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Climate Risk Spillovers and Sovereign Financing Conditions

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Abstract

Physical climate impacts strain public finances through direct economic effects, yet interconnected economies also face indirect climate exposure via global value chains. These climate spillovers can amplify fiscal costs and deteriorate sovereign financing conditions but are widely ignored. We investigate whether domestic climate impacts affect sovereign financing conditions, the degree of foreign climate transmission to financing conditions, and the relative magnitude of local versus global channels. We contribute through two innovations: First, deploying climate metrics based on daily data weighted by gridded economic activity, moving beyond current risk proxies. Second, constructing a novel spillover measure systematically mapping international linkages. Combining temperature, precipitation, and drought data with countries' value-added origins from Inter-Country Input-Output tables, we attribute financing condition changes to domestic and foreign climate. Financing conditions are measured by sovereign credit ratings from three major agencies. Deploying standard and quantile regression models for a panel of 75 countries for 2000-2022, we estimate average and heterogeneous local effects. We then disentangle domestic and foreign impacts to quantify climate spillovers through global value chains. Results are threefold. First, local temperature anomalies and drought conditions show significant negative relationships with sovereign ratings, with a one-unit increase associated with a 0.2 notch downgrade. Second, quantile analysis reveals temperature effects are approximately 10 times larger for countries at the 10th percentile than at the 90th, revealing climate risks disproportionately burden lower-rated sovereigns. Third, incorporating foreign climate exposure increases estimated effects by approximately 40% compared to local-only baselines. For some highly globalized economies, foreign spillovers even dominate domestic impacts. Thus, ignoring global climate spillovers can lead to a systemic misestimation of total climate costs. Findings reveal a critical blind spot for financial actors and have policy implications for developing risk mitigation strategies that weather-proof public finances against local and global climate shocks.

Keywords: Climate change, Climate risk propagation, Sovereign credit ratings, Public finance

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1 Introduction

Climate change impacts pose growing risks to fiscal sustainability worldwide. Rising temperatures, intensifying droughts, and shifting precipitation patterns can strain economic activities, eroding the tax revenues and fiscal buffers that underpin public finances and creditworthiness (Barrage, 2025). As climate change accelerates, understanding and addressing its implications for sovereign financing conditions has become critical for investors, financial regulators, and policymakers. For example, BlackRock, the world's largest asset manager, launched a sovereign bond ETF with holdings weighted by countries' level of climate risk to account for these changing dynamics (Financial Times, 2020), and a recent survey of 59 Ministries of Finance conducted by the Coalition of Finance Ministers for Climate Action (2025) highlights that the consequences of physical climate risk on public finances are a major concern. As a consequence, a growing body of research investigates the relationship between climate change and public financing conditions, demonstrating that climate has material implications for sovereign creditworthiness and borrowing costs. Forward-looking simulations and empirical evidence show that rising temperatures and acute physical impacts are associated with sovereign credit rating downgrades, particularly for highly exposed countries (Klusak et al., 2023; Cappiello et al., 2025). Studies also find that climate vulnerability is priced into sovereign bond markets through higher yields, especially for longer maturities, and that increases in borrowing costs are persistent over time (Bingler, 2022; Capelle-Blancard et al., 2019; Cevik and Jalles, 2022; Beirne et al., 2021; Boehm, 2022). In line, climate-augmented sovereign default models propose that climate damages negatively affect sovereign's cost and availability of financing and that adaptation stabilizes sovereign ratings (Barnett and Yannelis, 2024; Mallucci, 2020; Duffy, 2025).

