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

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Abstract

Climate change poses a significant risk to financial stability by impacting sovereign credit risk. Quantifying the exact impact is difficult as climate risk encompasses different components – transition risk and physical risk – with some of these, as well as the policies to address them, playing out over a long time horizon. In this paper, we use a large panel of 52 developed and developing economies over two decades to empirically investigate the extent to which climate risks influence sovereign yields. The results of a panel regression analysis show that transition risk is associated with higher sovereign yields, with the effect more pronounced for developing economies and for high-emitting countries after the Paris agreement. In contrast, high-temperature anomalies do not appear to be priced-in sovereign borrowing costs. At the same time, countries with high levels of debt tend to record higher sovereign yields as acute physical risk increases. In the medium term, using local projections, we find that sovereign yields respond significantly but also differently to different types of disaster caused by climate change. We also explore the nonlinear effects of weather-related natural disasters on sovereign yields and find a striking contrast in the impact of climate shocks on sovereign borrowing costs according to income level and fiscal space when the shock hits.

Keywords: Climate risk; sovereign risk; transition risk; temperature change; natural disasters
JEL Codes: C23; E62; H63; Q54

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1 Introduction

In addition to macroeconomic risks, specific fiscal risks may "*arise from the realization of contingent liabilities or other uncertain events, such as a natural disaster*" (IMF, 2018). Such risks can lead to fiscal outcomes that deviate significantly from expectations or forecasts. Climate change introduces a complex array of risks to public finances through multiple and often interdependent transmission channels. These include fiscal expenditures for adaptation and mitigation, re-allocation of resources from productive investments to new technologies, and the repricing of sovereign assets. Direct fiscal impacts arise from emergency aid and disaster reconstruction, while indirect effects may include lower tax revenues due to production disruptions, changes to commodity prices and increasing spending via food subsidies (Schuler, Oliveira, Mele, and Antonio, 2019).[1]

Despite the profound implications of climate-related risks for sovereign borrowing costs, systematic analysis of this relationship remains limited. Even more striking is that, while the sovereign bond market is one of the largest asset markets and figures prominently within institutional investors' portfolios, it has received significantly less attention in terms of climate risk pricing compared to equities (Zhang, 2022; Bolton and Kacperczyk, 2023; Faccini, Matin, and Skiadopoulos, 2023) and corporate bonds (Huynh and Xia, 2021). In addition, existing research on sovereign bond markets has mainly focused on either physical risks – examining specific climate-induced natural disasters or climate-vulnerability and resilience indicators e.g. Kling, Lo, Murinde, and Volz (2018); Beirne, Renzhi, and Volz (2021b); Cevik and Jalles (2022) or chronic risk e.g. Dell, Jones, and Olken (2012); Burke, Hsiang, and Miguel (2015)– or transition risks e.g. Collender, Gan, Nikitopoulos, Richards, and Ryan (2023), with few studies addressing both sources of risks comprehensively.

In this paper, we provide new empirical evidence through an in-depth empirical analysis based on a large cross-sectional dataset of 52 developing and developed countries and detailed

[1] Zenios (2022) suggests how integrated assessment models (IAMs) can be linked with stochastic debt sustainability analysis (DSA) to inform our understanding of climate risks to sovereign debt dynamics and assess the available fiscal space to finance climate policies.

climate-risk data for a time period that covers about two decades, from 2000 to 2023. In our analysis, we consider both sources of climate risk, i.e. *transition risk* and *physical risk*. In line with previous literature, we measure transition risk as annual carbon dioxide (CO_2) emissions per capita. We further differentiate physical risk into two dimensions: *chronic risk* measured by growth in annual temperature relative to the mean temperature between 1951 an 1980, and *acute risk*, measured by the frequency and severity of climate-related natural disasters and considering both the economic and human cost. Chronic risk captures long-term, gradual climate shifts while acute risks materialize over shorter time, often with immediate and severe consequences. We use data for natural disasters from EM-DAT, one of the most comprehensive, publicly available, datasets on natural disasters distributed by the Centre for Research on the Epidemiology of Disasters (CRED).[2]

After controlling for macroeconomic variables and time-invariant variables, the analysis reveals a strong positive relation between transition risk and 10-year sovereign bond yields. In particular, an increase in CO_2 emissions per capita has a positive and statistically significant impact on sovereign bond yields, the effect more pronounced for developing economies and for high-emitting countries after the Paris agreement. On the other hand, increased temperature changes are not related to higher sovereign borrowing costs, revealing that chronic physical risk has not been fully priced in sovereign bond yields. Although acute physical risk measures appear not to have a systematic impact on sovereign borrowing costs, we find interestingly that countries with high debt levels record higher sovereign yields as disasters increase both in frequency and associated human impact.

To further enhance our findings on the impact of acute risk on sovereign yields and better understand the mechanisms at play in the medium term, we use the local projections (LP) method of Jordà (2005). In particular, we consider the impact of different types of climate-related natural disasters both in terms of their frequency and severity. Across

[2] EM-DAT focuses on large disasters, i.e. disasters with human and economic losses with at least one of the following criteria: 10 fatalities; 100 affected people; a declaration of state of emergency; a call for international assistance.

all countries and for all types of disasters, the impact of climate-related natural disasters appears positive but relatively small. However, there is significant heterogeneity in response to different types of natural disasters and between income groups. The impact is immediate and steeper for more severe (e.g. droughts) and more frequent (e.g. storms) events. For advanced economies, the steepest and largest impact is observed from climate shocks related to extreme temperature and storms, which are respectively events with long duration and high frequency. In contrast, for emerging and developing economies, the response is more immediate and steeper for all types of disasters. Finally, we find that the impact of climate disasters on sovereign yields varies in a nonlinear fashion depending on the level of fiscal space when the shock hits. For low-debt countries, natural disasters are associated with a smaller impact, likely reflecting the robust fiscal response capabilities of these economies, where governments can afford to increase spending to aid recovery efforts.

This study provides valuable insights for investors and policymakers. First, the impact from climate change might be greater than previously anticipated[3]. Thus, policymakers need to better understand how transition efforts, such as lowering carbon emissions, affect the cost of borrowing. At the same time, the frequency and intensity of extreme weather events and natural catastrophes are increasing, a trend that may be exacerbated in the coming decades by long-term shifts in climate patterns. The differences in how climate-induced disasters affect different income groups highlight the challenges faced by developing countries where population is highly exposed to natural disaster risk. Finally, there is increasing awareness of climate change as a potential source of imbalance, especially for high-debt, fiscally vulnerable countries. We provide further evidence that there is a need for an international policy agenda aiming to address both climate and sovereign debt challenges, acknowledging that the cost of inaction compounds over time and might give rise to a vicious circle.

