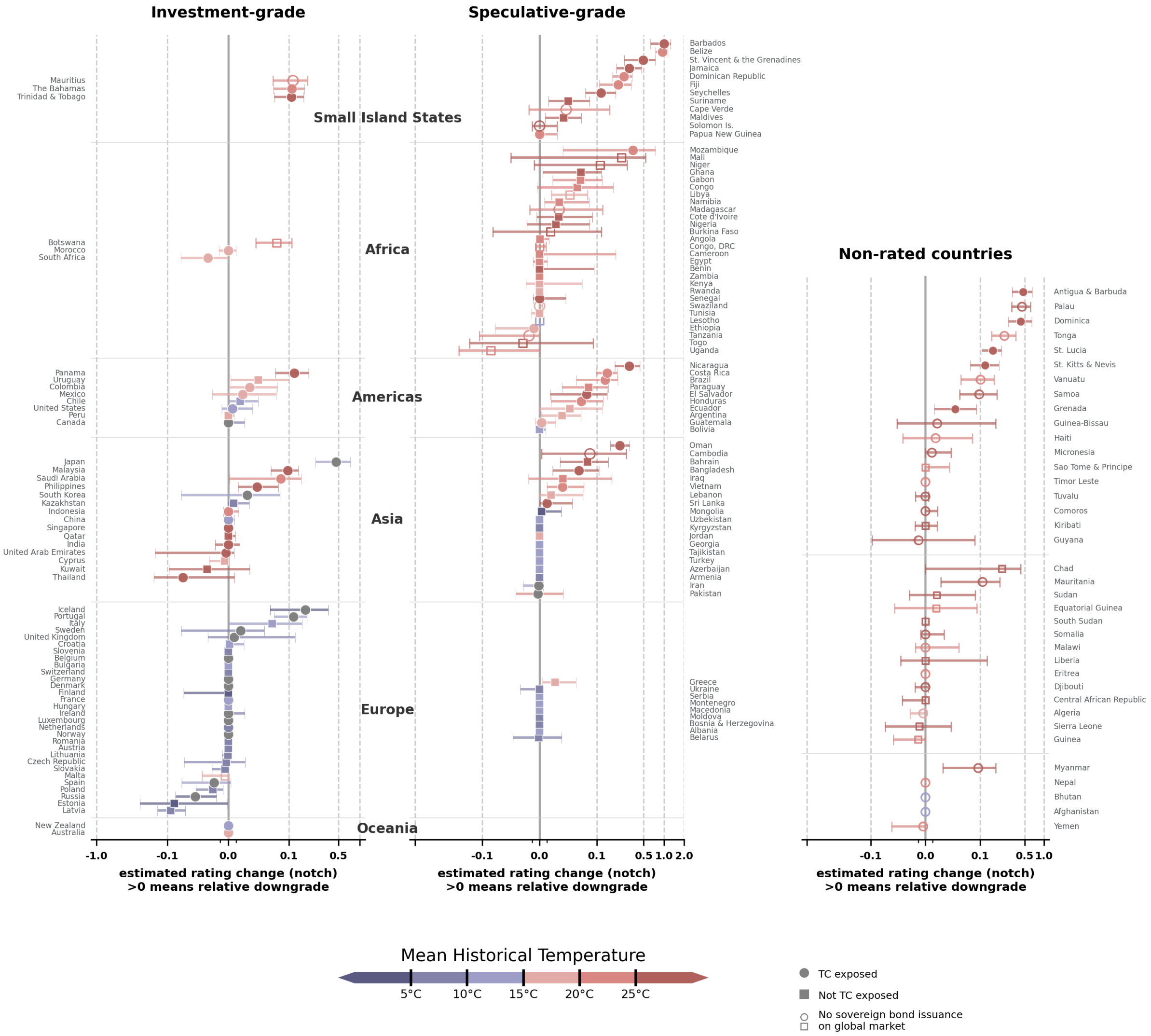