However, the current literature shares a critical blind spot. It focuses almost exclusively on local climate, implicitly treating economies as if they operate in isolation from global climate conditions. This overlooks a fundamental reality. In a world characterized by deep global economic integration, climate shocks in one country can indirectly impact macro-financial outcomes in other countries by propagating through international production and cross-border trade networks. For countries deeply embedded in global value chains, these foreign climate exposures - what we term climate risk spillovers - may considerably add to (or potentially diversify) the impacts of domestic climate change. Thus, by ignoring climate spillovers, the current static local perspective is prone to misestimation of total risk. This was also recently acknowledged by the UK Office for Budget Responsibility (2025) which emphasized that transnational spillovers could significantly increase climate-related fiscal costs, and in a study published by the European Central Bank which suggests that trade-related climate risk amplification could lead to GDP losses in the Euro Area up to 30 times higher than direct impacts alone (Fahr et al., 2024). Further evidence underscores the importance of considering external climate conditions, estimating that global temperature shocks have economic effects an order of magnitude larger than local shocks (Bilal and Känzig, 2024), with projected global GDP damages increasing from 11% to 40% (under SSP5–8.5) when including external weather (Neal et al., 2025). Zappalà (2025) shows that even sectors not experiencing direct heat shocks still bear economic losses from trade linkages with climate-exposed foreign sectors. Yet, despite its clear relevance, no study has systematically investigated whether and how climate spillovers affect sovereign financing conditions. Accordingly, existing policies, fiscal frameworks, and sovereign risk assessments may not fully internalize these risks.

This paper addresses this gap by investigating three core questions: First, do local climate impacts affect sovereign financing conditions, and which climate variables are key determinants? Second, to what degree do physical climate impacts in foreign countries transmit to domestic financing conditions? Third, what is the relative magnitude of local versus spillover channels, and how does this vary across countries? We make two key contributions. First, we move beyond crude climate vulnerability indices and the sole temperature focus in prior research by examining a wide set of actually realized climate impacts, including temperature, precipitation and drought metrics, that are currently under-explored. In doing so, we deploy state-of-the-art climate data based on daily observations weighted by gridded economic activity. This approach captures temporal and spatial granularity that is crucial for identifying heterogeneous climate impacts but has been widely neglected in similar studies. Second, we construct a novel climate spillover measure that links foreign climate impacts to domestic financing conditions through structural economic dependencies. This spillover metric is based on Inter-Country Input-Output tables that systematically track the flow of goods and services between economies, providing detailed information on countries' value-added origin. This approach not only allows us to attribute changes in financing conditions to both domestic and foreign climate exposure, but also provides a more accurate representation of structural economic dependencies than conventional surface level trade flow statistics. By implementing these data and methodological innovations, we aim to make climate impact assessments more comprehensive, economically sound, and policy-relevant.

Sovereign financing conditions are measured using sovereign credit ratings from Moody's, Standard & Poor's, and Fitch, as they represent governments' capacity to service its debt, directly shape borrowing costs of sovereign debt as the world's largest asset class, and serve as a benchmark across financial markets. Our analysis covers a panel dataset of 75 countries (35 advanced and 40 emerging economies) from 2000 to 2022, corresponding to roughly 130,000 unique observations. Deploying both standard and quantile two-way fixed-effects panel regressions, we exploit exogenous variation in climate to estimate average and heterogeneous local effects across the distribution. We then disentangle domestic and foreign climate risk components to quantify climate spillovers through global value chains.

Results are threefold. First, local temperature anomalies and drought conditions exhibit significant negative relationships with sovereign ratings, with a one-unit increase associated with a 0.2 notch downgrade, while precipitation measures show no effect. Second, quantile analysis reveals pronounced heterogeneity. Temperature effects are approximately 10 times larger for countries at the 10th percentile of the rating distribution than at the 90th, revealing climate risks disproportionately burden lower-rated sovereigns. Third, incorporating foreign climate exposure increases estimated effects by approximately 40% compared to the local-only baseline. For highly globalized economies such as Singapore or the Netherlands, foreign spillovers even dominate domestic impacts. Thus, ignoring global climate spillovers can lead to a systematic - typically downward - misestimation of total climate costs.

Findings reveal a critical blind spot and come with important implications. For financial authorities and investors aiming to comprehensively integrate climate risk into regulation and investment decisions, they underline the need to expand analytical frameworks beyond national boundaries to capture spillovers and wider climate risk interactions. For policymakers, particularly in highly globalized economies, effective climate risk assessments and mitigation strategies require not only domestic adaptation and resilience building, but also targeted trade diversification and strategic supply chain flexibility to weather-proof public finances against local and global climate shocks.

