Decoding climate-related risks in sovereign bond pricing: A global perspective *

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Abstract

Climate change can affect sovereign credit risk through both transition and physical channels, but the extent to which these risks are reflected in sovereign borrowing costs remains unclear. Using a panel of 52 advanced and developing economies over 2000–2023, we examine whether transition, chronic physical and acute physical risks influence sovereign bond yields. We find that transition risk is priced: higher greenhouse gas emissions are associated with higher sovereign yields, with stronger effects in developing economies. Chronic temperature-related risks do not appear to influence yields in levels. Acute physical risks have limited average effects in panel regressions, but local projection estimates show that natural disasters can raise borrowing costs in the medium term, especially in countries with weaker fiscal positions. These results suggest that the impact of climate shocks on sovereign borrowing costs depends not only on the hazard itself but also on underlying macro-fiscal conditions.

Keywords: Climate risk; sovereign risk; transition risk; temperature change; natural disasters

JEL Codes: C23; E62; H63; Q54

1 Introduction

Climate change has increasingly become a macro-critical factor for fiscal policy, debt sustainability, and sovereign risk. It can generate both immediate and longer-term fiscal pressures through several channels, including higher expenditures for adaptation and mitigation, re-allocation of resources away from productive investments towards new technologies, and the repricing of sovereign assets. Direct fiscal impacts typically arise from emergency assistance and disaster reconstruction, while indirect effects may include lower tax revenues due to production disruptions, changes in commodity prices or additional spending through food and energy support schemes (Schuler, Oliveira, Mele, and Antonio, 2019). These mechanisms may interact with sovereign debt dynamics in complex ways, as suggested for example in recent work on climate and fiscal sustainability Zenios (2022). Yet despite heightened policy attention, the way in which climate risks influence sovereign borrowing costs remains only partially understood. This is striking given that sovereign bond markets are among the largest asset classes globally, shape governments' fiscal capacity and play a central role in financing climate mitigation and adaptation efforts.

The macro-financial relevance of climate shocks becomes clearer when viewed through concrete cases. The 2011 Thailand floods – one of the most damaging climate-related disasters on record – caused losses exceeding 40 billion USD, disrupted global supply chains, and led to a notable rise in reconstruction spending. Sovereign yields increased as fiscal risks were reassessed. A similar pattern emerged after the 2022 Pakistan floods, which affected more than 30 million people and caused losses close to 10 percent of GDP, placing substantial strain on public finances and fuelling concerns about debt sustainability. Even advanced economies are not insulated: Europe's 2023 heatwaves and associated wildfires resulted in widespread infrastructure damage, major agricultural losses and a surge in emergency spending across several EU member states. Such episodes illustrate the channels through which climate shocks – both sudden and gradual – can affect sovereign borrowing conditions, yet systematic cross-country evidence on their pricing in global bond markets remains limited.

Broadly, climate risks can affect sovereign creditworthiness through three distinct but interrelated channels. Transition risk arises as economies adjust towards low-carbon growth paths, with implications for energy systems, industrial activity and fiscal revenues. Chronic physical risk, stemming from persistent shifts in temperature and precipitation, may depress productivity and increase recurrent fiscal pressures. Acute physical risk, materialising through climate-related natural disasters such as floods, storms, droughts and extreme temperatures, can generate sudden and substantial fiscal demands, reduce economic activity and trigger re-pricing of sovereign debt. Critically, these channels are unlikely to affect countries uniformly: exposure, adaptive capacity and fiscal space differ widely across advanced economies (AEs) and emerging and developing economies (EMDEs).

In this paper, we provide systematic cross-country evidence on the extent to which transition and physical climate risks are priced in sovereign bond markets. Our analysis covers 52 advanced and emerging economies over the period 2000–2023 and examines all major climate-risk dimensions jointly. Transition risk is proxied by annual greenhouse gas emissions relative to GDP, while chronic physical risk is captured through deviations in annual temperatures from long-run historical norms. To measure acute risk, we draw on detailed information from the EM-DAT database, including the frequency, severity and human impact of climate-related natural disasters. We complement panel regression models – which capture climate risk pricing in levels – with local projections that quantify the dynamic medium-term effects of different disaster types.

Our analysis yields several novel insights. First, transition risk is consistently priced into sovereign borrowing costs, with higher greenhouse gas emissions associated with higher 10-year (and 5-year) yields. This effect is especially pronounced in EMDEs and strengthens following the Paris Agreement, indicating growing investor attention to transition pathways. Second, chronic physical risks, measured by temperature anomalies, do not appear to be priced into sovereign yields in levels. Third, while panel regressions suggest that acute physical risks are not systematically priced, dynamic responses tell a different story: local

projections reveal meaningful and heterogeneous medium-term effects of climate-related disasters, particularly for EMDEs. The impact varies sharply across disaster types: droughts, storms and extreme temperature events raise yields significantly and persistently, with effects amplified in countries with limited fiscal space or during economic downturns. Finally, we show that most of these effects operate indirectly – via higher debt burdens, lower growth, and higher inflation – rather than through a separately priced "climate risk premium".

These findings have direct implications for fiscal and climate policy. Transition efforts matter for sovereign financing conditions today; physical risks may not yet be fully priced in levels but generate substantial dynamic pressures, especially for vulnerable, high-debt economies. As both the frequency of extreme events and the ambition of climate policy rise, considering climate risks within sovereign risk assessment and debt sustainability frameworks becomes increasingly essential.

The remainder of the paper proceeds as follows: Section 2 reviews the related literature. Section 3 describes the data and variables. Section 4 presents the panel regression results. Section 5 examines the medium-term dynamic effects of climate shocks using local projections. Section 6 concludes.

2 Background

Our research bridges the field that studies the determinants of sovereign bond yields and the field that specifically studies the impact of climate change risk thereon.

Determinants of sovereign bond yields and spreads have been extensively investigated. In general, the literature identifies domestic macroeconomic fundamentals as major determinants of government bond yields and sovereign risk (Edwards, 1986; Eichengreen and Mody, 1998; Arellano, 2008; Baldacci, Gupta, and Mati, 2011) or their volatility (Hilscher and Nosbusch, 2010). The importance of macroeconomic fundamentals is also confirmed by Duffie, Pedersen, and Singleton (2003). Studies from the conceptually related literature on sovereign risk, proxied by credit ratings, corroborate the previous findings revealing an asso-

ciation between a country's credit rating and a number of macroeconomic variables. These include GDP growth, inflation, external debt Cantor and Packer (1996), exchange reserves or the current account balance (Afonso, Gomes, and Rother, 2011; Ratha, De, and Mohapatra, 2011), fiscal balance, trade openness or institutions (Borio and Packer, 2004; Kling, Volz, Murinde, and Ayas, 2021), the political business cycle (Block and Vaaler, 2004), or fiscal transparency (Hameed, 2005). Furthermore, some empirical papers focus on extra-financial factors. In particular, given the increasing importance of sustainability factors, recent literature investigates the relationship between ESG performance and sovereign risk (Margaretic and Pouget, 2018; Capelle-Blancard, Crifo, Diaye, Oueghlissi, and Scholtens, 2019; Anand, Vanpée, and Lončarski, 2023).

There is a range of channels through which the cost of sovereign borrowing may be affected by climate change. First, adaptation and mitigation policies for climate change have fiscal consequences (Bachner, Bednar-Friedl, and Knittel, 2019). Higher mitigation spending creates transition risk and puts pressure on public finance, but leads to more benign climate change with milder impacts in terms of damages, growth and borrowing rates. Likewise, adaptation also moderates the impact of climate change, but with potentially large fiscal expenditures. Second, there is growing evidence that physical risks adversely impact sovereign creditworthiness and borrowing costs through multiple transmission channels (Melecky and Raddatz 2011; Koetsier 2017; Boehm 2022; Klusak, Agarwala, Burke, Kraemer, and Mohaddes 2023). Ex-post, natural disasters often lead to a higher likelihood of a subsequent sovereign debt crisis and, in fact, they have in the past been contributing factors to sovereign debt defaults.[1] Klomp (2015) and Klomp (2017) find that large-scale natural disasters increase significantly the onset probability of a sovereign debt default. More recently, Phan and Schwartzman (2024) find that disaster risk and default risk together lead to slow post-disaster recovery and heightened borrowing costs. Mallucci (2022) uses a quantitative sovereign default model and find that extreme weather restricts government's ability to issue debt. At

[1] https://www.moodys.com/research/doc--PBC_1191686?docid=PBC_1191686.

the same time, ex ante, disaster-prone economies face significantly higher public debt than economies that are less susceptible to disasters (Cabezon, Hunter, Tumbarello, Washimi, and Wu, 2019). Recent research has shown that climate-vulnerable developing countries incur a risk premium on their sovereign debt (Buhr, Volz, Donovan, Kling, Lo, Murinde, and Pullin, 2018). Kling, Lo, Murinde, and Volz (2018) investigate the impact of climate vulnerability, as measured by the Notre Dame Global Adaptation Initiative (ND-GAIN) sub-indices, on bond yields and find a significant effect. Beirne, Renzhi, and Volz (2021a), Beirne, Renzhi, and Volz (2021b) and Cevik and Jalles (2022) examine further the effect of climate change on sovereign risk by using vulnerability and resilience indices using a sample of advanced and emerging economies.

We depart from the traditional approach centered mainly on climate vulnerability indices and distinguish between chronic and acute physical risk in regression analysis, undertaking a thorough investigation of natural disaster data sourced from EM-DAT. Boehm (2022) shows that rising temperatures can considerably affect the creditworthiness of emerging economies and that temperature anomalies have a detrimental impact on sovereign bond performance. We extend these results to advanced economies. Importantly, we go one step further and through a LP analysis we unveil that there is a positive significant effect of the frequency of natural disasters. Cevik and Jalles (2024) use the LP method to estimate the impact of climate shocks on inflation and economic growth and derive impulse response functions in a panel setting. The subsequent analysis of the transmission channels shows that economies more vulnerable to external economic conditions exhibit distinct responses to climate events. Economies with greater external vulnerabilities, such as dependence on global commodity markets or sensitivity to capital flows, often experience more pronounced economic impacts from climate events due to amplified fiscal and financial pressures.