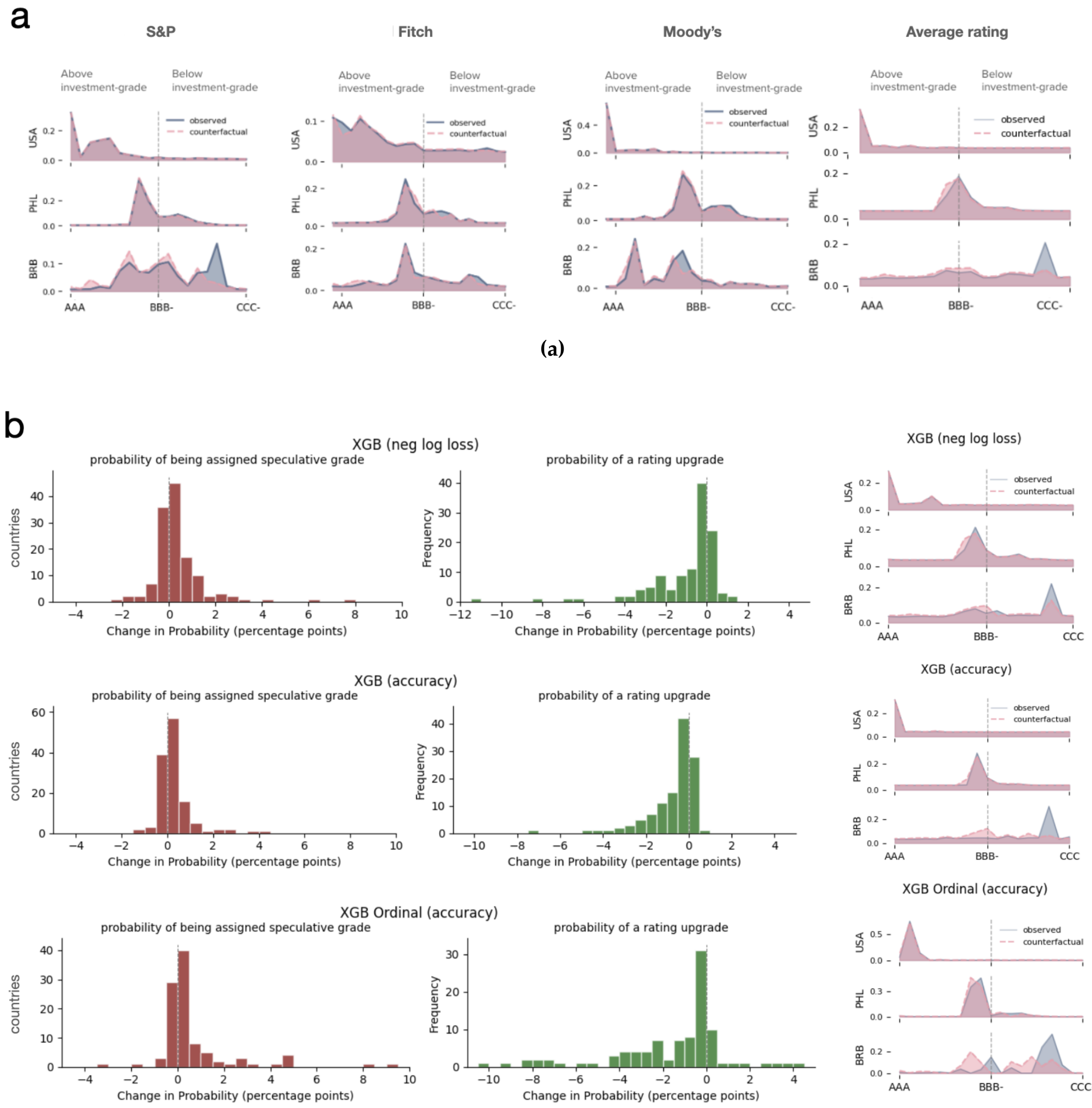