The remainder of this paper proceeds as follows. Section 2 situates our contribution in the relevant literature in more detail. Section 3 describes data sources and key variables. Section 4 outlines the empirical strategy for estimating local impacts and global spillover effects. Section 5 presents results. Section 6 concludes with policy implications and directions for future research.

2 Situating our contribution in the literature

The macroeconomic impact of climate change

Our work draws on three strands of research in climate economics and macro finance. First, constituting the contextual foundation, we build on climate damage research that documents substantial and oftentimes heterogeneous economic losses from climate change. Kahn et al. (2021) and Burke et al. (2015) project damages from changes in global temperatures to exceed 7% and 20% of world GDP by 2100, respectively. Building on this, more recent evidence by Bilal and Känzig (2024) accounting for global temperature suggests that each 1°C of warming lowers world income by 12%, while Callahan and Mankin (2022) estimate global damages from anthropogenic extreme heat at $16–50 trillion between 1992 and 2013. These central damage estimates, though consistently negative, have wide confidence intervals with uncertainty skewed toward severe negative outcomes (Tol, 2024). Integrating such tail risks, Dietz et al. (2021) show that accounting for climate tipping points increases the social cost of carbon by 25%. These macroeconomic damages translate directly into fiscal pressures. Barrage (2020) demonstrates that accounting for climate's fiscal consequences, such as increased costs for government services and adaptation, raises welfare gains (i.e., forgone damages) of efficient climate policy by 30%. Similarly, Seghini (2024) estimates that without deep emission cuts, climate-induced reductions in economic growth will shrink fiscal limits (the maximum amount of debt-to-GDP a government can accumulate without impairing the credibility of repayment), implying severe challenges to fiscal health.

Climate and sovereign financing conditions

Building on this, secondly, our work links to literature on climate risk and sovereign financing conditions. Prominently, Klusak et al. (2023) simulate climate-induced sovereign credit rating downgrades as early as 2030, rising to 81 sovereigns facing an average downgrade of 2.18 notches by 2100 under higher emissions scenarios. This translates to increases in annual interest payments on sovereign debt ranging from US$45–$67 billion under RCP 2.6 to US$135–$203 billion under RCP 8.5. Likewise, Cappiello et al. (2025) find higher temperature anomalies and acute physical impacts are linked to credit downgrades, particularly for high-exposure countries after the Paris Agreement. However, Bernhofen et al. (2024) argue that these estimates likely understate true risks, as they tend to ignore the materialization of acute extreme events. Deploying more granular catastrophe risk modelling they show that potential impacts on sovereign credit ratings are considerably larger than previously suggested, but crucially, these effects can be substantially mitigated through adaptation investments. Empirical studies of climate vulnerability and sovereign bond markets confirm these patterns, concluding that climate risk raises bond yields and spreads, particularly for lower-rated countries and longer-term maturities (Bingler, 2022; Capelle-Blancard et al., 2019; Cevik and Jalles, 2022). Further, Beirne et al. (2021) suggest that these climate-induced increases in public debt cost remain permanent, with Kling et al. (2018) quantifying the average increase at 1.2%. Moving beyond vulnerability proxies, Boehm (2022) directly analyze temperature changes, confirming a negative relationship with sovereign bond performance. Evidence from US municipal bonds shows that counties exposed to chronic risks or acute extreme weather events face higher borrowing costs for longer-maturity bonds, indicating that country-level insights also apply to local governments' finances (Acharya et al., 2022; Auh et al., 2022; Goldsmith-Pinkham et al., 2022; Jeon et al., 2025; Painter, 2020). Climate-extended sovereign default models confirm that expected climate damages negatively affect sovereign's cost and availability of financing, so that carbon abatement now, even when financed through additional borrowing, effectively lowers future capital costs to governments (Barnett and Yannelis, 2024; Mallucci, 2020). Agarwala et al. (2021) provide a taxonomy for tracing climate impacts through to sovereign risk, with Boitan (2023) and Zenios (2024) highlighting potential self-reinforcing "doom loops" between climate damages and debt sustainability. While not the focus of this paper, there is an equally rich literature on climate transition risk and public finances (Battiston and Monasterolo, 2020; Collender et al., 2023; De Angelis et al., 2024).