There are few papers on the transition risks which arise due to a country's adjustment process towards a greener economy in a government bond context. Painter (2020) finds that the impact that climate change risk has on the municipal US bond market is meaningful.

He measures the exposure a county has to climate change by expected mean annual loss from sea level rise as a percentage of GDP (Hallegatte, Green, Nicholls, and Corfee-Morlot, 2013). Although this is a forward-looking measure, we opt to use carbon emissions and focus on sovereign bonds for a large number of countries. More recently, Collender, Gan, Nikitopoulos, Richards, and Ryan (2023) show that climate transition risks are currently priced into sovereign bond yields and spreads.

3 Data

We use several sources to construct a panel dataset with annual observations for an original sample of 87 countries. First, we remove from the sample countries with severely underpopulated observations and keep those that have at least five years of data in, approximately, the last 25 years. This reduces the initial sample to 52 countries, for the years 2000-2023. The sample includes 26 AEs and 26 EMDEs, according to the BIS country classification. Table A1 shows the countries included in the analysis.

Table A2 describes the variables and their sources and Table A3 presents summary statistics. Economic and financial statistics are assembled from the IMF's International Financial Statistics (IFS) and the World Bank's World Development Indicators (WDI) database. More details on the variables are given in the next subsections.

3.1 Dependent variable

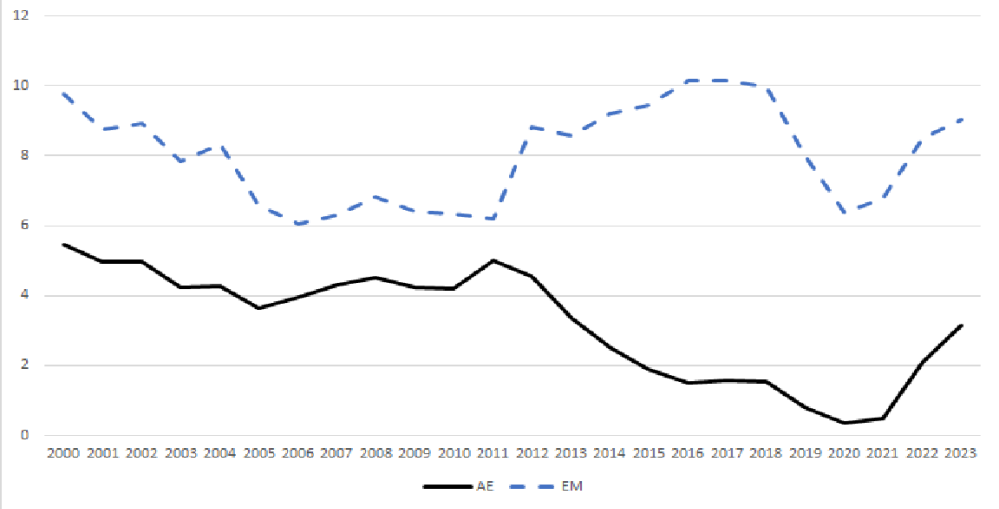
The dependent variable is countries' 10-year government bond yield.[2] This is inline with related research from Kling et al. (2018); Painter (2020); Beirne et al. (2021a); Klusak et al. (2023); Cevik and Jalles (2022); Collender et al. (2023) who employ 10-year government bond

[2] The sample does not include green and sustainable and sustainability-linked sovereign bonds. This type of bonds offers a way of linking issuance and climate-related economic strategies of governments. Green bond issuance has increased significantly in the past few years and especially since 2019. However, they remain marginal to sovereign issuance. As per 2024 Q1 they represent only 18 percent of total sovereign bond issuance and they are too few to materially influence governments' cost of financing. https://www.climatebonds.net/2024/06/record-start-year-sustainable-debt

yields to evaluate the cost of borrowing capital for governments in transitioning economies. We also run the main model for 5-year maturities to capture a shorter to medium-run period.[3] Sovereign yields are extracted from Bloomberg with a yearly frequency (end-year yields).

Figure 1 shows the annual generic yields of sovereign bonds averaged between the two groups of countries from 2000 to 2023. As shown, sovereign bond yields show a downward trend that is particularly pronounced for advanced economies. In the last three years, both groups of economies have experienced increases in their yields. However, while AEs' borrowing cost did not exceed 4%, EMDEs have experienced an increase in yields from 6% to 9%. These differences in yields are another reason to separate the results of emerging and advanced economies.

Figure 1. Average 10 year sovereign bond yields for AEs and EMDEs



3.2 Climate risk variables

For transition risk, we use total greenhouse gas emissions defined as *GHG* emissions per GDP, from EDGAR. Chronic risk is proxied by the difference in annual temperature relative

[3] Although yield spreads calculated as the difference between the interest rate paid by a country on its external US denominated debt and the US Treasury bond rate offered on debt of comparable maturity is widely accepted, we acknowledge that it might bring some complications, especially in climate risk analyses given that US exhibit a relatively high degree of both transition and physical climate risk exposure due to their generally low climate policy performance.

to the mean temperature between 1951 and 1980, extracted from the World Bank. For the second source of physical risk, we use the frequency of natural disasters related to climate change and their losses expressed as annual economic costs due to damages from natural disasters or the total number of people affected. Table A3 shows EMDEs experienced an average of total and uninsured losses from natural disasters similar to that of AEs, but with twice the volatility, as measured by the standard deviation.

We source natural disaster data from the International Disaster Database (EM-DAT), hosted by Universite Catholique de Louvain. Despite its limitations, this is one of the most comprehensive publicly available datasets that contains detailed information about more than 17,000 natural disasters worldwide since 1900. The database is compiled from several sources and distributed by the Centre for Research on the Epidemiology of Disasters (CRED). EM-DAT classifies disasters into two groups of hazards: natural and technological. The natural group is further classified into six broad groups; biological; climatological; geophysical; hydrological; meteorological and; extra-terrestrial, each one containing several disaster types and subtypes. Since 2000, the dataset has documented almost 10,000 natural disasters.[4] In addition, the database contains information such as the date and duration of each event, the damage caused, and the number of causalities. Total damage is the value of all economic losses directly or indirectly resulting from the disaster, in thousands of dollars adjusted for inflation. The human impact of disasters is described by the total number of deaths and the total number of people affected.[5]

From a climate perspective, the most relevant groups are the climatological, hydrological and meteorological ones. We focus on floods, storms, extreme temperature, droughts and wildfire.[6] Figure 2 shows the distribution of climate-related natural disasters in EM-DAT

[4] Natural disasters in EM-DAT include earthquake, mass movement (dry), volcanic activity, extreme temperature, fog, storm, flood, landslide, wave action, drought, glacial lake outburst, wildfire, epidemic, insect infestation, and animal accident.

[5] Which is the sum of the number of injured people due to the disaster, the number of people requiring immediate assistance due to the disaster and the number of people requiring shelter due to their house being destroyed or heavily damaged during the disaster.

[6] EM-DAT documentation reports that data on events prior to 2000 are particularly subject to reporting biases, and hence the analysis will not consider those.

by type and estimated impact. The most common type, by far, is floods, the second being storms. Each of the rest occurs about 10 times less frequently compared to the most frequent. In total, the dataset contains information on about 7,700 climate-related natural disasters. Although storms are the most costly natural disasters in economic terms, droughts have a far greater human toll in terms of affected, injured, and left homeless.[7]

Figure 3 shows the average duration (in days) of natural disasters by type. Interestingly, while droughts occur far less frequently, they last by about an order of magnitude longer compared to the second in ranking, exhibiting a mean duration of about 230 days. This is probably one of the reasons for its large human cost, shown in Figure 2. In contrast, the most frequent and impactful types of natural disaster, floods and storms, last, on average, ten and two days, respectively.

Figure 4 presents the distribution of climate-related natural disaster events by year and suggests that natural disasters are relatively uniformly distributed over time. However, this does not mean that there is no increase in disasters, especially when looking at specific types of event or specific locations. It is also uninformative about the intensity of disasters.

Table 1 presents average measures of frequency, duration, number of deaths, number of affected people, and damages for each type of disaster. For AEs, floods and storms are the most frequent, with average damages exceeding 1.4 billion USD per event, while droughts, though infrequent, have the longest duration and the highest economic damage. In contrast, EMDEs face floods more frequently and endure slightly longer droughts, with far higher numbers of people affected, in all types of natural disasters. Interestingly, although the average economic impact of natural disasters is almost always greater in absolute terms in AEs than in EMDEs, the damage, when measured as a share of GDP, is often comparable or even twice as large in EMDEs. This indicates that the stress on the economies of the latter is substantially higher.

[7] It should be emphasized that these figures are likely underestimates of the actual numbers, as mentioned in the database documentation.

Figure 2. Distribution of climate-related natural disaster events (left panel) and their human and economic impact (right panel) by type, since 2000. Average economic impact is reported in % of GDP.