The remainder of this paper is structured as follows: Section 2 gives an overview of the related literature. Section 3 describes data and variables used. Section 4 presents the panel

[3] https://www.ngfs.net/sites/default/files/medias/documents/ngfs_first_comprehensive_report_-_17042019_0.pdf

regression models. In section 5, we discuss in-depth the various results of the local projection analyses. 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 association 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.[4] 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 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 et al. (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 et al. (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

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

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 et al. (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

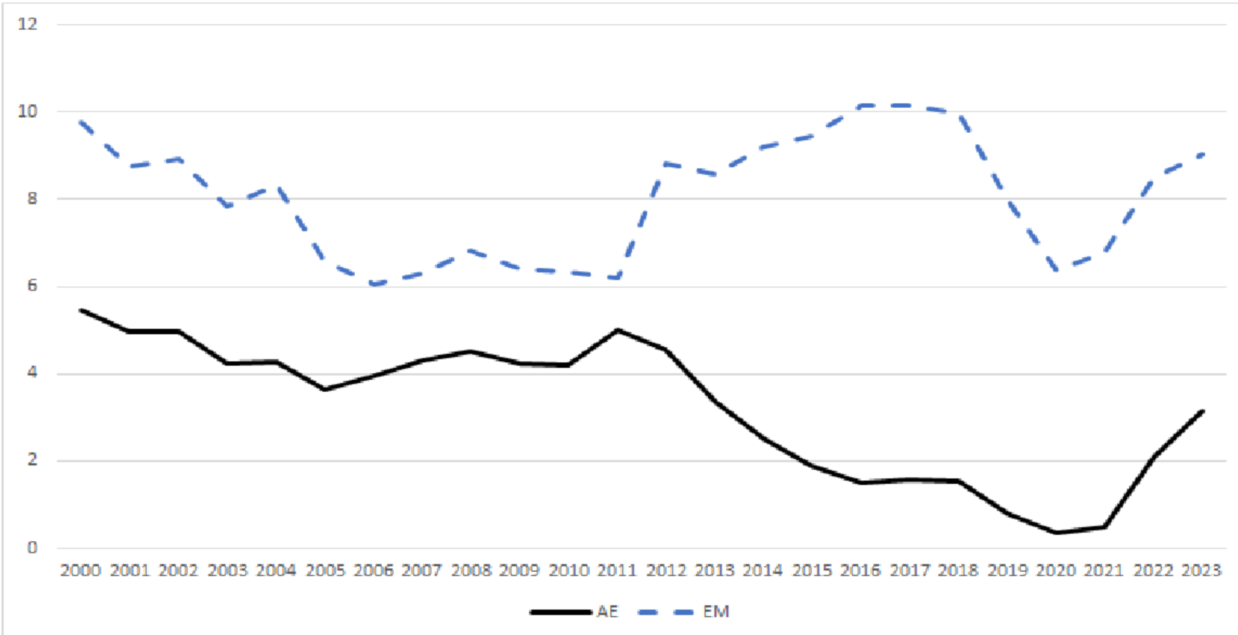
The dependent variable is countries' 10-year government bond yield.[5] This is inline with related research from Kling et al. (2018); Painter (2020); Beirne et al. (2021a); Klusak et al. (2023); Cevik and Jalles (2022); Collender et al. (2023) who employ 10-year government bond yields to evaluate the 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.[6] 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.

[5] 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

[6] 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.

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



3.2 Climate risk variables

The data on transition and chronic risk are extracted from the World Bank. The former is defined as CO_2 emissions per capita. The latter is proxied by the difference in annual temperature relative to the mean temperature between 1951 and 1980. The rise in temperature is one of the most significant risks and the risk most studied by climatologists. 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 that the AEs have, on average, higher carbon emissions per capita compared to the EMDEs and experienced a higher temperature growth. However, 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.[7] 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[8].

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.[9] Figure 2 shows the distribution of climate-related natural disasters in EM-DAT 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.[10]

[7] 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.

[8] 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.

[9] 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.

[10] 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.