The missing dimension: Climate spillovers

The third strand of literature, where the key research gap lies, relates to climate spillovers[1]. Despite the progress on climate and public finance research, most if not all existing studies suffer from a critical blind spot: They focus almost exclusively on isolated local climate impacts, implicitly assuming that domestic economies are practically unaffected by climate shocks in foreign countries (Dingel et al., 2019; Fahr et al., 2024). However, this assumption is demonstrably false. External local climate shocks are known to oftentimes propagate through international production networks and cross-border trade linkages. For instance, the severe floods in Thailand in 2011, a key hard drive manufacturing base, not only severely damaged local

[1] Also coined "transnational", "borderless", or "cascading" climate impacts

capital but also disrupted supply chains so that car and electronics manufacturers abroad had to curtail production (Reuters, 2011). Obviously, this can affect sales, sectoral GDP and tax revenues, and thereby fiscal and financing conditions. By ignoring these climate spillovers, existing literature systematically under-represents the global scale of climate change and its economic ramifications. This recognition has spurred a growing body of empirical work aimed at quantifying climate's cross-border transmission channels into macro-financial performance. A recent report by Ranger et al. (2025) identifies significant risks to UK resilience from transnational climate impacts transmitted via infrastructure and supply chains. Jones and Olken (2010) show that temperature increases in poor countries negatively impact export growth, which of course also implies an effect on the importing country. Feng and Li (2021) find that exposure to foreign climate risk in key trade partners lowers the aggregate stock market valuation in the home country. Similarly, exposure to external temperature shocks are found to result in damages similar to the direct effect of local temperature (Bilal and Känzig, 2024), with the inclusion of external (i.e., global) weather conditions increasing damage to world GDP in 2100 from 11% to 40% under SSP5-8.5 (Neal et al., 2025). So, for countries with low direct climate change exposure and high adaptive capacity, spillovers can present a substantial risk beyond local climate costs. For example, in the US, trade-related spillovers are estimated to be responsible for 16% of the total costs of climate change (Schenker, 2013). Using input-output linkages to investigate the underlying spillover dynamics, Fahr et al. (2024) suggest that trade can amplify climate-related losses to levels up to 30 times higher than local impacts alone would suggest, with the average loss from spillovers exceeding 11% of GDP in the Euro Area. Zappalà (2025) provide further evidence that sectors not experiencing direct heat shocks still bear economic losses through trade linkages with affected foreign sectors. While conceptually there are several other channels (e.g., migration) through which foreign climate impacts can be transmitted to domestic economies, this article focuses on trade as a key transmission mechanism, as it is most directly observable and linked to standard measures of global economic activity.

Research gap and contribution

Existing studies on climate change and sovereign financing conditions show three key limitations. First, they tend to rely on crude proxies of climate impacts, such as broad exposure and vulnerability indices rather than actual climate observations. Even the few studies using climate data typically restrict analysis to temperature anomaly, leaving other impact signals such as precipitation patterns or drought conditions unexplored. Second, they utilize aggregate country-year-level data, neglecting spatial and temporal granularity crucial for understanding heterogeneity of climate risks. Third and most importantly, they focus narrowly on local climate while ignoring indirect external effects, potentially resulting in systematic misestimation of total risks. Even where climate risk spillovers are considered, we argue that exposure proxies deployed are prone to measurement errors. For instance, Bilal and Känzig (2024), Feng and Li (2021) and Dingel et al. (2019) use trade shares and geographical distance as a spillover proxy. However, these metrics fail to capture deeper structural economic dependencies. Country A may not trade much with Country B directly but may rely on B's (intermediate) inputs via Country C. Climate shocks in B would effectively shape economic outcomes in A, yet remain invisible in bilateral trade balance between A and C. Put differently, trade data represents surface-level economic flows, but not necessarily structural dependencies within the integrated global economy. For example, while 4.0% of Germany's 2022 gross imports came from Ireland, it was 2.7% of foreign value added in final demand. And while 8.3% of German imports came from the United States, it was 10.7% of foreign value added.[2] So, using standard trade metrics at face value would overestimate economic connectedness to Ireland by 48% and underestimate reliance on the United States by 22%. On sectoral level, these disparities can be even more pronounced. To address these limitations, this study implements the following steps. First, we deploy state-of-the-art climate data on actually realized observations of physical climate change rather than proxy indices. Second, we capture a higher degree of spatial and temporal granularity by accounting for gridded economic activity and utilizing daily climate input data. Third, we use data from Inter-Country Input-Output tables that systematically track flows of goods and services between economies, more accurately capturing underlying structural economic linkages between domestic and foreign countries. Leveraging information on countries' value added origin and share, we construct a novel climate spillover metric that serves as a foreign climate risk attribution factor. By implementing these data and methodological innovations, we aim to make impact assessments of climate change on sovereign finances more comprehensive, economically sound, and policy-relevant.