Figure S31. The change in sovereign credit rating associated with historical tropical cyclones and climate change. Values are plotted separately for countries with investment-grade (left) and speculative-grade ratings (center), and non-rated countries (right), with positive values indicating a relative downgrade in expected rating. Colors are based on each country's mean historical temperature. Circle markers indicate countries exposed to TCs (in gray for extra-tropical countries falling outside tropical latitudes ±23.5°) and square markers indicate countries not exposed to TCs. Empty markers indicate countries that have not issued sovereign bonds in the international market. 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.



(a)

(b)

Figure S32. 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.

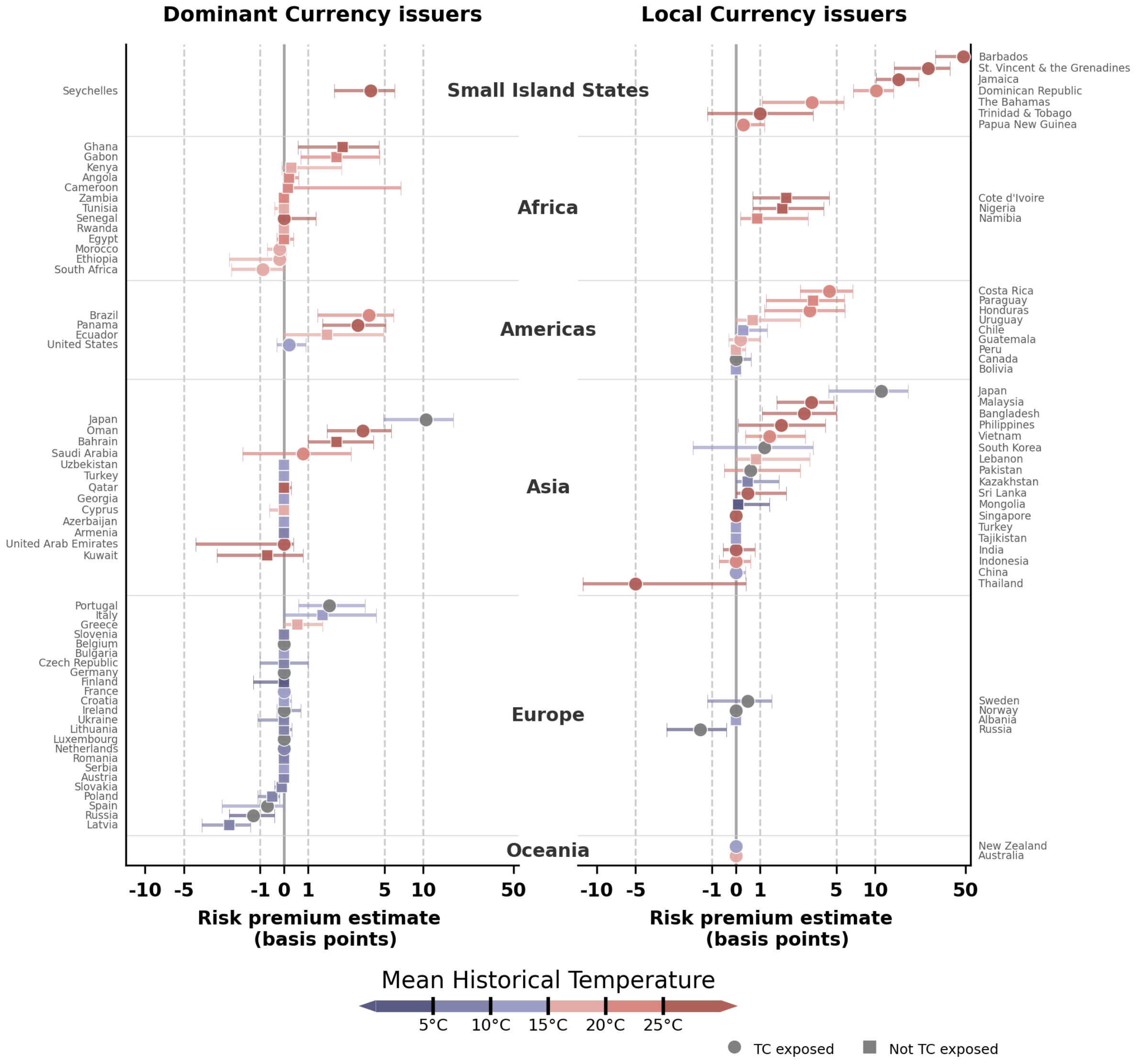


Figure S33. The change in borrowing cost attributed to historical tropical cyclones and climate change. Values are plotted separately for countries with that issue predominantly in a dominant currency, local currency, and estimates for non-rated countries. Colors are based on each country's mean historical 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.

Table S1. Country and time coverage of four panel datasets

Dataset	Source	Period	Total countries	SIDS	TC-exposed (>cat3)*	>1°C warming
Yield (10y sov.)	Bloomberg	1990–2022	57	0	9	42
Coupon (10y mat.)	Bloomberg + LSEG	1980–2023	115	12	21	89
Rating	S&P, Moody's, Fitch	1980–2023	146	16	24	116
LP debt panel	IMF	1980–2019	186	34	33	143

SIDS = Small Island Developing States
TC-exposed (>cat3) = countries ever exposed to category 3 wind speeds (>50 m/s), excluding countries that fall outside tropical latitudes (±23.5).