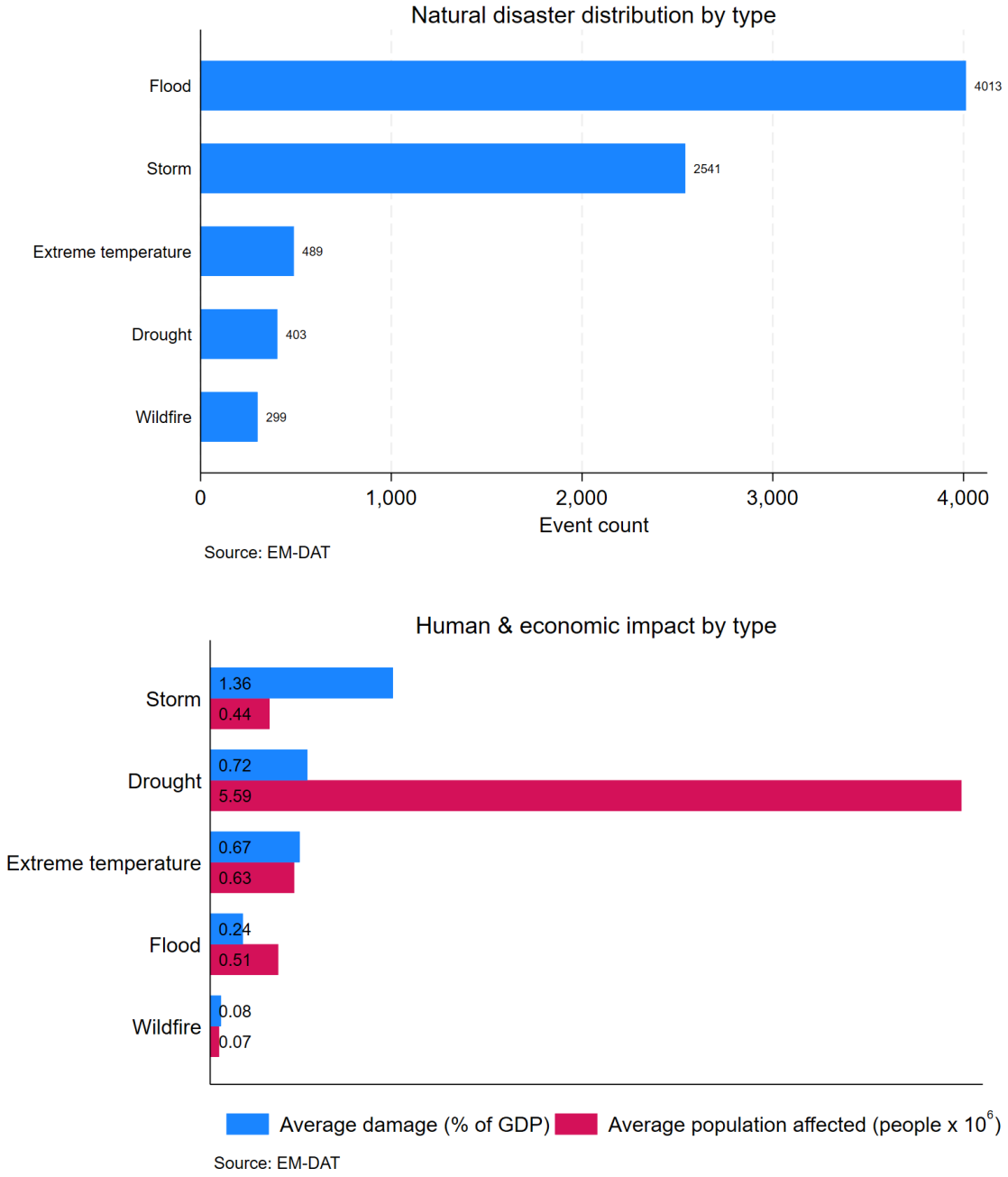


Figure 3. Average duration of climate-related natural disaster events by type, since 2000.

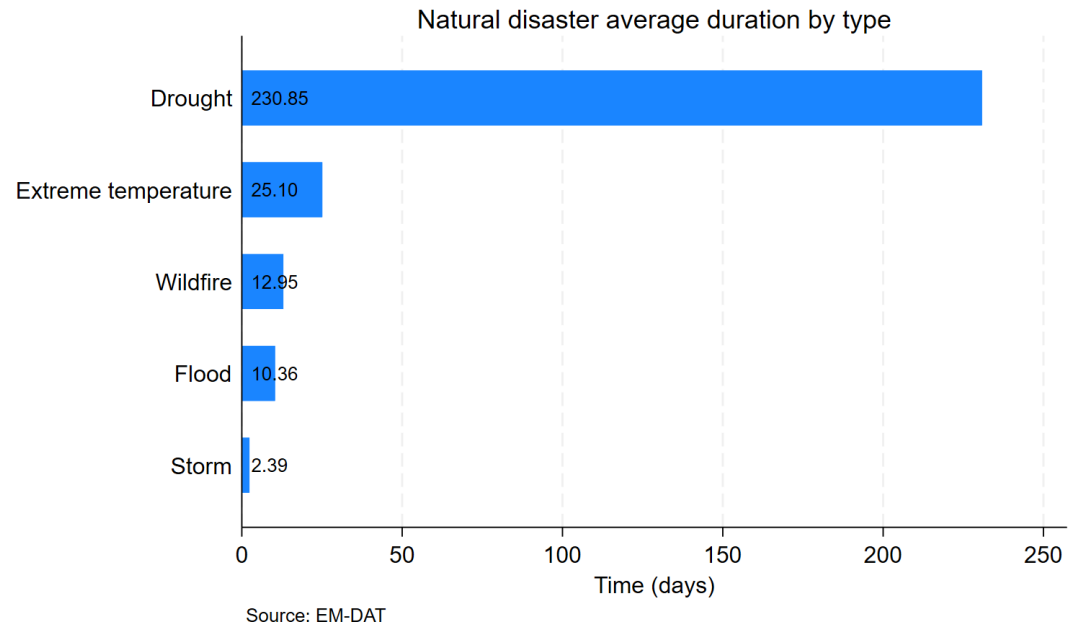


Figure 4. Distribution of climate-related natural disaster events by year.

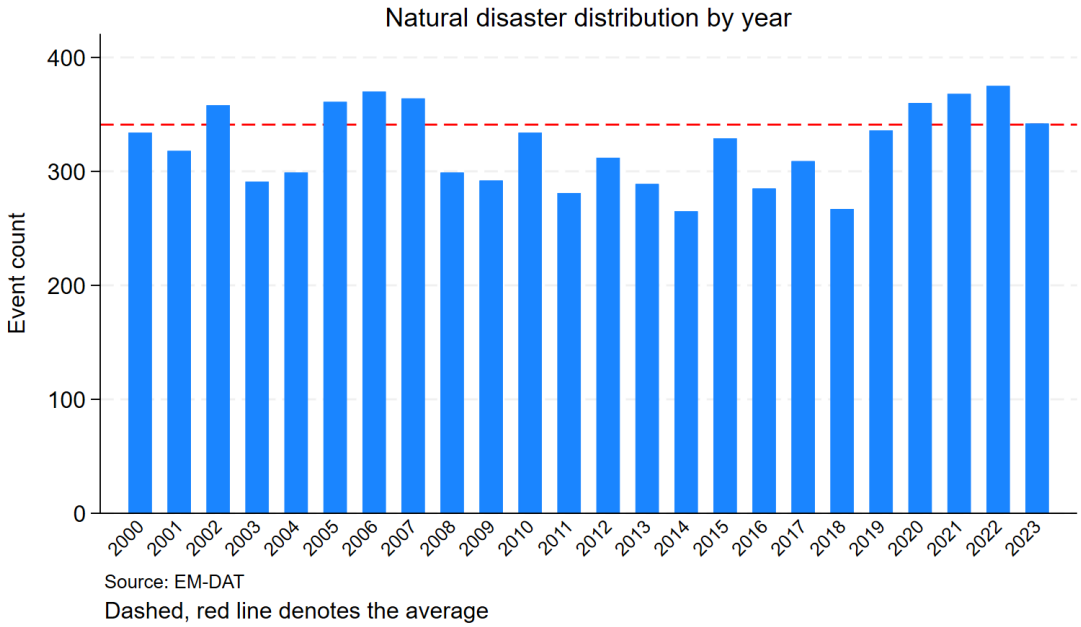


Table 1. Climate-related natural disasters: Frequency and severity. Statistics calculated for the country sample of Table A1, from 2000 until 2023.

	All	Drought	Extreme temperature	Flood	Storm	Wildfire
AE						
Frequency	1436	19	141	440	751	128
Duration (avg., in days)	7.57	245.50	27.46	5.52	3.06	15.85
Deaths (avg.)	149	144	1035	8.48	15.30	13.28
Affected (avg.)	127727.50	26000	10706	48298	238287	12620
Damages (avg., in bn USD, adjusted)	2.56	5.66	1.83	1.43	3.24	1.35
Damages (avg., % of GDP)	0.06	0.20	0.14	0.06	0.05	0.07
EMDE						
Frequency	1746	50	88	975	669	42
Duration (avg., in days)	7.95	255.29	22.72	9.27	2.44	5.38
Deaths (avg.)	47.76	61.00	122.94	34.81	55.86	12.51
Affected (avg.)	1268499	8693631	2838348	1120503	868496	260959
Damages (avg., in bn USD, adjusted)	0.80	1.59	3.30	0.97	0.48	0.31
Damages (avg., % of GDP)	0.13	0.23	0.23	0.12	0.13	0.12

3.3 Control variables

Through the analysis, we select the most appropriate macroeconomic and fiscal controls for the model specifications based on the literature on the determinants of sovereign bonds. First, we include GDP growth and consumer price index. The high growth rates in countries point to a better ability to repay debt in the future (Cantelmo, Giovanni, and Papageorgiou, 2023). As for the inflation rate, although the overall impact on yields might be ambiguous, a high inflation rate increases the overall uncertainty and implicitly impacts the yields of bonds. To control for the strength of a government finances, we employ tax revenues as a percentage of GDP with the expected impact being positive. To account for exchange rate effects, we control for a country's (log) exchange rate vis-a-vis the U.S. dollar. From Table A3 the comparison of the two country groups reveals the expected disparities in macroeconomic characteristics.

Furthermore, countries differ in their ability to withstand climate change; for example, countries with more diversified economies can cope better with climate risks and absorb them more easily. Importantly, the institutional framework of a country also matters (Borio and Packer, 2004; Kling et al., 2021). For this reason, we use two variables to account for the institutional quality of a country, namely the government efficiency and political stability

measures(Cevik and Jalles, 2024).

4 Panel data regressions: A historical perspective

In this section, we investigate whether climate risk has influenced sovereign yields by estimating a fixed-effect panel regression model. The advantage of this approach is that it allows us to estimate average effects of climate risk over a large sample of countries over a long period of time, exploiting both the cross-sectional and time period variation. In our specification, we include both physical and transition risks, as both sources of climate risk can influence sovereign yields directly and indirectly. Furthermore, we differentiate between the two sources of physical risks: (i)*chronic risk* and (ii)*acute risk*.