3 Data

Sovereign financing data: As a measure of sovereign risk and indicator of financing conditions, we use the annual average of foreign currency long-term sovereign credit ratings by Moody's, Standard & Poor's, and Fitch Ratings, provided by Kose et al. (2022). To consolidate data across credit rating agencies, ratings were converted into a numerical scale from 1 to 21, where high (low) values indicate high (low) ratings.[3] Sovereign credit ratings are of interest not only because national governments are among the largest issuers in global capital markets, turning sovereign debt into the world's largest asset class, but also because they reflect governments' financing conditions and the capacity to service its debt. They are a prerequisite for issuing sovereign bonds, and play a central role in obtaining investment by signaling the level of risk associated with investing in a given country. Determined by specialized rating agencies based on a mix of quantitative and qualitative factors including economic performance, institutional strength, fiscal sustainability, and exposure to a variety of risks (financial, geopolitical, environmental, etc.), credit ratings shape borrowing costs. Moreover, sovereign ratings often serve as benchmarks for other asset classes, frequently imposing a ceiling effect. For example, rating agencies rarely rate municipalities or private companies higher than the issuer's country, and ratings have substantial power to explain bond yield spreads (Cantor and Packer, 1996).

[2]Source: OECD TiVA database (2025 edition)

[3]The converting scheme for sovereign credit ratings is presented in Appendix A.1

Climate data: We leverage climate data at the GADM0 spatial boundary from Gortan et al. (2024). This includes daily temperature (measured in Celsius degrees, °C) and precipitation (in millimeters, mm) sourced from the ERA5 reanalysis of historical observations at a resolution of 0.25°×0.25°, and the monthly Standardized Precipitation Evapotranspiration Index (SPEI) at a 0.5°resolution based on CSIC v2.7. SPEI is a drought index that combines the effects of precipitation and evapotranspiration on water balance, assessing both the severity and duration of drought conditions (i.e., water scarcity). Temperature, precipitation and SPEI are available weighted by population density, night-time light intensity, and cropland to account for gridded economic activity. Moreover, variables are provided not weighted by any spatial economic indicator, but only by the area of each grid cell. Following the latest climate impact literature, we compute several annualized metrics which have been widely motivated and tested (Waidelich et al., 2024): mean temperature, temperature anomaly, daily temperature variability, total precipitation, extreme daily precipitation, number of wet days ($P > 1$mm), and standardised monthly precipitation deviations, as well as mean SPEI as a measure of drought.[4]

Value added data: We extract data on the share and origin of countries' value added content in final demand from the OECD Trade in Value Added (TiVA) database derived from OECD's Inter-Country Input-Output tables.[5] This value added metric represents the domestic economy's relative reliance on foreign economies by showing the share of Country i's final consumption attributable to value added from Country y. The advantage of the TiVA database is that it provides a statistical infrastructure that maps flows of production, consumption, investment within countries and flows of international trade between countries, broken down by economic activity and by country, globally and for a time period that is meaningful for our analytical purpose.