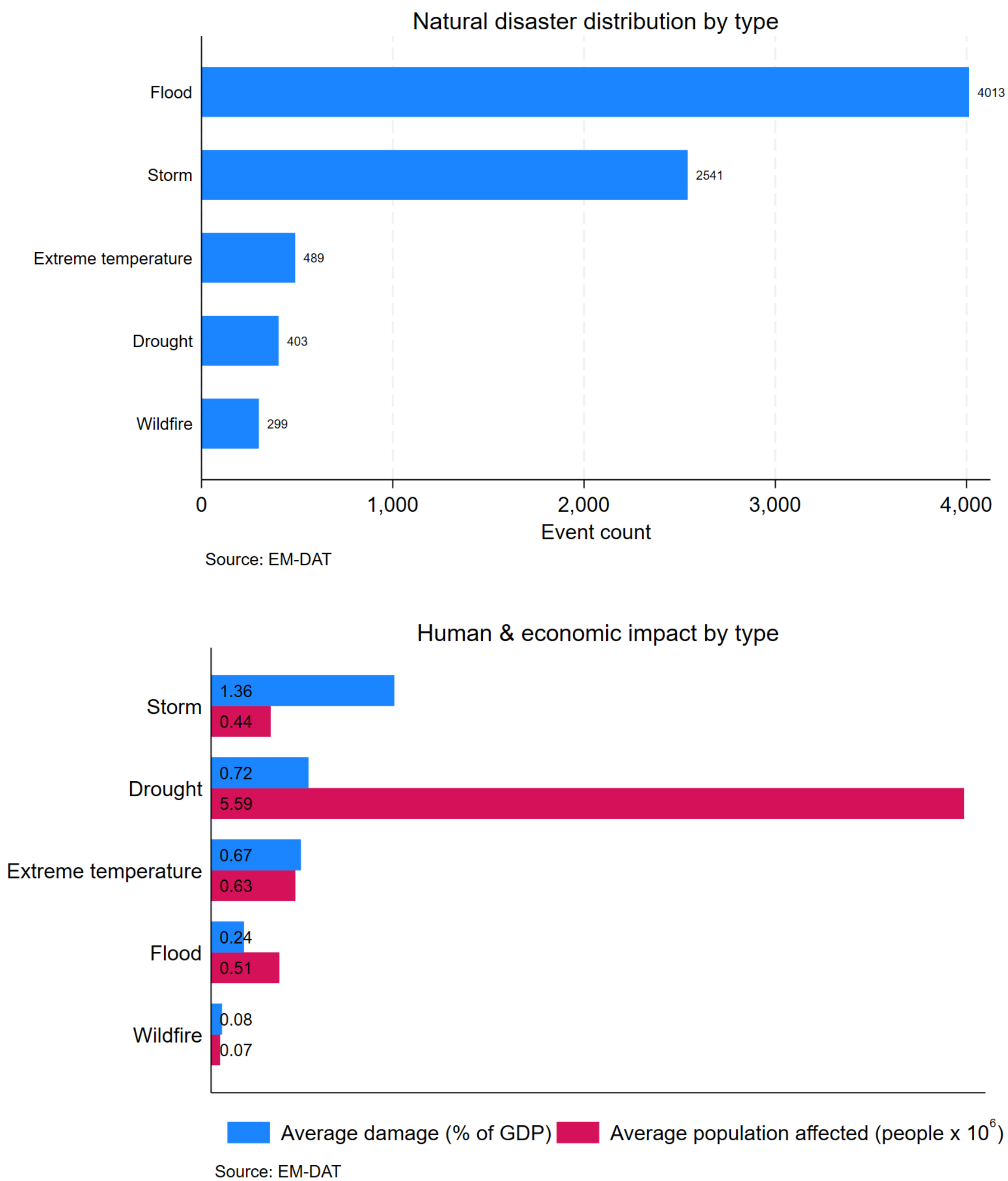


Figure 3 shows the average duration (in days) of natural disasters by type. Interestingly, while droughts occur far less frequently, they last by about an order of magnitude longer compared to the second in ranking, exhibiting a mean duration of about 230 days. This is probably one of the reasons for 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 3. Average duration of climate-related natural disaster events by type, since 2000.

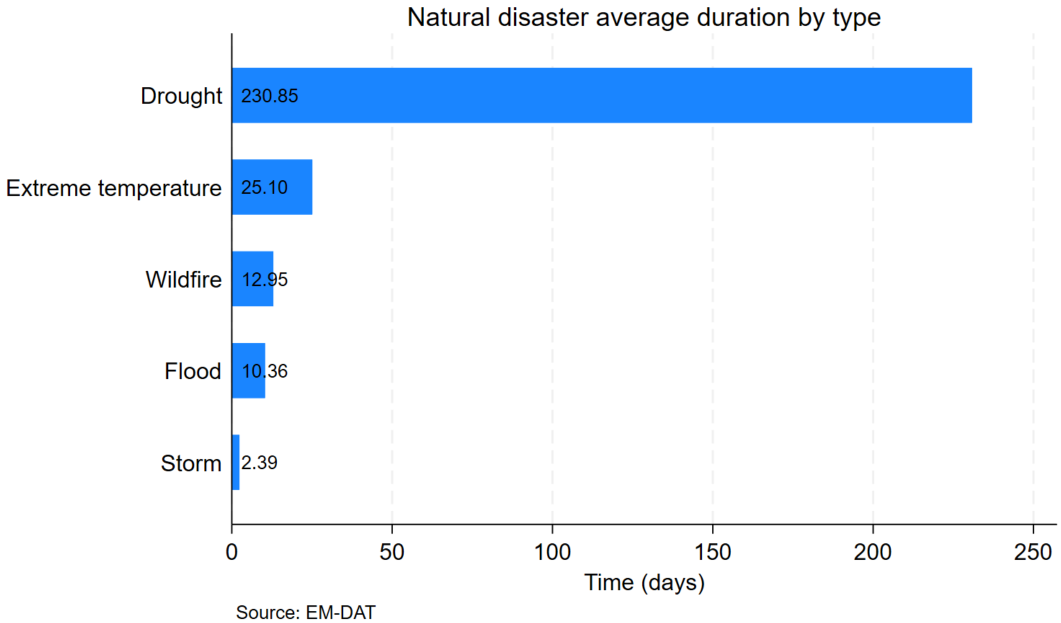


Figure 4 presents the distribution of climate-related natural disaster events by year and suggests that natural disasters are relatively uniformly distributed over time. However, this does not mean that there is no increase in disasters, especially when looking at specific types of event or specific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

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

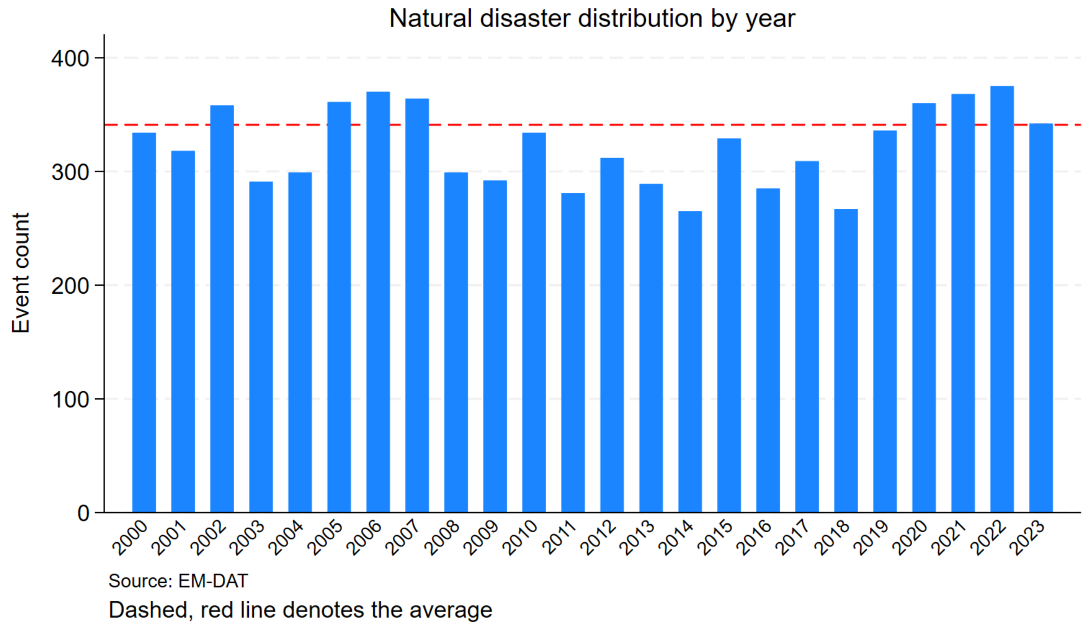


Table 1 presents average measures of frequency, duration, number of deaths, number of affected people, and damages for each type of disaster. For AEs, floods and storms are the most frequent, with average damages exceeding 1.4 billion USD per event, while droughts, though infrequent, have the longest 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.