As the scale of the transition to a greener economy required to address climate risk increases, the cost of implementing mitigation policies is expected to rise, with implications for public finance. This should be reflected in a rising risk premium on sovereign borrowing costs captured in the corresponding bond yields. We thus expect climate risk measures to be positively associated with an increase in sovereign bond yields and as a result an increase in expected government borrowing costs. We postulate that the intensity of carbon dioxide emissions, as a measure of transition risk, is positively related to sovereign bond yields. Finally, we expect severe climate events such as natural disaster events to also influence sovereign yields. Both the frequency and intensity of such events increase over time with a potential more persistent total effect on the economy. Severe natural disasters have a real impact on the economy in terms of lower GDP growth, and this effect tends to be comparatively large for developing countries, e.g.Cavallo, Becerra, and Acevedo (2022), Shabnam (2014), Khan, Anwar, Sarkodie, Yaseen, and Nadeem (2023).[8]

[8] Cavallo et al. (2022) take into account all types of natural disasters, including geophysical ones, occurring during 1970-2019 for a sample of developing and developed countries, as recorded by EM-DAT. They rank natural disasters by associated mortality and consider particularly severe events. They find that during the year of the disaster, real GDP per capita growth declines by 3.7 percentage points on average compared to the average pre-disaster growth. They also find that the occurrence of a natural disaster affects real GDP per capita growth in the medium term (six years after the disaster), suggesting that affected economies suffer a loss that is not subsequently offset by above-average post-disaster growth.

Our baseline specification is the following:

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate_risk_{i,t-1} + \delta' X_{i,t-1} + \epsilon_{i,t}. \quad (1)$$

where $Y_{i,t}$ is the log of sovereign bond yields, $Climate_risk_{i,t}$ denotes either transition risk and measured by (log) GHG emissions per GDP, or chronic risk and measured by annual temperature changes relative to the mean temperature between 1951 and 1980, or acute physical risk measured by the frequency of climate-induced natural disasters (number of natural disasters) and their economic and human impact. For the economic impact, we use total economic costs (% GDP) and total uninsured costs (% GDP). For human impact, we use the total number of people affected (% total population).[9] $X_{i,t-1}$ includes tax revenues as a share of GDP, inflation, GDP growth, (log) exchange rate, government efficiency and political stability indicators. To account for potential endogeneity, we use the lag of the control variables. To control for time-invariant characteristics and other unobserved country-specific variables we include country α_i and time β_t fixed effects when appropriate. $\epsilon_{i,t}$ represents the error term. We use standard errors clustered at the country level.

As a baseline, we estimate equation 1 for each of the climate risk variables by using the standard fixed effects model. We start with a specification including the transition risk and then the chronic physical risk. Next, we investigate the impact of acute physical risk on sovereign yields and repeat the baseline specification for the number of climate-related natural disasters and the three measures of losses due to climate-induced disasters. Table 2 shows the results. The coefficient for GHG is positive and statistically significant, indicating that transition risks are priced in sovereign yields and suggesting that progress in climate transition performance is associated with lower 10-year maturity bond yields (Collender

[9] EM-DAT reports total damages and total insured damages. We calculate total uninsured losses as the difference between these two. We divide losses with GDP in local currency unit and the USD exchange rate at yearly frequency from World Bank data. Similarly, we divide total number of people affected with population from World Bank data.

et al., 2023). However, increased chronic physical risks do not appear to be associated with higher sovereign yields (Dell, Jones, and Olken, 2012; Burke, Hsiang, and Miguel, 2015; Boehm, 2022)). At the same time, models (3)-(6) show that variables for acute risk are generally not statistically significant, with the only exemption the number of disasters which is slightly significant. In a recent paper, Cappiello, Ferrucci, Maddaloni, and Veggente (2025) find that acute physical risk variables explain sovereign credit ratings, but only marginally in terms of economic impact.[10] Overall, the model provides robust results that transition risk appears to shift up the sovereign's cost of borrowing. However, the model above is reduced-form and therefore the findings do not allow making causal statements. Although endogeneity concerns were addressed, it is not possible to fully exclude that some bias may still arise from omitted variables, measurement errors in variables, and reverse causality.

4.1 Distinction between countries

Given the varying development status of countries in our sample, we also conduct heterogeneity analysis by splitting our sample of countries into developed and EMDEs (emerging market and developing economies). Tables 3 repeat the baseline specification presented for the two groups of countries: AEs and EMDEs using the BIS classification. The analysis reveals that the effect of transition risk is significantly more pronounced for developing economies. This could partially suggest that the large imposition of green financial policies by advanced economies offsets the transition risk premium (Cheng, Gupta, and Rajan, 2023). However, developing countries with higher carbon emissions and a less sustainable growth trajectory will find it more difficult to smoothly transition to a decarbonized economy, thereby raising transition risks. This will further impact projections for economic growth, fiscal health, and external sector vulnerability, which, in turn, will feed into markets' perceptions of their risk profile and raise yields on sovereign bonds. Finally, physical risk is partially priced in sovereign yields with a difference between the significance of frequency or

[10] Table B1 in the Appendix includes all three climate risks in one specification.

Table 2. Baseline model with climate risk

The table reports coefficient estimates and standard errors (in parentheses) from estimates using the transition risk in model (1), the chronic risk in model (2) and acute physical variables in models (3)-(6). The dependent variable is the 10-year sovereign bond yield. Definitions for all variables are in Table A2. Estimation method is OLS with country and time fixed effects, and standard errors clustered at the country level. The sample period is 2000-2023. The lower part of the table also reports the number of observations and the R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
GHG	0.992***					
	(0.126)					
Temperature		−0.025				
		(0.024)				
NaturalDisasters			0.041*			
			(0.020)			
TotalCosts/GDP				−0.009		
				(0.026)		
TotalUninsured/GDP					−0.034	
					(0.035)	
TotalAffected/Population						−0.003
						(0.003)
TaxGDP	−0.006	−0.004	−0.021	−0.022	−0.022	−0.021
	(0.011)	(0.011)	(0.016)	(0.015)	(0.015)	(0.015)
Inflation	−0.007	−0.003	0.000	0.001	0.001	0.000
	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
GDPgrowth	−0.029***	−0.033***	−0.033***	−0.034***	−0.034***	−0.033***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ExchangeRate	0.542***	0.334*	0.403**	0.398**	0.396**	0.400**
	(0.139)	(0.196)	(0.175)	(0.177)	(0.178)	(0.177)
PoliticalStability	−0.001	0.000	−0.001	−0.001	−0.001	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GovernmentEfficiency	−0.013*	−0.010*	−0.007	−0.007	−0.007	−0.008
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	759	785	585	585	585	585
R-squared	0.893	0.865	0.862	0.861	0.861	0.861
Country	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes

severity for advanced and developing economies.[11]

[11] We also divide the countries into high and middle/low income countries using the World Bank indicator for 2021, while to go one step further, we also split developing countries using the ND-GAIN indices (below and above median ranking) which capture a country's overall susceptibility to climate-related disruptions and capacity to deal with the consequences of climate change. However, since our sample of developing countries is small and biased toward higher income developing countries, only one-third of the EMDEs observations is below the median ND-Gain we decided to leave these results out of our analysis.

Table 3. Advanced vs emerging and developing economies and climate risk

The table reports coefficient estimates and standard errors (in parentheses) from estimations for the advanced economies in models (1), (3), (5) and (7) and for the emerging and developing economics in models (2), (4), (6) and (8). The dependent variable is the 10-year sovereign bond yield. Definitions for all variables are in Table A2. Estimation method is OLS with country and time fixed effects, and standard errors clustered at the country level. The sample period is 2000 – 2023. The lower part of the table also reports the number of observations and R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) AE	(2) EMDE	(3) AE	(4) EMDE	(5) AE	(6) EMDE	(7) AE	(8) EMDE
GHG	0.076	0.749***						
	(0.375)	(0.140)						
Temperature			−0.043	−0.037				
			(0.033)	(0.047)				
NaturalDisasters					0.026	0.024		
					(0.033)	(0.018)		
TotalAffected/Population							0.006**	−0.001
							(0.003)	(0.003)
Observations	453	348	477	350	309	310	299	305
R-squared	0.893	0.876	0.889	0.846	0.879	0.864	0.876	0.861
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

4.2 Further results

Given the importance of the Paris agreement in raising public awareness of climate change, we also study whether the relevance of climate-related risks for sovereign borrowing costs changed after this exogenous event. We estimate a double difference-in-differences model for transition risk and *PostPA*, a dummy variable that takes the value of one for years after the Paris Agreement entered into force at the end of 2015. We also estimate a triple difference-in-differences model for transition risk, *PostPA* and *LowEmitters*, a dummy that equals one if a country has emissions per capita lower than the 75th quantile distribution in that year. The results in Table 4 column (3) show that following the Paris Agreement, countries with greater exposure to transition risk receive comparatively higher sovereign yields, suggesting that credit investors are increasingly recognizing the importance of transition risk.

As extreme weather events become more frequent and severe, the economic costs (as the costs of adaptation) are likely to put considerable strain on government finances, which will in turn raise government borrowing costs and lead to a feedback loop for more strained public finances. We test whether countries with better fiscal stance receive relatively lower sovereign yields as acute physical risk intensifies. The results in Table 5 from a double interaction with a *LowDebt* dummy which equals to one if a country has tax revenues to GDP ratio lower than the median of the distribution show a partial effect.

Finally, the impacts of climate risks, particularly chronic risks such as temperature increases, can exhibit nonlinear patterns, with effects intensifying beyond certain thresholds. We tested the nonlinear effects of temperature rise using interaction terms with GDP growth or squared temperature changes (Burke et al., 2015). Interestingly, results in Table 6 show that there are nonlinear effects, indicating that the positive effect of chronic risk on sovereign yields increases with the country's growth rate.