Tables

Table S2. Sovereign rating coverage by credit-rating agency

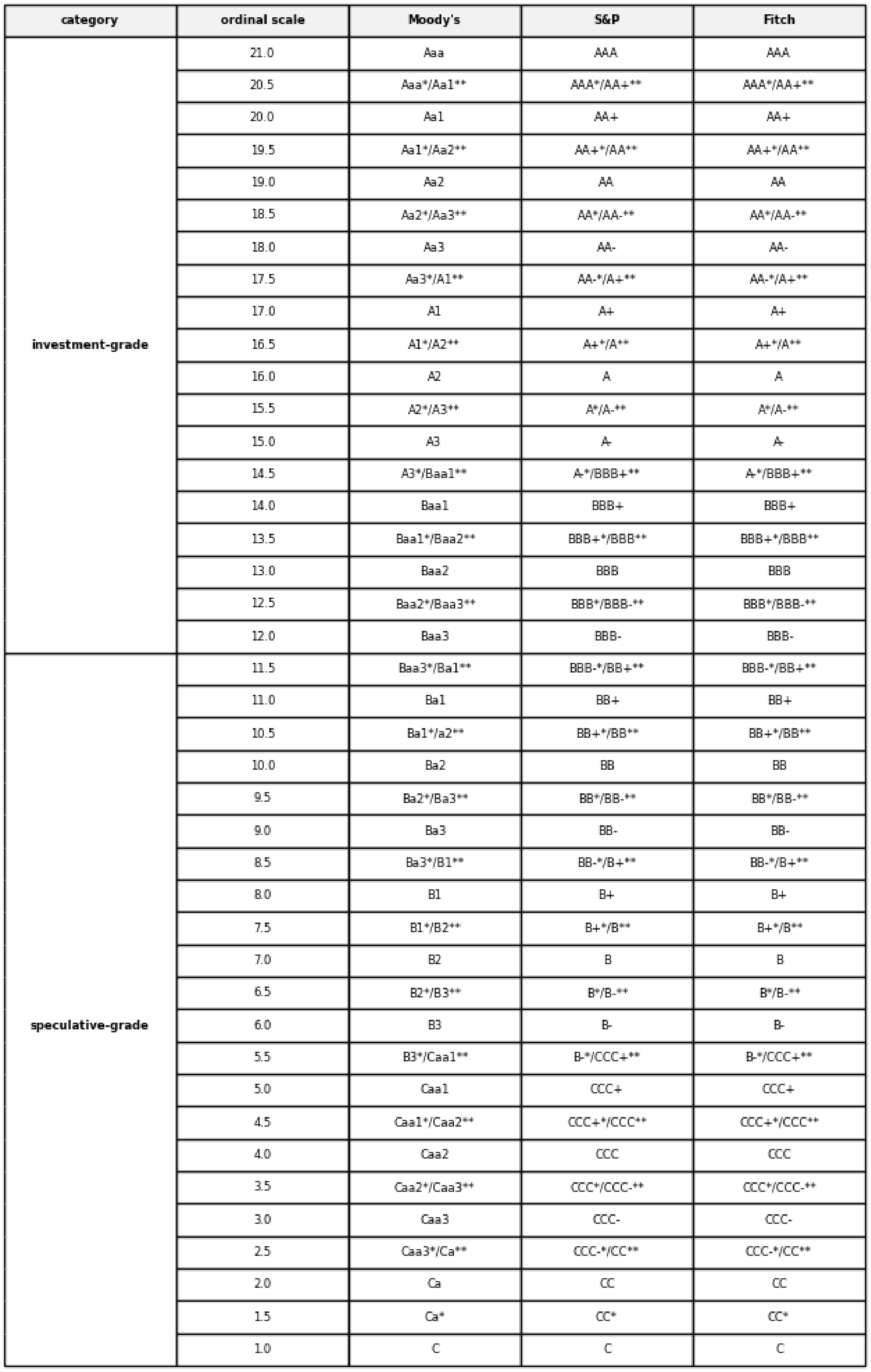
Agency	Group	Total countries	SIDS	First rating >2000
S&P	**Total (ever rated)**	**129**	**11**	**47**
	Investment grade	61	1	4
	Speculative grade	65	9	40
Moody's	**Total (ever rated)**	**136**	**14**	**46**
	Investment grade	58	2	2
	Speculative grade	76	12	42
Fitch	**Total (ever rated)**	**118**	**7**	**61**
	Investment grade	57	0	10
	Speculative grade	56	6	46
Any agency	**Total (ever rated)**	**147**	**16**	**51**
	Investment grade	65	3	3
	Speculative grade	80	13	46
Non-rated	—	**48**	**20**	—

Total (ever rated) = sovereign countries with at least one rating from the agency in any year before 2023. Non-sovereign rated entities (e.g., Bermuda, Cayman Islands, Hong Kong, Isle of Man, Jersey, Macau, Montserrat, Aruba) are excluded.
Investment-grade classification based on 2019. Sums fall short of the Total as some ever-rated countries had no rating in 2019 (either receiving their first rating after 2019, or rating temporarily withdrawn). Any agency is the union of the three agencies' coverage. Non-rated refers to sovereign countries without a 2019 rating from any of the three agencies.
First rating >2000 = countries whose earliest rating was after 2000.

Table S3. Robustness Checks

Category	**Specification**
Model specifications	• Testing TCs and temperature shocks separately • Testing TC bin impacts separately using LP Diff-in-Diff with various clean control conditions • 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 & Jina 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)

Table S4. 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.



category	ordinal scale	Moody's	S&P	Fitch
investment-grade	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+
	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-
speculative-grade	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-**
	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 S5. Predicting credit ratings (by subset)