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

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

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 general government debt 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 and developing a more climate-friendly economy 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).[11]

Our baseline specification is the following:

[11] 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.

$$Y_{i,t} = \alpha_i + \beta_t + \gamma Climate\_risk_{i,t-1} + \delta' X_{i,t-1} + \epsilon_{i,t}. \tag{1}$$

where $Y_{i,t}$ is the log of sovereign bond yields, $Climate\_risk_{i,t}$ denotes either transition risk and measured by (log) CO_2 emissions per capita, 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).[12] $X_{i,t-1}$ includes government debt 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 CO_2 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 et al., 2023). However, increased chronic physical risks do not appear to be associated

[12] 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.

with higher sovereign yields (Dell et al., 2012; Burke et al., 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.[13] 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

[13] 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)
CO_2	1.014***					
	(0.150)					
Temperature		−0.027				
		(0.027)				
NaturalDisasters			0.045*			
			(0.022)			
TotalCosts/GDP				−0.008		
				(0.033)		
TotalUninsured/GDP					−0.038	
					(0.037)	
TotalAffected/Population						−0.006
						(0.006)
DebtGDP	0.005***	0.003*	0.002	0.002	0.002	0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Inflation	−0.010**	−0.008	−0.003	−0.004	−0.003	−0.003
	(0.005)	(0.005)	(0.009)	(0.010)	(0.010)	(0.010)
GDPgrowth	−0.024***	−0.028***	−0.030***	−0.030***	−0.030***	−0.029***
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ExchangeRate	0.538***	0.502**	0.558***	0.572***	0.571***	0.576***
	(0.149)	(0.191)	(0.127)	(0.129)	(0.129)	(0.129)
PoliticalStability	0.001	0.003	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GovernmentEfficiency	−0.010*	−0.004	−0.002	−0.001	−0.001	−0.001
	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	727	747	565	550	550	550
R-squared	0.903	0.873	0.874	0.871	0.871	0.871
Country	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes	Yes

severity for advanced and developing economies.[14]

[14] 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
CO_2	0.172	0.939***						
	(0.271)	(0.186)						
Temperature			−0.035	−0.035				
			(0.035)	(0.052)				
NaturalDisasters					0.027	0.036*		
					(0.027)	(0.020)		
TotalAffected/Population							0.007**	−0.002
							(0.003)	(0.005)
Observations	460	290	484	287	322	261	310	254
R-squared	0.909	0.891	0.905	0.855	0.903	0.873	0.900	0.870
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 debt 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 CO_2 in that year is below the 75th quantile of CO_2 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)
CO_2 × PostPA	−0.053		
	(0.080)		
CO_2 × LowEmitters		0.242	0.190
		(0.214)	(0.267)
LowEmitters × PostPA			1.582**
			(0.627)
CO_2 × LowEmitters × PostPA			−0.642**
			(0.265)
Observations	727	727	727
R-squared	0.844	0.903	0.844
Country	Yes	Yes	Yes
Time	No	Yes	No

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 CO_2 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

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 Debt/GDP 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	−0.013			
	(0.038)			
TotalCosts/GDP × LowDebt		−0.079*		
		(0.046)		
TotalUninsured/GDP × LowDebt			−0.075	
			(0.062)	
TotalAffected/Population × LowDebt				−0.010
				(0.009)
Observations	643	625	625	625
R-squared	0.879	0.877	0.877	0.877
Country	Yes	Yes	Yes	Yes
Time	No	Yes	Yes	Yes

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) CO_2 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)	
CO_2total	0.992***			
	(0.129)			
RenewRatio		−0.242***		
		(0.063)		
Temperature × GDPgrowth			0.025***	
			(0.007)	
Observations	727	530	747	747
R-squared	0.907	0.907	0.877	0.878
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)
CO_2	1.299***					
	(0.244)					
Temperature		−0.036				
		(0.046)				
NaturalDisasters			0.061**			
			(0.026)			
TotalCosts/GDP				0.019		
				(0.050)		
TotalUninsured/GDP					−0.017	
					(0.064)	
TotalAffected/Population						−0.006
						(0.008)
Observations	708	725	550	535	535	535
R-squared	0.865	0.826	0.828	0.825	0.825	0.826
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:

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

where $Y_{i,t+h}$ represents 10-year sovereign yields (log); $ND_{i,t}$ is the climate shock variable which is measured by either the number of climate-related disaster events (frequency) or the associated total damages (% GDP) (severity) and treated as an exogenous event that cannot be anticipated nor correlated with past changes in sovereign yields[15]; $X_{i,t}$ is the vector of control variables as in the panel regression analysis; α_t^h 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.[16]

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

[15] 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.

[16] 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.

natural disaster or to an additional average total damage (% GDP). We estimate the model 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.[17]

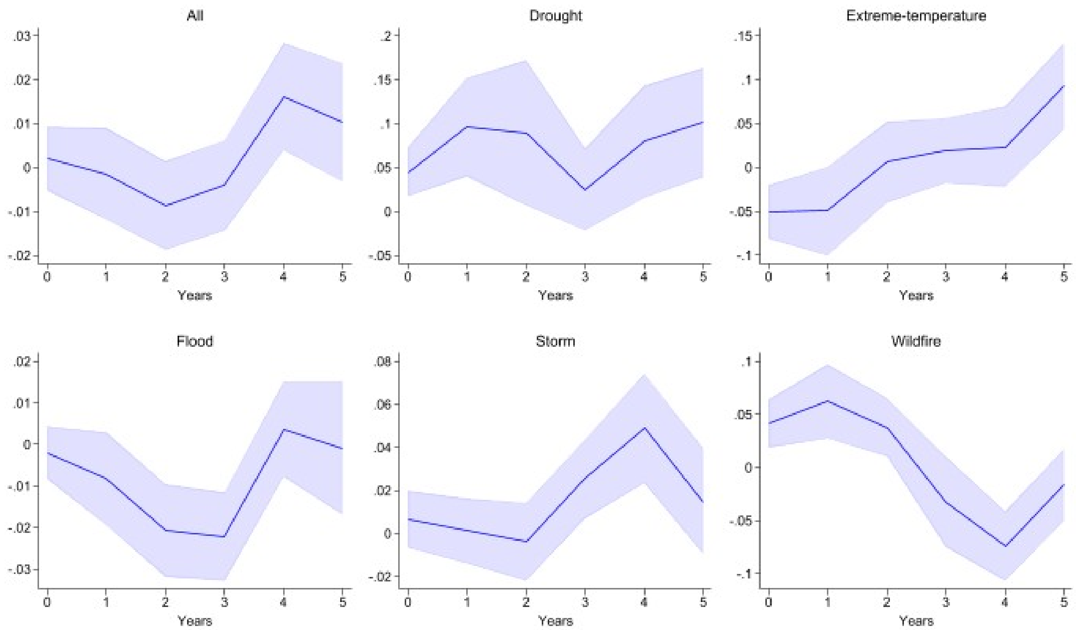
The impulse response functions in Figure 5 and Figure 6 demonstrate that there is heterogeneity in the response of 10-year sovereign yields to climate shocks related to the frequency and severity of each type of natural disaster. The yields experience the largest increases in response to climate shocks related to droughts. These are the natural disasters with the longest mean duration and the highest human toll. Although shocks related to storms, the most common type of natural disasters, also have positive effects on yields, their impact is significant only for the third year after the incidence of the event.