Table 4. High emitters and Paris agreement
The table reports coefficient estimates and standard errors (in parentheses) from estimates for the double interaction between post-Paris agreement dummy and transition risk variable in model (1), double interaction between LowEmitters dummy and transition risk variable in model (2), and triple interaction between post-Paris agreement dummy, transition risk variable and LowEmitters dummy in model (3). The LowEmitters dummy is equal to one for a country if GHG in that year is below the 75th quantile of GHG per capita distribution of that year. Estimation method is OLS with standard errors clustered at the country level. The sample period is 2000-2023. The lower part of the table also reports the number of observations and the R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
GHG × PostPA	0.227***		
	(0.084)		
GHG × LowEmitters		0.596**	0.664*
		(0.270)	(0.386)
LowEmitters × PostPA			−2.892
			(2.375)
GHG × LowEmitters × PostPA			−0.319
			(0.281)
Observations	759	759	759
R-squared	0.842	0.896	0.847
Country	Yes	Yes	Yes
Time	No	Yes	No

Table 5. High debt and physical risk
The table reports coefficient estimates and standard errors (in parentheses) from estimates for the double interaction between LowDebt dummy and acute physical risk variables. The LowDebt dummy is equal to one for a country if TaxGDP in that year is below the median of distribution of that year. Estimation method is OLS with standard errors clustered at the country level. The sample period is 2000-2023. The lower part of the table also reports the number of observations and the R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
NaturalDisasters × LowDebt	0.075*			
	(0.039)			
TotalCosts/GDP × LowDebt		−0.118**		
		(0.050)		
TotalUninsured/GDP × LowDebt			−0.144**	
			(0.060)	
TotalAffected/Population × LowDebt				−0.003
				(0.006)
Observations	624	624	624	624
R-squared	0.876	0.874	0.874	0.874
Country	Yes	Yes	Yes	Yes
Time	No	Yes	Yes	Yes

4.3 Robustness

Finally, we perform sensitivity checks to validate the robustness of our baseline empirical results. First, we estimate our model with different types of fixed effects and without

adjusting standard errors with clustering (Abadie, Athey, Imbens, and Wooldridge, 2023). Second, we use alternative measures for the transition risk. Instead of carbon emissions intensity, we tried using GHG total emissions in column (1) of Table 6 and the results remain unchanged. As a final check, we use the logarithm of the proportion of renewable energy use from the World Bank as an alternative measure of the transition risk (Collender et al., 2023). Increasing renewable energy use can significantly reduce climate risk, and countries with higher renewable energy consumption have a discount on their sovereign borrowing costs. The results in column (2) in Table 6 validate that transition risk positively impact sovereign yields. Finally, we run the baseline model for 5-year maturities in Table 7 and results remain unchanged.

Table 6. Different transition risk variables and nonlinear effect of temperature
The table reports coefficient estimates and standard errors (in parentheses) from estimates using (log) GHG total in model (1), (log) ratio of renewable in model (2), double interaction between chronic risk and real GDP growth in model (3). Estimation method is OLS with standard errors clustered at the country level. The sample period is 2000-2023. The lower part of the table also reports the number of observations and the R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	
GHGtotal	0.953***			
	(0.120)			
RenewRatio		−0.211***		
		(0.062)		
Temperature × GDPgrowth			0.024***	
			(0.006)	
Observations	759	531	785	785
R-squared	0.896	0.892	0.870	0.871
Country	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes

Table 7. Climate risk with 5-year yields

The table reports coefficient estimates and standard errors (in parentheses) from estimations using the transition risk variable in model (1), the chronic physical variable in model (2) and the acute physical in models (3)-(6). In all models the dependent variable is the 5-year sovereign bond yield. Definitions for all variables are in Table A2. Estimation method is OLS with country fixed effects, and standard errors clustered at the country level. The sample period is 2000 – 2023. The lower part of the table also reports the number of observations and the R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
GHG	1.233***					
	(0.200)					
Temperature		−0.026				
		(0.037)				
NaturalDisasters			0.051**			
			(0.026)			
TotalCosts/GDP				−0.011		
				(0.050)		
TotalUninsured/GDP					−0.056	
					(0.074)	
TotalAffected/Population						−0.002
						(0.005)
Observations	743	769	574	574	574	574
R-squared	0.862	0.828	0.822	0.820	0.821	0.821
Country	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes

5 Local projection model: Medium-term effects of natural disasters

To determine whether climate shocks as measured by the occurrence of climate-related natural disasters or their intensity impact sovereign yields in the medium term, we employ the local projections method developed by Jordà (2005), in which impulse responses are derived from separate regressions for each forecast horizon $t+h$, conditional on a given set of variables at time t. The regression model is:

$$Y_{i,t+h} = \beta^h ND_{i,t} + \sum_{j=1}^{3} \gamma_j^h Y_{i,t-j} + \sum_{j=1}^{3} \delta_j^h X_{i,t-j} + \alpha_i + \lambda_t + \epsilon_{i,t+h} \tag{2}$$

where $Y_{i,t+h}$ represents 10-year sovereign yields (log); $ND_{i,t}$ is the climate shock which measures the associated total damages (% GDP) (severity) and treated as an exogenous event that cannot be anticipated nor correlated with past changes in sovereign yields[12]; $X_{i,t}$ is the vector of control variables as in the panel regression analysis; λ_t are time fixed effects and α_i^h are country fixed effects. Following Montiel Olea and Plagborg-Møller (2021), we include lags of the dependent variable to augment local projections. In our LP baseline analysis, we consider three lags of all control variables, but we also assess the sensitivity of the estimates when using up to five lags. [13]

The main parameter of interest is β associated with $ND_{i,t}$, which measures the change in sovereign bond yields from period t to $t+h$ due to a climate shock related to one more natural disaster or to an additional average total damage (% GDP). We estimate the model

[12] EM-DAT defines disasters as situations or events which overwhelm local capacity, necessitating a request for external assistance at the national or international level. Disasters are unforeseen and often sudden events that cause significant damage, destruction, and human suffering. Also, following Cevik and Jalles (2024) large-scale climate events are considered to be country-wide shocks.

[13] In the lag selection process, we followed the recommendation in Montiel Olea and Plagborg-Møller (2021) and adopted a conservative approach, favoring more lags over fewer. This approach generally entails minimal asymptotic efficiency costs and has a negligible impact on finite samples. However, as stated in Montiel Olea and Plagborg-Møller (2021), the inclusion of sufficient control variables should always be prioritized over the determination of the exact number of lags, ensuring that the model adheres to the conditional mean independence condition, which is more important than the precise number of lags.

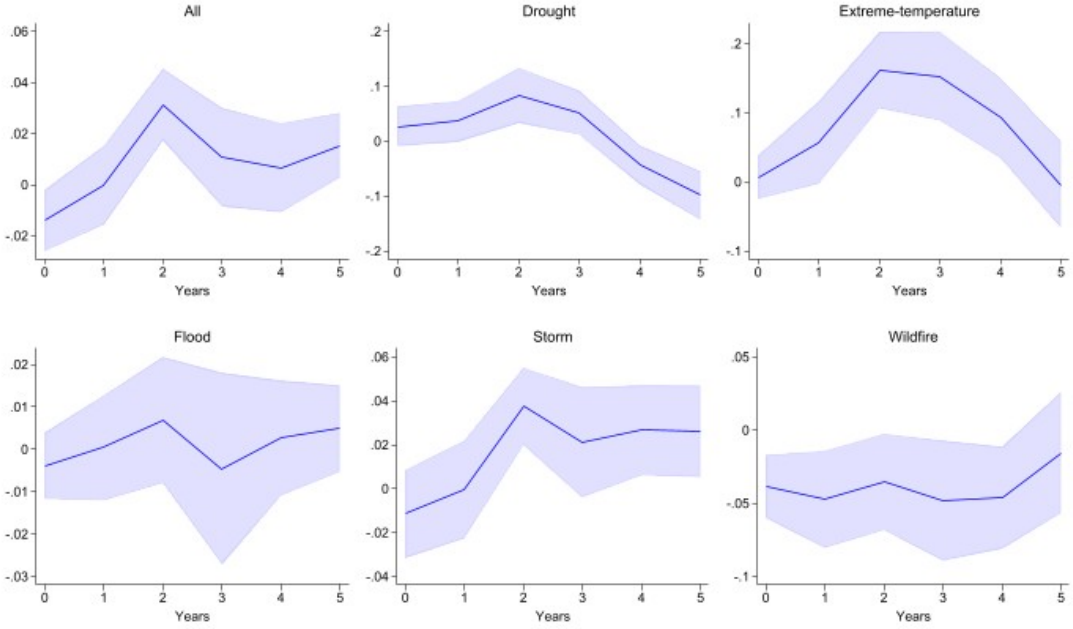
using ordinary least squares and impulse response functions are then employed by plotting the estimated β with 68 percentage confidence intervals over a five year period. As Cevik and Jalles (2024) mentions, *bands that correspond to a 68 percent posterior probability — or one standard deviation shock - provide a more precise estimate of the true probability.* As for the climate shock variable, we also consider separately the five different types of climate-related events: droughts, storms, floods, wildfires, and extreme temperature.[14]

The impulse response functions in Figure 5 demonstrate that there is heterogeneity in the response of 10-year sovereign yields to climate shocks related to the severity of each type of natural disaster. The yields experience the largest increases in response to climate shocks related to droughts and extreme temperatures. This is not surprising as droughts are the natural disasters with the longest average duration and impose the greatest human toll. Extreme temperatures, while less persistent, exert significant economic pressure: heat-waves drive up energy demand and healthcare costs, whereas cold snaps damage crops and infrastructure. Their impact on sovereign yields peaks around two years after the event. Storm-related shocks also raise yields, with most of their impact emerging after roughly one year and remaining elevated even five years after the event. Interestingly, wildfires tend to diminish sovereign yields, possibly reflecting a loss of GDP growth due to disruptions to key sectors (Reiner, Pathirana, Sun, Lenzen, and Malik, 2024).