Variable	All	above_IG	below_IG	SIDS	TC_exposed1	TC_exposed2
Public debt/GDP	-0.0372***	-0.0435***	-0.0271***	-0.0468***	-0.0344***	-0.0291**
	(0.0058)	(0.0060)	(0.0085)	(0.0160)	(0.0118)	(0.0124)
GDP per capita (log)	2.3743***	2.4999**	2.6826***	6.6867***	2.0594	3.0711
	(0.8278)	(1.1924)	(0.7936)	(1.7786)	(1.6641)	(2.9446)
GDP growth	-0.0277	-0.0781***	0.0176	0.0031	-0.0664*	-0.0287
	(0.0177)	(0.0230)	(0.0206)	(0.0410)	(0.0395)	(0.0489)
Primary balance	-0.0441**	-0.0287	-0.0753***	-0.1635**	-0.0541	-0.0344
	(0.0181)	(0.0197)	(0.0215)	(0.0827)	(0.0563)	(0.0695)
Current account/GDP	0.0259*	0.0243	0.0233*	-0.0037	0.0592**	0.0497
	(0.0136)	(0.0205)	(0.0129)	(0.0258)	(0.0296)	(0.0364)
Crisis (sovereign default)	-0.0428	-0.0641	-0.0960	0.0101	0.3593	0.3189
	(0.1802)	(0.2543)	(0.2775)	(0.2056)	(0.2662)	(0.2297)
Sovereign default (past 5y)	-0.4591**	-0.5645*	-0.1013	-0.1878	-0.4372	-0.3072
	(0.2217)	(0.2901)	(0.3069)	(0.4549)	(0.2780)	(0.5456)
WGI: Regulatory Quality	1.7173***	2.2412***	0.5330	-0.1992	0.5467	0.5981
	(0.3837)	(0.4773)	(0.5498)	(0.7577)	(0.5114)	(0.7806)
WGI: Rule of Law	1.2071**	0.9366	1.3889*	1.5019***	1.6617**	1.9194
	(0.4850)	(0.5925)	(0.8382)	(0.4725)	(0.8126)	(1.1743)
WGI: Political Stability	0.4106	0.3325	0.4604	-1.4359***	-0.4063	-0.6258
	(0.2547)	(0.3426)	(0.3318)	(0.4571)	(0.4672)	(0.9152)
Inflation	-0.0243***	-0.0608***	-0.0234***	-0.0390	-0.0605***	-0.0676***
	(0.0094)	(0.0225)	(0.0083)	(0.0302)	(0.0159)	(0.0149)
Unemployment	-0.1241***	-0.1651***	-0.0237	0.0373	-0.0933*	-0.0351
	(0.0363)	(0.0463)	(0.0309)	(0.0447)	(0.0494)	(0.0837)
Constant	-6.4465	-9.6140	-10.9394*	-46.4795***	-3.5828	-14.8572
	(6.8099)	(12.4743)	(6.2834)	(13.8637)	(16.9632)	(29.2614)
Observations	1730	1057	673	162	454	256
R-squared	0.963	0.947	0.788	0.9	0.963	0.963
Number of countries	94	54	40	9	24	13
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time period	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019
Frequency	Annual	Annual	Annual	Annual	Annual	Annual

Standard errors in parentheses, clustered by ISO. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
below_IG: countries with <BBB- credit rating in 2019.
SIDS: Small Island Developing States.
TC_exposed1: countries exposed to >cat1 wind speeds, excluding countries that fall outside tropical latitudes (±23.5°).
TC_exposed2: countries exposed to >cat3 wind speeds, excluding countries that fall outside tropical latitudes (±23.5°).

Table S6. Predicting credit ratings (year FE)

Variable	All	+ below_IG	+ SIDS	+ TC_exposed1	+ TC_exposed2	+ below_IG and TC_exposed2
Public debt/GDP	-0.0214***	-0.0203***	-0.0195***	-0.0212***	-0.0203***	-0.0198***
	(0.0064)	(0.0061)	(0.0058)	(0.0063)	(0.0060)	(0.0059)
GDP per capita (log)	1.4529***	1.0980***	1.3947***	1.4353***	1.3863***	1.0891***
	(0.3226)	(0.2850)	(0.3201)	(0.3210)	(0.3256)	(0.2882)
GDP growth	-0.0763**	-0.0858**	-0.0916***	-0.0781**	-0.0905***	-0.0934***
	(0.0328)	(0.0340)	(0.0327)	(0.0323)	(0.0336)	(0.0348)
Primary balance	-0.0502	-0.0397	-0.0361	-0.0495	-0.0457	-0.0379
	(0.0355)	(0.0336)	(0.0321)	(0.0351)	(0.0348)	(0.0336)
Current account/GDP	-0.0070	0.0067	0.0013	-0.0079	-0.0066	0.0057
	(0.0250)	(0.0233)	(0.0229)	(0.0251)	(0.0245)	(0.0231)
Crisis (sovereign default)	-0.6217**	-0.4472*	-0.5613**	-0.6202**	-0.5582**	-0.4247*
	(0.2650)	(0.2536)	(0.2598)	(0.2651)	(0.2646)	(0.2522)
Sovereign default (past 5y)	-1.3629***	-1.0793***	-1.1912***	-1.3568***	-1.3723***	-1.1090***
	(0.3162)	(0.3076)	(0.3128)	(0.3197)	(0.3140)	(0.3021)
WGI: Regulatory Quality	1.7391***	1.1037***	1.4046***	1.7553***	1.8494***	1.2226***
	(0.4160)	(0.3893)	(0.4165)	(0.4352)	(0.4129)	(0.3779)
WGI: Rule of Law	1.2886***	1.6753***	1.4601***	1.2790***	1.1722***	1.5740***
	(0.4159)	(0.3723)	(0.3992)	(0.4246)	(0.4080)	(0.3562)
WGI: Political Stability	-0.5949**	-0.5051*	-0.3610	-0.5929**	-0.5378*	-0.4792*
	(0.2795)	(0.2596)	(0.2624)	(0.2797)	(0.2806)	(0.2670)
Inflation	-0.0641***	-0.0569***	-0.0652***	-0.0647***	-0.0634***	-0.0571***
	(0.0188)	(0.0170)	(0.0180)	(0.0190)	(0.0181)	(0.0168)
Unemployment	-0.1233***	-0.1239***	-0.1219***	-0.1258***	-0.1342***	-0.1302***
	(0.0300)	(0.0275)	(0.0298)	(0.0339)	(0.0310)	(0.0285)
below_IG_dummy		-1.7837***				-1.6320***
		(0.4300)				(0.3845)
SIDS_dummy			-1.8180***			
			(0.5218)			
TC_exposed1_dummy				-0.1067		
				(0.4280)		
TC_exposed2_dummy					-0.8961*	-0.5266
					(0.4864)	(0.4141)
Constant	1.9471	5.6087**	2.4994	2.1496	2.7084	5.7445**
	(2.8097)	(2.5425)	(2.7814)	(2.8142)	(2.8459)	(2.5688)
Observations	1730	1730	1730	1730	1730	1730
R-squared	0.869	0.88	0.878	0.869	0.873	0.881
Number of countries	94	94	94	94	94	94
Country fixed effects	No	No	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time period	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019
Frequency	Annual	Annual	Annual	Annual	Annual	Annual