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 7) and developing economies (Figure 8).[18] For AEs, impulse responses suggest that climate shocks related to extreme temperature have the largest, more immediate and more persistent impact on sovereign borrowing costs. At the same time, the impact from storms and droughts becomes significant after the second year after the shock hits. In other words, in AEs, what has the most significant impact are those disasters causing unusually many deaths and have large monetary damages. For EMDEs, the response is much more immediate and more severe for all types of disasters. The strongest reaction over longer horizons is with respect to droughts. Storms also have positive effects, although their impact is generally smaller. This could suggest that developing economies face increased sovereign risk in the aftermath

[17] 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.

[18] Frequency of natural disasters shows a large heterogeneity between the two group of economies as well as within the debeloping countries.

Figure 5. Impact of climate shocks on sovereign yields: Disaster frequency



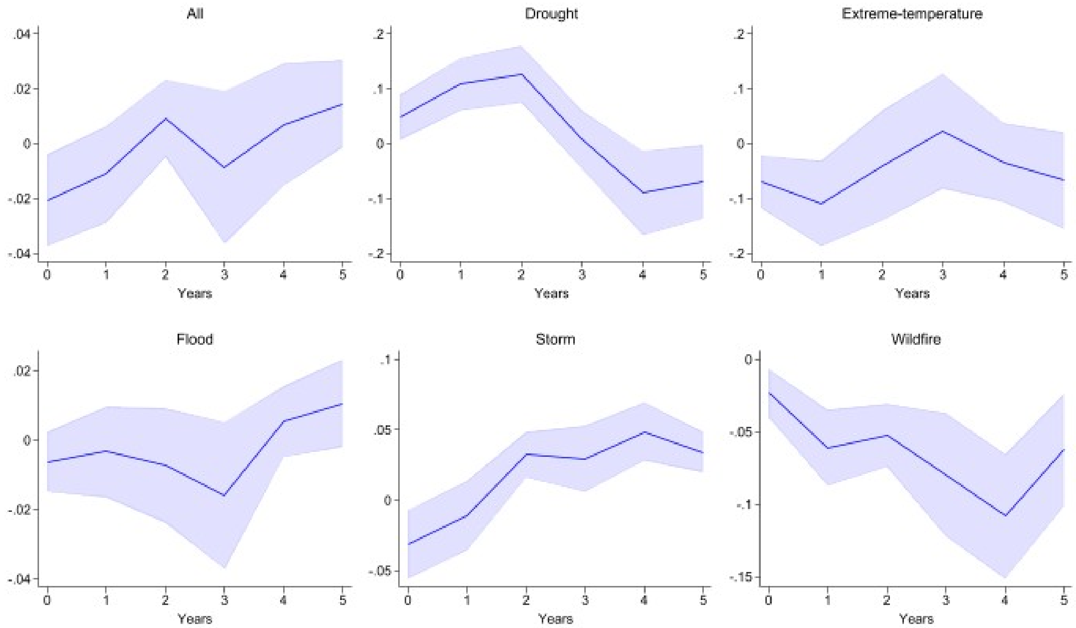
Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (2). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock as measured by the occurrence 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.

of such events, potentially due to their dependence on agriculture and natural resources, which are directly affected by these disasters. The more muted response for AEs could reflect better-developed infrastructure and financial mechanisms to manage these risks.[19]

Overall, the difference in the magnitude and timing of responses between advanced and emerging markets reflects the vulnerability of emerging markets to climate-related risks. Sovereign yields in these economies are more sensitive, likely due to weaker institutional frameworks and greater exposure to economic and financial shocks following natural disasters. Developing economies are considered to be exposed to this type of 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).

[19] The responses when we replace 10-year yields with 5-year yields are shown in the Appendix.

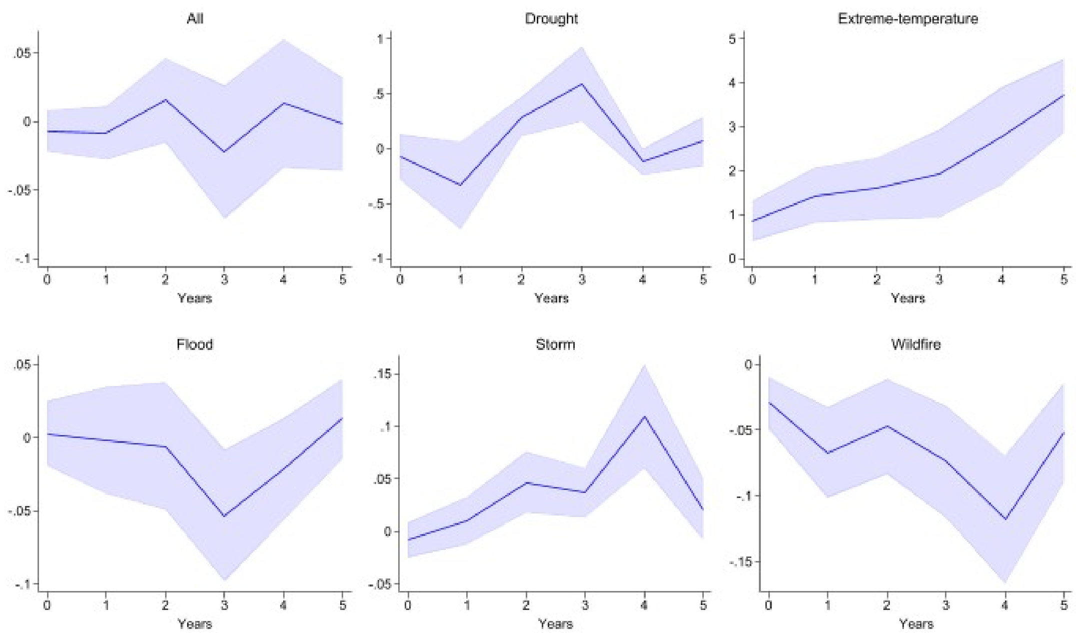
Figure 6. Impact of climate shocks on sovereign yields: Disaster severity



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 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.