We also explore the impact of a climate shocks as measured by the total associated damages on 10-year sovereign yields when splitting the sample between advanced (Figure 6) and developing economies (Figure 7). For AEs, the impulse responses indicate that shocks related to extreme temperatures have the largest, most immediate, and most persistent effect on sovereign borrowing costs. In contrast, the impact of storms and droughts becomes significant only after the second year following the shock. In other words, in AEs, disasters that cause exceptionally high mortality and substantial monetary losses exert the greatest influence. For EMDEs, all disaster types tend to raise sovereign borrowing costs, with

[14] In regressions for individual types of natural disasters we always control for the occurrence of any other climate related disaster. This does not affect the estimated responses significantly.

Figure 5. Impact of climate shocks on sovereign yields



Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (2). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock as measured by the total damages of natural disasters (% GDP). Shaded areas refer to 68% confidence intervals. The first panel is for all climate related natural disasters, i.e. drought, extreme-temperature, flood, storm and wildfire.

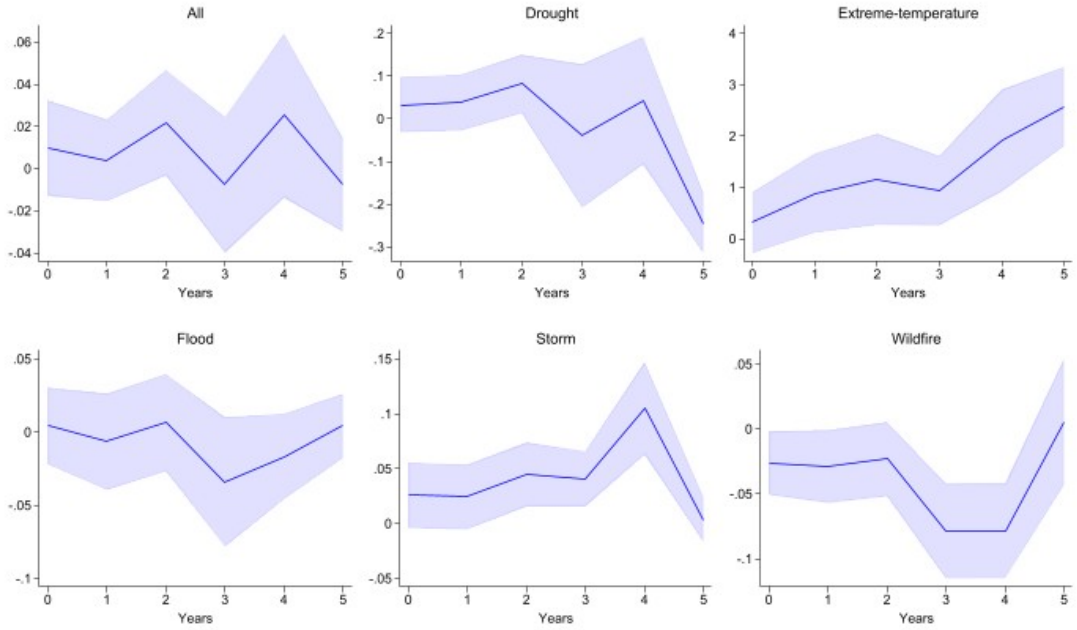
droughts producing the strongest long-term response. Storms and floods also have positive effects, although their impact generally materializes with a delay. This pattern suggests that developing economies face heightened sovereign risk in the aftermath of such events, likely due to their reliance on agriculture and natural resources, which are directly affected by these shocks. The more muted response in AEs may reflect stronger infrastructure and more sophisticated financial mechanisms for managing climate-related risks.[15]

Overall, the difference in responses between advanced and emerging markets reflects the vulnerability of emerging markets to climate-related risks. EMDEs economies are considered to be exposed to climate risk due to their geographic location and propensity to experience natural climate-related disasters, while they also face greater challenges following natural disasters (Boehm, 2022; Beirne et al., 2021b). On the other hand, advanced economies

[15] Responses based on 5-year yields are reported in the Appendix.

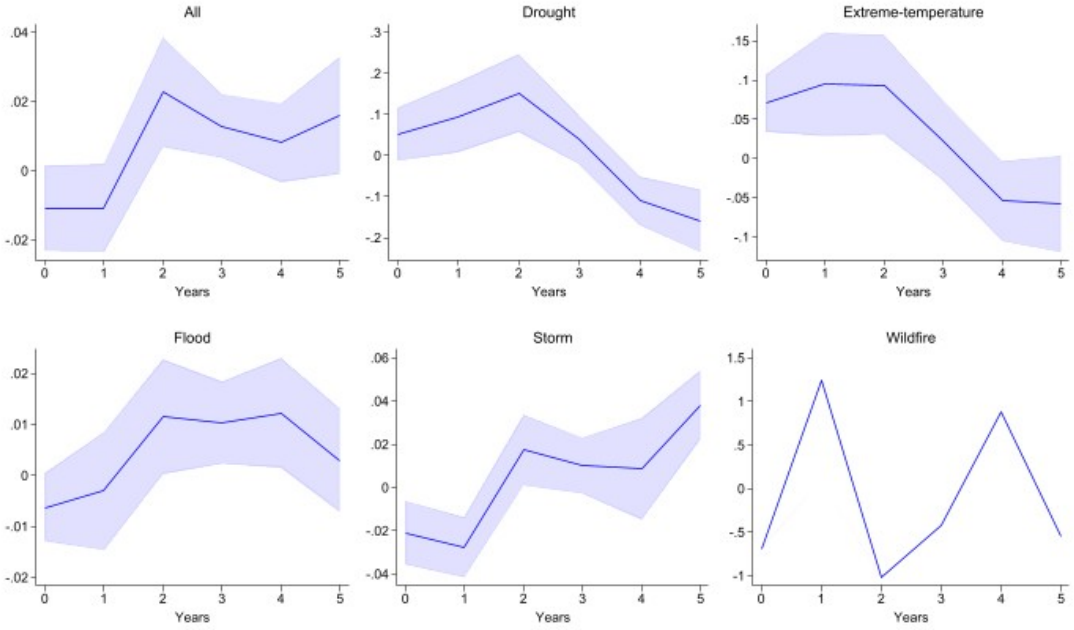
typically have a greater ability to manage extreme climate events. In any case, our resulting sub-samples are rather small, which reduces the statistical power of our analysis.

Figure 6. Advanced economies impact of climate shocks on sovereign yields



Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (2). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock measured by the total damages of natural disasters (% GDP). Shaded areas refer to 68% confidence intervals. The first panel is for all climate related natural disasters, i.e. drought, extreme-temperature, flood, storm and wildfire.

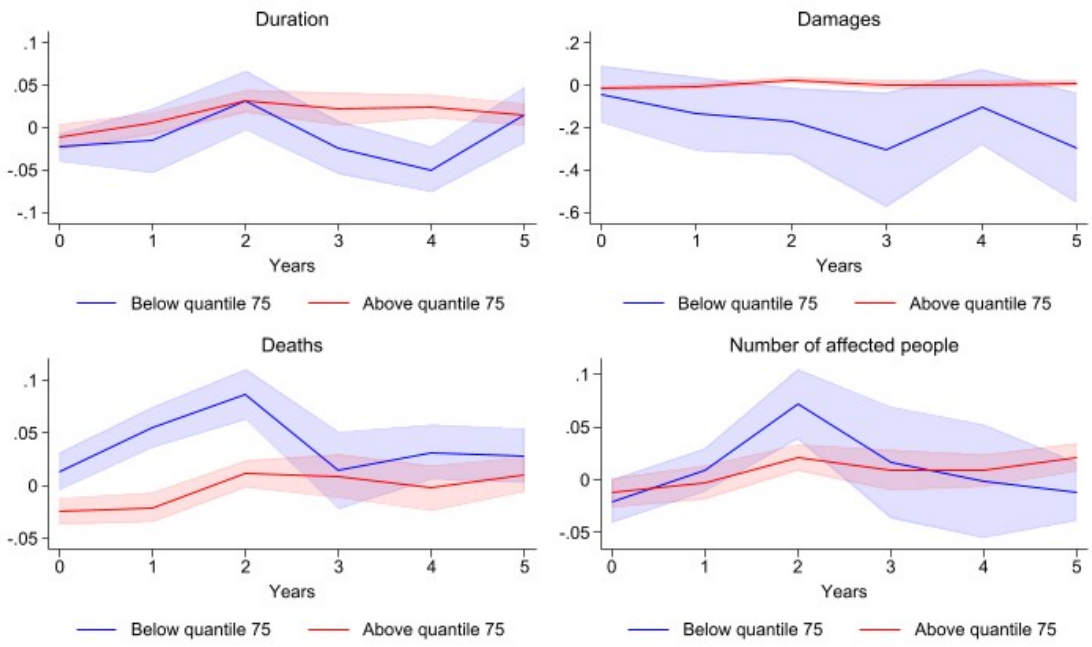
Figure 7. EMDEs impact of climate shocks on sovereign yields



Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (2). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock measured by total damages of natural disasters (% GDP). Shaded areas refer to 68% confidence intervals. The first panel is for all climate related natural disasters, i.e. drought, extreme-temperature, flood, storm and wildfire.

To further assess the impact of the severity of climate shocks as measured by total damages (% GDP) due to climate-related events on sovereign yields, we estimate the equation (2) using a binary indicator to classify events as severe high vs. severe low events using four different severity measures – duration, total damages, deaths and affected population. A high-severity event is one above the 75th percentile. Figure 8 shows that the medium-term positive impact of climate shocks on sovereign yields comes from high- and low-severity events in terms of duration, economic damages (% GDP), number of affected people (% population), and number of deaths (% population). we find a limited or negligible impact of high-severity events which can be attributed not only to their rarity — very few events fall into this category — but also to the possibility that their consequences may unfold over a much longer horizons. Most importantly, the results highlight that the severity of natural disasters, even when they are not outright catastrophes, plays an important role in influencing sovereign yields.

Figure 8. Impact of climate shocks on sovereign yields: Different severity measures



Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (2). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock as measured by four different measures of severity of natural disasters. Shaded areas refer to 68% confidence intervals.