Standard errors clustered by ISO. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

below_IG: countries with <BBB- credit rating in 2019.

SIDS: Small Island Developing States.

TC_exposed1: countries exposed to >cat1 wind speeds, excluding countries outside tropical latitudes (±23.5°).

TC_exposed2: countries exposed to >cat3 wind speeds, excluding countries outside tropical latitudes (±23.5°).

Table S7. Predicting coupons (year fixed effect)

Variable	All (no rating)	All (full)	+ country FE	+ below_IG	+ TC_exposed	+ below_IG x TC_exposed
Public debt/GDP	0.0074***	0.0045***	0.0060	0.0046***	0.0046***	0.0042***
	(0.0018)	(0.0016)	(0.0038)	(0.0016)	(0.0016)	(0.0016)
GDP per capita (log)	-0.2622	0.0148	-0.1317	0.0873	-0.0173	0.0783
	(0.1810)	(0.1690)	(1.0825)	(0.1617)	(0.1774)	(0.1794)
GDP growth	-0.1322***	-0.1477***	-0.1318***	-0.1501***	-0.1468***	-0.1442***
	(0.0371)	(0.0391)	(0.0456)	(0.0400)	(0.0390)	(0.0390)
Primary balance	-0.0007	-0.0276	-0.0190	-0.0312	-0.0295	-0.0319
	(0.0278)	(0.0233)	(0.0245)	(0.0235)	(0.0223)	(0.0228)
Current account/GDP	-0.0195	-0.0083	-0.0177	-0.0082	-0.0002	-0.0086
	(0.0186)	(0.0151)	(0.0277)	(0.0149)	(0.0178)	(0.0149)
Sovereign credit rating		-0.1899***	-0.1550**	-0.1932***	-0.2003***	-0.1932***
		(0.0404)	(0.0740)	(0.0407)	(0.0396)	(0.0402)
Crisis (sovereign default)	0.1830	0.1456	-0.2227	0.0785	0.1290	0.1466
	(0.2539)	(0.2532)	(0.3705)	(0.2601)	(0.2591)	(0.2587)
Sovereign default (past 5y)	0.3747	0.3619	0.1978	0.2600	0.3685*	0.3288
	(0.2513)	(0.2223)	(0.2956)	(0.2196)	(0.2233)	(0.2119)
WGI: Regulatory Quality	-0.0436	0.3127	1.0783***	0.3620	0.3816	0.2910
	(0.3318)	(0.3091)	(0.3545)	(0.3055)	(0.2794)	(0.3124)
WGI: Rule of Law	-0.5339	-0.2279	-0.3521	-0.2036	-0.2092	-0.2013
	(0.3312)	(0.3312)	(0.7766)	(0.3203)	(0.3203)	(0.3209)
WGI: Political Stability	0.2645	0.0886	0.1462	0.1095	0.1360	0.1234
	(0.1842)	(0.1539)	(0.4142)	(0.1538)	(0.1617)	(0.1533)
Inflation	0.1630***	0.1140***	0.1241***	0.1103***	0.1129***	0.1156***
	(0.0329)	(0.0346)	(0.0463)	(0.0353)	(0.0345)	(0.0346)
Unemployment	0.0183	0.0349**	0.0919***	0.0367**	0.0366**	0.0370**
	(0.0345)	(0.0157)	(0.0311)	(0.0157)	(0.0152)	(0.0158)
below_IG_dummy				0.5580**		
				(0.2607)		
TC_exposed_dummy					0.2773**	
					(0.1146)	
below_IG_x_TC_expo						0.6896*
						(0.3558)
Constant	10.4454***	9.9214***	9.7878	8.9159***	10.1284***	9.4414***
	(1.6221)	(1.4681)	(8.6084)	(1.3805)	(1.4851)	(1.5466)
Observations	5818	5789	5789	5789	5789	5789
R-squared	0.879	0.892	0.898	0.892	0.892	0.892
Number of countries	82	81	81	81	81	81
Country fixed effects	No	No	Yes	No	No	No
Currency fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time period	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019
Frequency	Annual	Annual	Annual	Annual	Annual	Annual