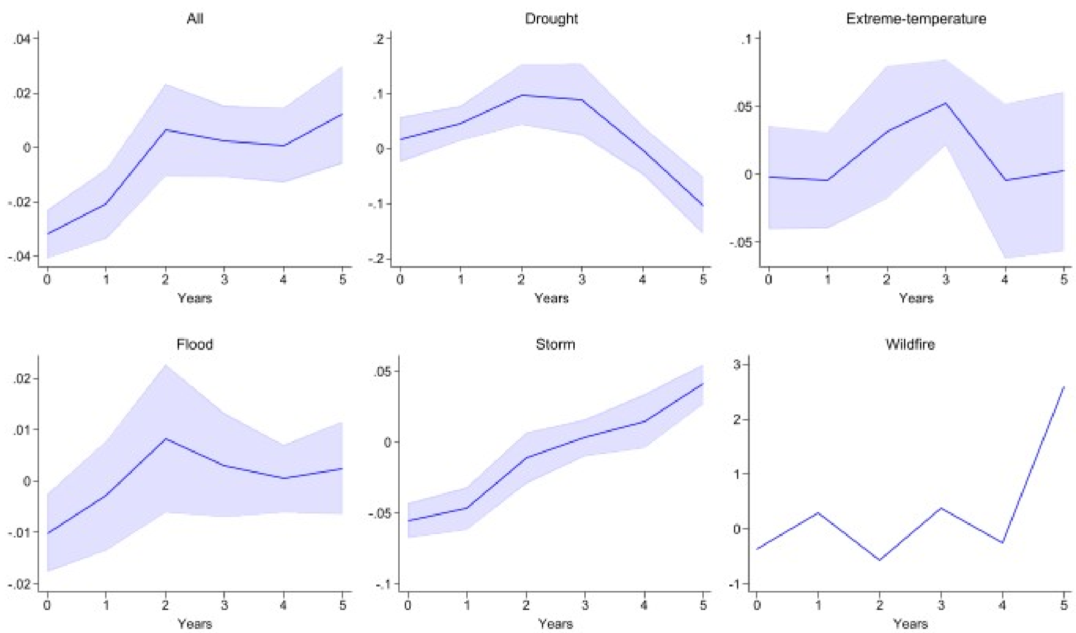
On the other hand, advanced economies typically have a greater ability to manage extreme climate events. In any case, our resulting sub-samples are rather small, which reduces the statistical power of our analysis.

Figure 7. 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.

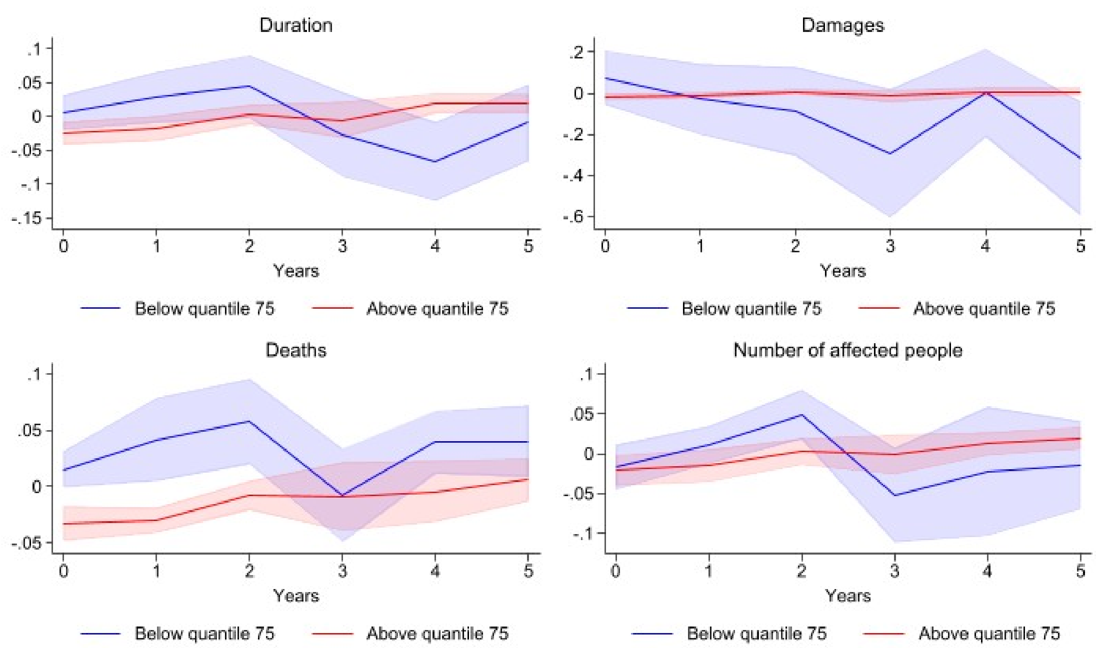
Figure 8. EMDEs impact of climate shocks on sovereign yields



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 9 shows that the medium-term positive impact of climate shocks on sovereign yields comes from high- and low-severity events in terms of duration, number of affected people (% population), and number of deaths (% population). However, in long-term for duration only high-severity events drive the impact. The results highlight that the severity of natural disasters plays an important role in influencing sovereign yields.

Figure 9. 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

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

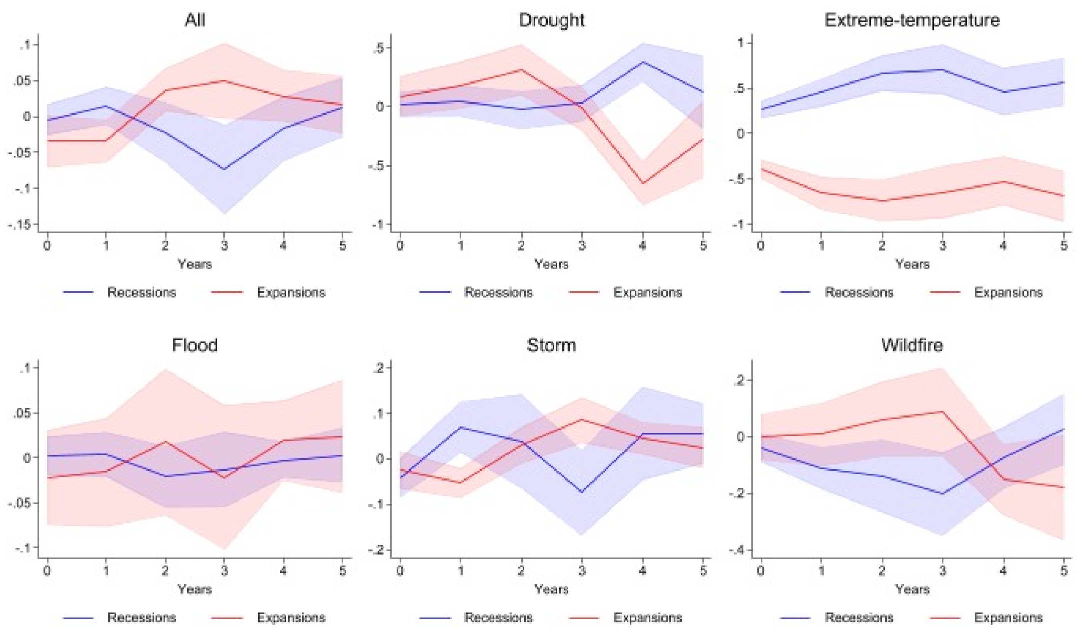
where $z_{i,t}$ is either the real GDP growth or the public debt-to-GDP, standardized to have mean zero and standard deviation one.[20] The coefficients β_L^h and β_H^h capture the impact of climate shocks in cases of recessions (low debt) and expansions (high debt) respectively. Following Cevik and Jalles (2024), we choose $\gamma = 1.5$.