5.1 Additional analysis: Nonlinear effects

We explore whether initial macro-fiscal conditions at the time of the shock influence the impact of climate shocks as measured by total damages (% GDP) on sovereign yields using a variant of LP to estimate state-dependent impulse response functions. In particular, we use a model similar to the smooth transition autoregressive (STAR) model proposed by Granger and Teräsvirta (1993), which allows the effect of climate shocks to change smoothly between states, thus making the response more stable and precise (ADB, Furceri, and IMF, 2016; Cevik and Jalles, 2024). Accordingly, the augmented LP model takes the following form:

$$Y_{i,t+h} = \beta_L^h F(z_{i,t}) ND_{i,t} + \beta_H^h (1 - F(z_{i,t})) ND_{i,t} + \sum_{j=1}^{3} \gamma_j^h Y_{i,t-j} + \sum_{j=1}^{3} \delta_j^h X_{i,t-j} + \alpha_i^h + \alpha_t^h + \epsilon_{i,t+h} \tag{3}$$

with

$$F(z_{i,t}) = \frac{exp(-\gamma z_{i,t})}{1 + exp(-\gamma z_{i,t})}$$

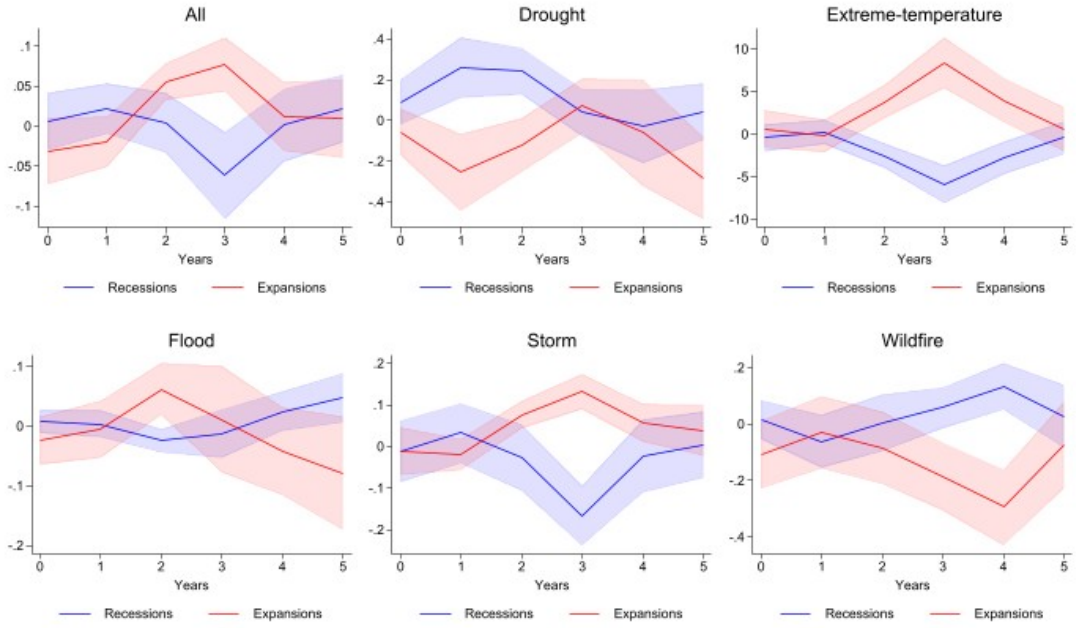
where $z_{i,t}$ is either the real GDP growth or the public debt-to-GDP, standardized to have mean zero and standard deviation one.[16] The coefficients β_L^h and β_H^h capture the impact of climate shocks in cases of recessions (low debt) and expansions (high debt) respectively. Following Cevik and Jalles (2024), we choose $\gamma = 1.5$.

The results, presented in Figure 9 and Figure 10, show that both the state of the economy and the available fiscal space play a critical role in determining how climate shocks affect the growth of sovereign yields, which also varies with the type of event. The impact of natural disasters heterogeneous. Droughts have a higher impact during recessions, while extreme temperatures tend to be associated with higher borrowing costs during expansions. For all disasters, the impact of sovereign borrowing costs is higher during the first year in recessions

[16] The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(z_{i,t})$, so that this can be interpreted as the probability of being in a given space state.

compared to expansions. In addition, The impact of storms and extreme temperatures is higher in countries with lower fiscal space compared to countries that are less fiscally constrained.

Figure 9. Disasters and the role of business cycle

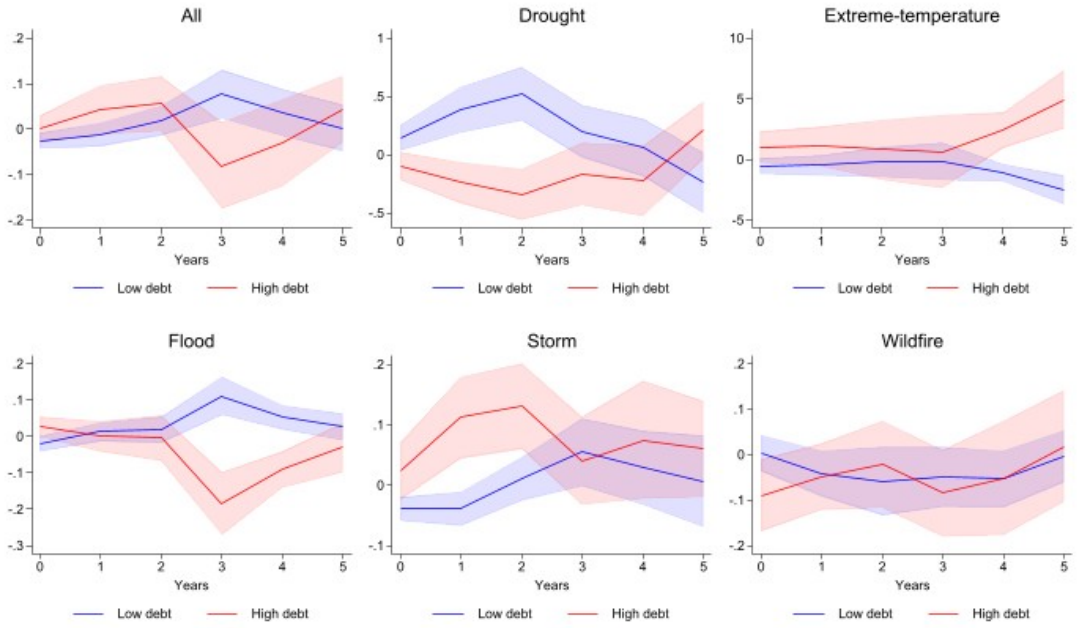


Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (3). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock as measured total damages (% GDP). The first panel is for all climate related natural disasters, i.e. drought, extreme-temperature, flood, storm and wildfire. Shaded areas refer to 68% confidence intervals.

As a last exercise and to determine whether climate risk, in the form of climate-related natural disasters, is well priced in sovereign yields, we complement the baseline model presented with the following model allowing for a simplified "risk premium decomposition". The objective is to isolate the portion of sovereign yields that can be attributed specifically to climate-related natural disasters, after accounting for standard macroeconomic risk factors.

First, we estimate a very similar model of sovereign yields on macro-financial variables as in eq. 2, excluding the natural disaster variable from the regression. Second, we calculate the residuals from this model to capture unexplained variation and regress these residuals

Figure 10. Disasters and the role of fiscal space



Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (3). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock as measured total damages (% GDP). The first panel is for all climate related natural disasters, i.e. drought, extreme-temperature, flood, storm and wildfire. Shaded areas refer to 68% confidence intervals.

on climate-related natural disaster variables to isolate the climate risk premium:

$$\epsilon_{i,t+h} = \lambda^h ND_{i,t} + \nu_{i,t+h} \tag{4}$$

where the coefficient λ^h represents the additional yield attributable to climate risk, after controlling for standard macroeconomic factors. It quantifies the additional yield investors require as compensation for the risk associated with natural disasters, beyond what is explained by traditional macroeconomic variables.

Table 8 shows the regression results. The effect natural disasters in the baseline local projection regressions is significant, but the coefficient λ^h from the risk premium decomposition is mostly not. This suggests that natural disasters impact sovereign yields primarily through their broader effects on general economic conditions, such as increased government debt, reduced GDP growth, and higher inflation. If the estimated coefficient λ^h from the risk

premium decomposition would be significant, this would indicate that natural disasters have a distinct and measurable effect on sovereign yields, beyond what is explained by traditional macroeconomic factors. Thus, we interpret the results as that investors do not explicitly distinguish climate risk related to natural disasters (physical climate risk) as a separate factor when pricing sovereign yields. Instead, they perceive the impact of natural disasters as part of the overall economic risk profile.

Table 8. Simplified risk premium decomposition

Panel A: Total damages

	Dependent variable: residuals				
	(h=1)	(h=2)	(h=3)	(h=4)	(h=5)
Total costs of NDs	-2.538	-3.524	-4.232*	-4.671	-4.388
	(3.221)	(2.158)	(2.315)	(3.571)	(3.579)
Observations	399	399	399	339	367
R^2	0.011	0.018	0.007	0.005	0.004

Panel B: Frequency

	Dependent variable: residuals				
	(h=1)	(h=2)	(h=3)	(h=4)	(h=5)
Frequency of NDs	-0.198	-0.232**	-0.215	-0.215	-0.219
	(0.188)	(0.098)	(0.139)	(0.237)	(0.237)
Observations	399	399	399	399	367
R^2	0.043	0.052	0.012	0.007	0.007

Note: *p<0.1; **p<0.05; ***p<0.01

6 Conclusions

There is growing evidence that climate-related risks matter for financial markets, but their role in sovereign bond pricing has remained less clear than in other asset classes. This paper provides new empirical evidence on how transition, chronic and acute physical risks relate to sovereign borrowing costs across 52 advanced and developing economies over 2000–2023.

Our findings show that transition risk is reflected in sovereign borrowing costs: countries with higher greenhouse gas emissions tend to face higher yields, with stronger effects in emerging and developing economies. Chronic physical risks, measured through temperature anomalies, do not appear to influence yields in levels.

The picture is different for acute risks. While panel estimates reveal limited average effects of climate-related natural disasters, the local projection results show that specific disasters can increase borrowing costs in the medium term. These effects vary by type of event and are larger in countries with limited fiscal space, indicating that macro-fiscal conditions shape how climate shocks feed through sovereign risk.