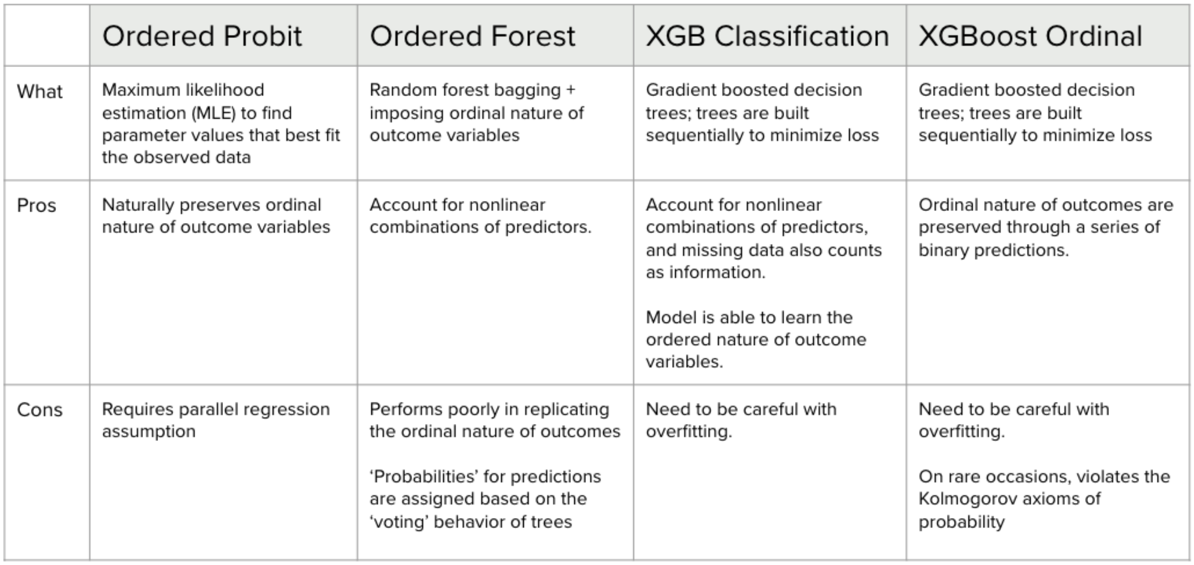
Standard errors clustered by ISO. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
below_IG: countries with <BBB- credit rating in 2019.
TC_exposed: countries exposed to >cat1 wind speeds, excluding countries outside tropical latitudes (±23.5°).

Table S8. Predicting coupons (US 10 yr yield and VIX)