The results, presented in Figure 10 and Figure 11, show that both the state of the economy and available fiscal space play critical roles in determining how climate shocks affect sovereign yields growth in terms of magnitude and persistence over the long run, which also varies with the type of the event. The impact of weather-related disasters is lower in countries with greater fiscal space compared to countries that are fiscally constrained.

As a last exercise and to determine whether climate risk, in the form of climate-related

[20] 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.

Figure 10. Disasters and the role of business cycle



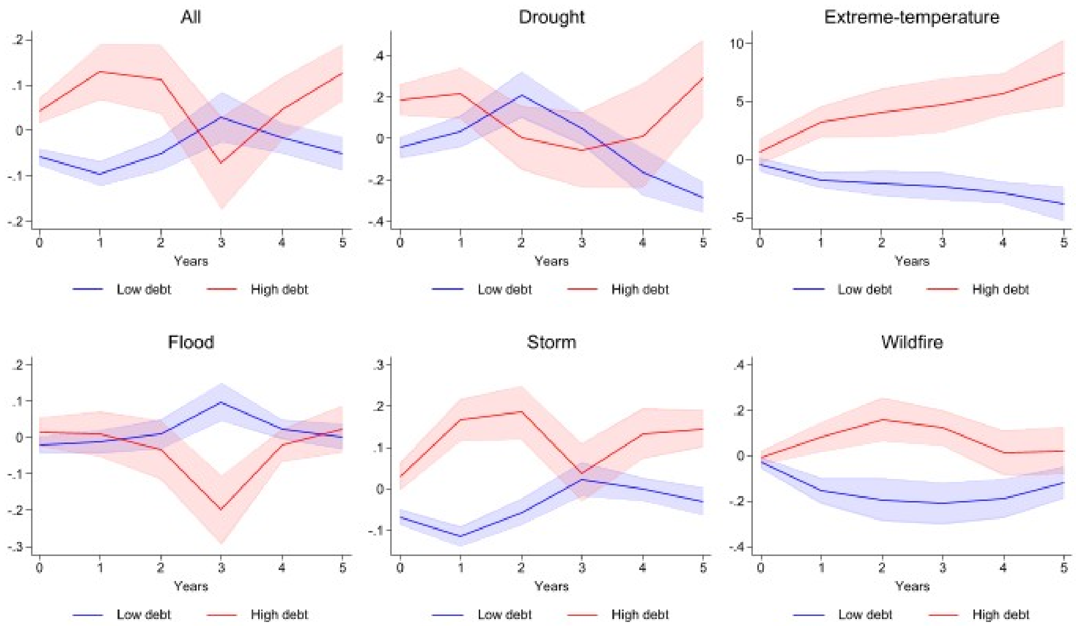
Note: The figure shows impulse response functions constructed from regression results of the lag-augmented local projection model in equation (3). Solid lines display the coefficients of (non-cumulative) responses of the sovereign yields over the five years following a climate shock as measured total 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.

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

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

Figure 11. 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.

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 carbon emissions are increasingly priced in the equity and option markets (Bolton and Kacperczyk 2021; Ilhan, Sautner, and Vilkov 2021; Bolton and Kacperczyk 2023; Sautner, Van Lent, Vilkov, and Zhang 2023) and that extreme local weather events affect asset prices (Hong, Li, and Xu 2019). This study adds new insights into the impact of climate-related shocks on sovereign bond yields, with a focus on both physical and transition risks. Using an extensive dataset from 2000 to 2023, we employ panel regression models and local projections to assess the effects of climate risks on sovereign yields. Our findings highlight several important takeaways for both policymakers and investors.

First, the results indicate that transition risks are priced into sovereign bond yields. Developing economies, which have in general implemented less green financial policies and have lower fiscal capacity, tend to experience higher borrowing costs as they navigate the transition toward greener economies. This underscores the importance of proactively managing transition risks to minimize their financial impact.

Second, chronic physical risks, such as rising temperatures, and acute physical risks, such as natural disasters do not show to play a significant role in influencing sovereign yields in the long-term. However, short to medium-term effects emerge when considering the frequency and severity of disaster events induced by climate change, especially in developing markets, which are more vulnerable to external shocks and economic disruptions following climate-related disasters.

Third, our analysis of the nonlinear effects of climate risk reveals that climate change emerges as a potential source of imbalance especially for high-debt, fiscally vulnerable countries. Low-income countries face the dual challenge of debt pressures and increased vulnerability to climate change. Climate-related shocks are growing in intensity and frequency while the ability of developing countries to address climate challenges is heavily impaired by unsustainable debt burdens ("climate debt trap") highlighting the need for an international policy agenda to address both climate and debt challenges.[21]

[21] https://unctad.org/system/files/official-document/presspb2022d12_en.pdf

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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 %)
CO_2	World Bank	Annual carbon dioxide emissions (changes, in metric tons per capita)
Temperature	World Bank	Annual temperature change relative to 1951-1980
NaturalDisasters	EM-DAT	Total number of climate-rated natural disasters (changes)
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)
DebtGDP	IMF	Central government debt (% 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	1,001	4.612	4.020	-0.531	33.105	3.791
DebtGDP	45	1,020	62.421	53.899	3.901	261.289	38.171
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	1,293	1.754	1.209	-0.694	8.363	2.206
CO_2	52	1,092	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	916	1.110	0.018	0	71.991	4.171
AE							
10y yield	25	543	2.939	2.950	-0.531	23.263	2.236
DebtGDP	24	552	72.898	59.966	7.202	261.289	45.378
GDPgrowth	25	575	2.106	2.242	-14.839	24.475	3.437
Inflation	25	575	2.182	1.875	-4.478	19.705	2.336
ExchangeRate	25	625	0.351	-0.081	-0.694	5.049	1.137
CO_2	25	525	8.294	7.635	2.927	20.470	3.788
Temperature	25	575	1.329	1.282	-0.341	3.550	0.633
TotalCosts/GDP	25	386	0.092	0.011	0	1.244	0.183
TotalUninsured/GDP	25	386	0.064	0.007	-0.047	0.786	0.133
TotalAffected/Population	25	410	0.307	0.002	0	71.991	3.791
EMDE							
10y yield	26	441	6.595	5.402	0.409	33.105	4.302
DebtGDP	20	445	47.931	46.563	3.901	97.053	19.161
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	643	3.004	2.297	-0.454	8.363	2.174
CO_2	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	4.503	0.365
TotalUninsured/GDP	26	478	0.084	0.002	0	3.386	0.306
TotalAffected/Population	26	506	1.760	0.112	0	30.923	4.352