We also find that climate shocks influence borrowing costs mainly through their impact on debt, growth and inflation, rather than via a distinct climate-specific risk premium. Countries with weaker fiscal positions therefore have less room to absorb climate shocks and may face greater financing pressures as climate risks accumulate.

Taken together, these results point to several implications for policy. Transition policies have immediate consequences for sovereign financing conditions. Physical risks may not yet be fully incorporated into yield levels, but they can create meaningful fiscal pressures over time, especially in economies that are already close to their fiscal limits. As climate-related events become more frequent and more severe, the combination of rising climate exposure and constrained fiscal capacity may amplify existing debt vulnerabilities. This strengthens the case for policy efforts that address climate and debt challenges together, particularly in economies where both constraints are already binding.

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A Additional information on data

Table A1. Countries in the analysis
Country groups according to the BIS classification. In parenthesis the countries which are excluded from the analysis due to small sample size of the dependent variable.

Country group	No.	Countries
Advanced economies (AE)	26 (28)	Australia, (Austria), Belgium, Canada, Cyprus, Denmark, (Estonia) Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Latvia Lithuania, Netherlands, New Zealand, Norway, Portugal, Slovakia Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
Emerging market and developing economies (EMDE)	26 (32)	(Albania), Argentina, (Bahamas), Botswana, Brazil, Chile, China Colombia, Costa Rica, Croatia, Czech Republic, Dominican Republic El Salvador, (Georgia), Guatemala, Hungary, Israel Jamaica, Malaysia, Mauritius, (Mongolia), Panama, Philippines, Poland Romania, South Africa, South Korea, Thailand, (Trinidad and Tobago) Turkey, Ukraine, (Uruguay)

Table A2. Description and sources of the main variables

Variable	Source	Description
10y yield	Bloomberg	10-year maturity government bond annual interest rate (in %)
GHG	EDGAR	Annual greenhouse gas emissions (CO_2-equivalent)
Temperature	World Bank	Annual temperature change relative to 1951-1980
NaturalDisasters	EM-DAT	Total number of climate-rated natural disasters
TotalCosts/GDP	EM-DAT	Total costs from natural disasters (% of GDP)
TotalUninsured/GDP	EM-DAT	Total costs minus insured costs (% of GDP)
TotalAffected	EM-DAT	Number of affected people (% population)
TaxGDP	World Bank	Compulsory transfers to central government for public purposes, excluding fines, penalties, most social security contributions, with refunds treated as negative revenue (% of GDP)
GDPgrowth	World Bank	Real GDP growth (%) in constant national currency
Inflation	World Bank	Consumer price index
ExchangeRate with USD	BIS	Exchange rate as units of national currency per 1 USD (log)
PoliticalStability	World Bank	Political Stability and Absence of Violence/Terrorism: Percentile Rank measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.
GovernmentEfficiency	World Bank	Government Effectiveness: Estimate captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.

Table A3. Summary statistics

Variable	No. of countries	No. of obs.	Mean	Median	Min.	Max.	SD
All countries							
10y yield	52	949	4.553	4.029	-0.531	33.105	3.667
TaxGDP	45	1,154	18.771	18.425	7.461	37.613	5.776
GDPgrowth	52	1,196	2.831	2.936	-29.100	24.475	3.959
Inflation	52	1,196	4.064	2.559	-4.478	72.400	6.235
ExchangeRate	52	1,242	1.741	1.203	-0.694	8.363	2.197
GHG	52	1,248	6.299	5.857	0.788	20.470	3.861
Temperature	51	1,162	1.171	1.117	-1.305	3.550	0.622
TotalCosts/GDP	51	864	0.093	0.005	0	4.503	0.297
TotalUninsured/GDP	51	864	0.075	0.004	-0.047	3.386	0.245
TotalAffected/Population	51	901	1.116	0.018	0	71.991	4.198
AE							
10y yield	25	534	3.049	2.993	-0.531	23.263	2.414
TaxGDP	24	588	20.948	22.034	7.904	37.613	6.035
GDPgrowth	25	598	2.138	2.277	-14.839	24.475	3.469
Inflation	25	598	2.281	1.944	-4.478	19.705	2.411
ExchangeRate	25	624	0.512	-0.081	-0.694	4.956	1.386
GHG	25	525	8.294	7.635	2.927	20.470	3.788
Temperature	25	598	1.315	1.269	-0.341	3.550	0.629
TotalCosts/GDP	25	386	0.092	0.011	0.000	1.244	0.183
TotalUninsured/GDP	25	386	0.064	0.007	-0.047	0.786	0.133
TotalAffected/Population	25	404	0.312	0.002	0.000	71.991	3.819
EMDE							
10y yield	26	415	6.488	5.341	0.409	33.105	4.076
TaxGDP	20	566	16.509	15.613	7.461	28.037	4.494
GDPgrowth	26	598	3.524	3.891	-29.100	15.836	4.287
Inflation	26	598	5.847	3.834	-1.550	72.400	8.101
ExchangeRate	26	618	2.982	2.188	-0.454	8.363	2.168
GHG	26	546	4.376	3.791	0.788	12.216	2.905
Temperature	25	564	1.019	0.950	-1.305	3.026	0.578
TotalCosts/GDP	26	478	0.093	0.002	0.000	4.503	0.365
TotalUninsured/GDP	26	478	0.084	0.002	0.000	3.386	0.306
TotalAffected/Population	26	497	1.769	0.113	0.000	30.923	4.378

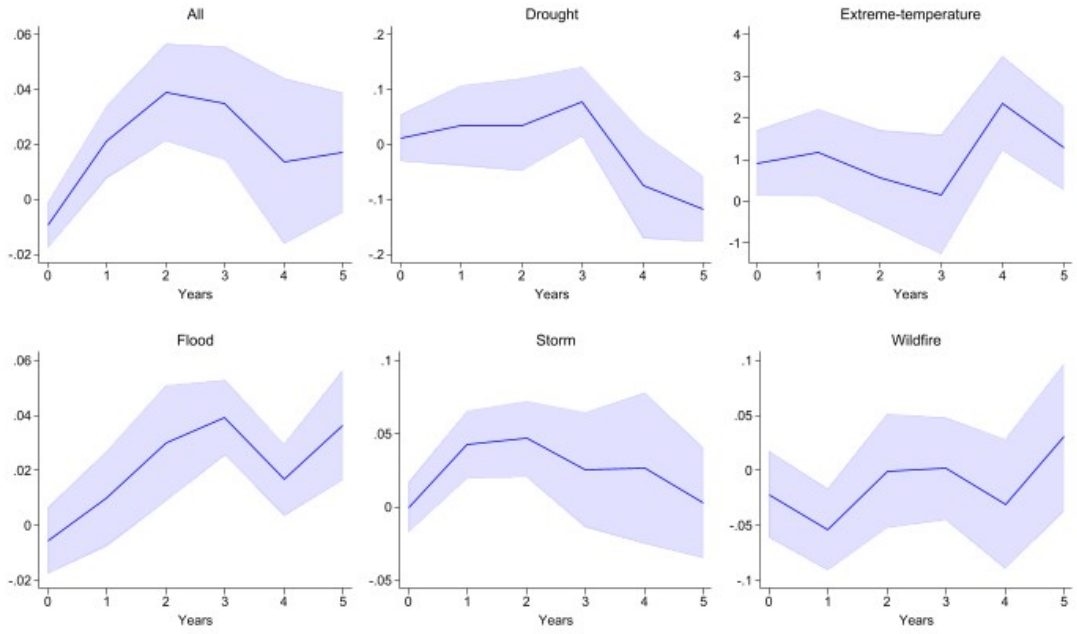
Note: The number of countries and observations refers to non-missing values for each of the variables over the 2000–2023 period.

B Additional regression results

Table B1. All climate risk
The table reports coefficient estimates and standard errors (in parentheses) from estimates using the transition together with chronic risk in model (1) and acute physical variables in models (2)-(5). The dependent variable is the 10-year sovereign bond yield. Definitions for all variables are in Table A2. Estimation method is OLS with country fixed effects, and standard errors clustered at the country level. The sample period is 2000-2023. The lower part of the table also reports the number of observations and the R-squared. The ***, **, and * marks denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
GHG	0.959***	0.896***	0.902***	0.903***	0.895***
	(0.130)	(0.157)	(0.157)	(0.156)	(0.157)
Temperature	−0.008	0.025	0.022	0.023	0.024
	(0.022)	(0.027)	(0.029)	(0.029)	(0.029)
NaturalDisasters		0.038			
		(0.023)			
TotalCosts/GDP			−0.031		
			(0.026)		
TotalUninsured/GDP				−0.059*	
				(0.035)	
TotalAffected/Population					−0.003
					(0.003)
TaxGDP	−0.005	−0.019	−0.019	−0.019	−0.019
	(0.011)	(0.016)	(0.016)	(0.016)	(0.016)
Inflation	−0.006	−0.004	−0.003	−0.002	−0.003
	(0.005)	(0.007)	(0.007)	(0.007)	(0.008)
GDPgrowth	−0.029***	−0.028***	−0.028***	−0.028***	−0.027***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
ExchangeRate	0.504***	0.503***	0.493***	0.491**	0.496***
	(0.155)	(0.159)	(0.163)	(0.164)	(0.162)
PoliticalStability	−0.001	−0.002	−0.002	−0.002	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GovernmentEfficiency	−0.012**	−0.010*	−0.009*	−0.009*	−0.010*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	738	532	532	532	532
R-squared	0.892	0.885	0.885	0.885	0.885
Country	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes

Figure B1. Impact of climate shocks on 5-year sovereign yields: Disaster severity



Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (2). Solid lines display the coefficients of (non-cumulative) responses of the 5-year sovereign yields over the five years following a climate shock as measured by total damages (% GDP) of natural disasters. Shaded areas refer to 68% confidence intervals. The first panel is for all climate related natural disasters, i.e. drought, extreme-temperature, flood, storm and wildfire.