Variable	All (no rating)	All (full)	+ country FE	+ below_IG	+ TC_exposed	+ below_IG x TC_exposed
Public debt/GDP	0.0062***	0.0041**	0.0021	0.0043**	0.0042**	0.0037**
	(0.0015)	(0.0017)	(0.0036)	(0.0017)	(0.0017)	(0.0016)
GDP per capita (log)	-0.4230**	-0.2527	-3.4728***	-0.1950	-0.2859	-0.1610
	(0.1754)	(0.2198)	(1.0487)	(0.2183)	(0.2271)	(0.2275)
GDP growth	-0.0777**	-0.0959**	-0.0928***	-0.0980**	-0.0960**	-0.0933**
	(0.0377)	(0.0396)	(0.0336)	(0.0405)	(0.0390)	(0.0384)
Primary balance	-0.0593***	-0.0732***	-0.0574**	-0.0755***	-0.0751***	-0.0766***
	(0.0194)	(0.0187)	(0.0272)	(0.0187)	(0.0182)	(0.0183)
Current account/GDP	-0.0257	-0.0125	-0.0277	-0.0125	-0.0052	-0.0130
	(0.0220)	(0.0201)	(0.0259)	(0.0202)	(0.0220)	(0.0199)
Sovereign credit rating		-0.1176**	-0.0485	-0.1189**	-0.1247**	-0.1220**
		(0.0504)	(0.0878)	(0.0505)	(0.0509)	(0.0501)
Crisis (sovereign default)	0.3359	0.3671	-0.0756	0.3152	0.3571	0.3674
	(0.2559)	(0.2461)	(0.3423)	(0.2504)	(0.2475)	(0.2551)
Sovereign default (past 5y)	0.3585	0.4456*	0.1855	0.3641	0.4563*	0.4004
	(0.2827)	(0.2556)	(0.2997)	(0.2735)	(0.2537)	(0.2569)
WGI: Regulatory Quality	-0.2035	0.0376	0.4264	0.0725	0.0936	0.0124
	(0.3306)	(0.2848)	(0.3325)	(0.2810)	(0.2635)	(0.2854)
WGI: Rule of Law	-0.2257	-0.0717	0.1142	-0.0539	-0.0542	-0.0465
	(0.3202)	(0.3286)	(0.6109)	(0.3277)	(0.3135)	(0.3211)
WGI: Political Stability	0.3759*	0.2611	0.3101	0.2792	0.3005	0.3072*
	(0.1969)	(0.1772)	(0.4050)	(0.1761)	(0.1865)	(0.1761)
Inflation	0.1576***	0.1186***	0.1161**	0.1158***	0.1183***	0.1207***
	(0.0378)	(0.0391)	(0.0480)	(0.0396)	(0.0387)	(0.0389)
Unemployment	0.0287	0.0602***	0.0902***	0.0619***	0.0619***	0.0629***
	(0.0374)	(0.0219)	(0.0325)	(0.0220)	(0.0211)	(0.0218)
below_IG_dummy				0.4553		
				(0.3475)		
TC_exposed_dummy					0.2496**	
					(0.1240)	
below_IG_x_TC_expo						0.9331**
						(0.4677)
US 10-yr bond yield	0.8387***	0.8849***	0.6883***	0.8933***	0.8861***	0.8816***
	(0.0691)	(0.0722)	(0.0920)	(0.0741)	(0.0727)	(0.0722)
VIX	0.0340***	0.0401***	0.0312***	0.0407***	0.0406***	0.0395***
	(0.0093)	(0.0101)	(0.0117)	(0.0103)	(0.0101)	(0.0099)
Constant	8.2816***	7.1922***	33.9822***	6.2843***	7.3834***	6.5019***
	(1.7462)	(1.7101)	(8.8679)	(1.7335)	(1.7257)	(1.8108)
Observations	5818	5789	5789	5789	5789	5789
R-squared	0.862	0.874	0.888	0.874	0.874	0.875
Number of countries	82	81	81	81	81	81
Country fixed effects	No	No	Yes	No	No	No
Currency fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No
Time period	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019	1996-2019
Frequency	Annual	Annual	Annual	Annual	Annual	Annual

Standard errors clustered by ISO. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
below_IG: countries with <BBB- credit rating in 2019.
TC_exposed: countries exposed to >cat1 wind speeds, excluding countries outside tropical latitudes (±23.5°).

Table S9. Table listing different rating prediction models that were tested in this study, their pros and cons.



	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 S10. Table listing the prediction variables, definitions, and data source used in the XGB model.

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 S11. sovereign credit rating impact

Panel	n	Mean	Median	Full range
All countries	181	-0.063	-0.014	$[-0.948, +0.139]$
Investment grade	63	-0.022	-0.000	$[-0.491, +0.139]$
Speculative grade	78	-0.088	-0.033	$[-0.948, +0.123]$
Non-rated	40	-0.077	-0.022	$[-0.500, +0.023]$
SIDS	33	-0.192	-0.120	$[-0.948, +0.009]$

Rating notch impact computed as $\mathbb{E}[\text{rating} \mid \text{obs}] - \mathbb{E}[\text{rating} \mid \text{cf}]$, using the XGB classifier's predicted rating distribution. Negative values indicate downgrade in the expected rating.
Investment-grade and speculative-grade classification is based on the max rating across S&P, Moody's, and Fitch in 2019.
SIDS = Small Island Developing States

Table S12. Summary of TC-attributable debt-to-GDP impacts, 1980-2019

Scope	n	Impact
All TC-exposed	85	17.6%
TC-exposed latitude ±23.5	65	20.1%
SIDS	27	31.7%

impact = mean of within-country median impact as share of observed debt ratio ((obs-cf)/obs) across time period 1980–2019.
Sample restricted to sovereign countries with at least one TC year with >18 m/s wind speed.
SIDS = Small Island Developing States.

Table S13. Summary of TC and temperature-attributable GDP impacts, 1980-2019.

Channel	Scope	*n*	impact
Combined (TC & temp)	All countries	186	−11.7%
	TC-exposed	87	−14.9%
	TC-exposed (latitude ±23.5)	67	−18.6%
	SIDS	35	−21.4%
TC only	All countries	87	−4.0%
	TC-exposed	87	−4.0%
	TC-exposed (latitude ±23.5)	67	−4.5%
	SIDS	29	−7.6%
Temperature only	All countries	186	−7.8%
	TC-exposed	87	−8.3%
	TC-exposed (latitude ±23.5)	67	−10.8%
	SIDS	35	−11.5%

impact = mean of within-country median impact (-(cf-obs)/cf) across time period 1980-2019. Negative values indicate observed GDP below the no-warming counterfactual.
Combined counterfactual = combined TC and temperature shocks; TC-only and temp-only rows isolate each channel separately. The combined effect is non-additive.
TC-exposed= sovereigns with at least one above-tropical-storm-strength TC year in 1980-2019.