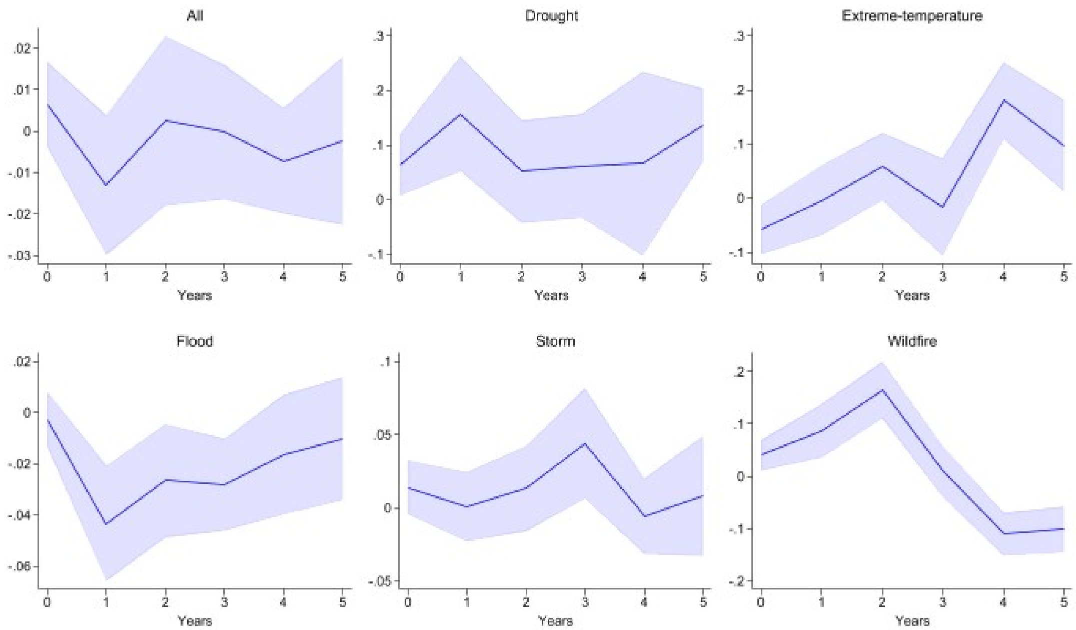
Note: The number of countries and observations refers to non-missing values for each of the variables over the 2000–2023 period.

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.

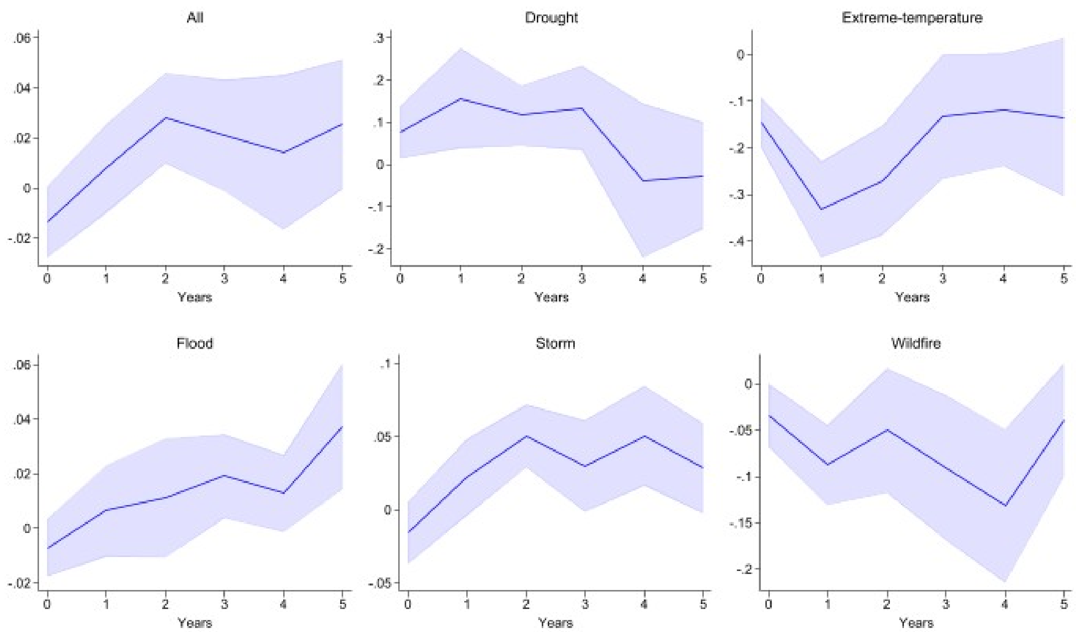
	(1)	(2)	(3)	(4)	(5)
CO_2	0.938***	1.057***	1.157***	1.155***	1.151***
	(0.144)	(0.180)	(0.188)	(0.188)	(0.189)
Temperature	−0.002	0.037	0.044	0.044	0.045
	(0.026)	(0.031)	(0.033)	(0.033)	(0.034)
NaturalDisasters		0.015			
		(0.013)			
TotalCosts/GDP			0.003		
			(0.029)		
TotalUninsured/GDP				−0.017	
				(0.034)	
TotalAffected/Population					−0.002
					(0.004)
DebtGDP	0.005***	0.006***	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Inflation	−0.009**	−0.007	−0.011	−0.011	−0.011
	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
GDPgrowth	−0.025***	−0.025***	−0.023***	−0.023***	−0.023***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ExchangeRate	0.442**	0.415**	0.460**	0.460**	0.463**
	(0.181)	(0.168)	(0.177)	(0.177)	(0.179)
PoliticalStability	0.001	−0.001	0.000	0.000	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
GovernmentEfficiency	−0.008	−0.006	−0.005	−0.005	−0.006
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	724	533	504	504	504
R-squared	0.901	0.903	0.904	0.904	0.904
Country	Yes	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes	Yes

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



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 the occurrence 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.

Figure B2. 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.

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