Other data: In addition, we collect a variety of control data from the IMF and World Bank Group. Key varibles include GDP growth, GDP per capita, debt-to-GDP, average sovereign debt maturity, current account-to-GDP, fiscal balance, primary balance-to-GDP, inflation, unemployment, and political stability. For purpose of heterogeneity analysis, we also include a measure of countries' degree of economic globalisation from the KOF Globalisation Index (Gygli et al., 2019). Merging these data inputs yields an initial panel dataset containing 80 countries over 28 years (1995 to 2022). Five countries[6] are dropped due to missing sovereign credit rating, climate, or control data. Years prior to 2000 are dropped because of a large number of missing values in sovereign credit ratings. All economic and financial variables are winsorized at the 99% level. This results in a panel with 75 countries, of which 35 advanced and 40 emerging economies[7], from 2000 to 2022 (with SPEI only available until 2020), corresponding to 1,725 unique observations and roughly 130,000

[4]Formulas for calculating these climate variables are presented in Appendix A.2
[5]Indicator "FD_VA_SH: Value added origin shares" from OECD TiVA database (2025 edition)
[6]BRN, MMR, STP, HKG, TWN
[7]A list of countries and corresponding ISO3 codes can be found in Appendix A.3

observations when considering input-output linkages (value added flows) between countries.

Table 1: Key descriptive statistics (full sample, 2000-2022)

Statistic	N	Mean	St. Dev.	Median	Min	Max
Temp. Anomaly (°C)	1,725	1.1	0.6	1.1	−1.0	3.3
Temp. Variability (average monthly SD of daily temp.)	1,725	2.0	1.0	2.0	0.3	4.5
Precip. Total (mm p.a.)	1,725	1,087.0	726.7	911.3	0.0	5,144.0
Precip. Extreme (mm p.a.)	1,725	12.7	26.3	0.0	0.0	254.7
Precip. WetDays (No. p.a.)	1,725	192.0	87.3	189	0	366
Precip. Deviation (standardized monthly)	1,725	−0.04	0.4	−0.1	−1.2	1.8
SPEI (water balance drought index)	1,575	−0.1	0.3	−0.1	−1.3	1.1
Sovereign credit rating	1,635	14.4	5.0	14.3	1.3	21.0
Domestic value added share (%)	1,725	71.4	9.6	72.6	38.9	91.9
GDP growth p.a. (%)	1,725	3.4	3.7	3.4	−9.0	13.1
GDP per cap (k$)	1,725	33.3	25.2	29.2	1.3	129.0
Debt to GDP (%)	1,715	55.4	35.3	48.0	3.0	226.1
Average debt maturity (years)	740	7.0	2.7	6.7	1.5	14.7
Current account to GDP (%)	1,680	−0.2	6.3	−0.9	−25.7	26.9
Fiscal balance (% of GDP)	1,722	−2.2	4.1	−2.4	−13.2	17.0
Primary balance (% of GDP)	1,699	−0.5	3.6	−0.6	−11.7	15.8
Inflation (%)	1,687	4.5	6.0	2.8	−1.2	43.5
Unemployment (%)	1,531	7.4	4.6	6.4	0.6	25.0
Political stability	1,650	0.1	0.9	0.3	−2.3	1.6
KOF (economic globalisation) index	1,679	65.1	15.5	67.2	31.1	93.1

4 Methodology

4.1 Local climate

As a foundational question, close to the latest research but going beyond temperature alone, we first test whether climate is considered in sovereign credit ratings at all. We use a standard Two-Way-Fixed-Effects (TWFE) model including a climate term. Importantly, aligned with standard literature, this is a local climate term representing the respective climate variable in country i. And even though as we argue, this local-only approach ignores the global dimension from trade-related spillover impacts, it is a useful baseline specification to investigate the relevance of climate for ratings in general before exploiting our novel spillover channel for a more nuanced assessment of direct (i.e., domestic) versus indirect (i.e., foreign) impacts. The model is inspired by the well-known ratings model of Cantor and Packer (1996) and other key explanatory variables widely observed in the literature, to which we add the climate term:

$$\mathrm{Y}_{i,t} = \tilde{\beta}_0 + \tilde{\beta}_1 \,\mathrm{CR}_{i,t-1} + \tilde{\beta}_2 \, Z_{i,t-1} \, + \, \gamma_t \, + \, \alpha_i + \, \varepsilon_{i,t} \tag{1}$$

where Y is a country's sovereign credit rating and CR a climate risk metric from the set of computed climate variables covering temperature anomaly, daily temperature variability, total precipitation, extreme daily precipitation, number of wet days, standardised monthly precipitation deviations, and drought conditions (mean monthly SPEI). Fluctuations in these (short-run) climate variables provide idiosyncratic variation as they are largely driven by physical processes such as weather, ocean cycles, or radiative forcing, that are plausibly exogenous to contemporaneous

country-level economic or political shocks. Further, Z is a vector of control variables including (log) GDP per capita, GDP growth, debt-to-GDP, current-account-to-GDP, inflation, unemployment, and an indicator of political stability. α and γ are country and year fixed effects accounting for time-invariant factors and unobserved inter-temporal trends that are homogeneous across countries, respectively. To account for potential heteroskedasticity, robust standard errors clustered at the country level are deployed.
As an alternative specification, we estimate a quantile panel regression to capture conditional and potentially heterogeneous effects of the determinants of ratings by allowing the coefficients to vary across different points of the dependent variable's distribution. For a given quantile $\tau \in (0, 1)$, the model is expressed as:

$$Q_{Y_{it}}(\tau \mid Z_{i,t-1}, \alpha_i, \gamma_t) = \alpha_i + \gamma_t + \beta_1^\tau \mathrm{CR}_{i,t-1} + \sum_{k=2}^{K} \beta_k^\tau Z_{k,i,t-1} + \varepsilon_{it}^\tau \tag{2}$$

where $Q_{Y_{it}}(\tau \mid Z_{i,t-1}, \alpha_i, \gamma_t)$ is the conditional τ-th quantile of sovereign credit ratings, α_i and γ_t country and time fixed effects, β_1^τ the coefficient of interest for the impact of the climate risk variable on rating quantile τ. β_k^τ are quantile-specific coefficients for the same k control variables $Z_{i,t-1}$ described above. $\varepsilon_{it}(\tau)$ is the quantile error term. Bootstrapped standard errors are deployed as they do not impose strong parametric assumptions and account for heteroskedasticity and autocorrelation. This quantile method allows effects to vary across the distribution of Y_{it}, offering insights beyond the average impacts identified by standard TWFE models. It thus highlights asymmetric rating responses to climate impacts at lower versus upper parts of the distribution, and can accommodate nonlinear relationships without imposing a strict functional form.

4.2 Global climate spillovers

4.2.1 Constructing a climate risk spillover metric

To account for structural global economic linkages, we construct a metric that captures the indirect climate risk a country absorbs from its counterpart countries (i.e., trade partners) due to value added reliance. We call this spillover metric the transnational climate exposure (TCE) metric. TCE construction is based on the foreign value added content in domestic final demand. Foreign value added dependency (FVAD) tells us what share of country i's final consumption is attributable to value added from country y. Hence, it signals the domestic economy's relative reliance on foreign economies, accounting for multi-stage multi-country production:

$$\mathrm{FVAD}_{i,y,t} = \frac{\mathrm{FVA}_{i,y,t}}{\sum_y \mathrm{FVA}_{i,y,t}} \times 100 \tag{3}$$

where FVA is the foreign value added embodied in domestic final demand. FVAD shows, for the total domestic demand of a country i, the share of the value added from foreign country y in domestic country i total value added consumed. So, FVAD provides a value added perspective of an economy's relative connectedness to other economies, independent of whether or not there are direct imports. Then, we construct the TCE as a FVAD-weighted exposure to foreign countries' climate risk, representing how much a country depends on climate-vulnerable external production sources:

$$\mathrm{TCE}_{i,t} = \sum_{y} (\mathrm{FVAD}_{i,y,t} \cdot \mathrm{CR}_{y,t}) \tag{4}$$

where CR is the foreign climate risk metric (i.e., temperature anomaly). Similarly to the TCE, we define national climate exposure (NCE) as the climate risk in country i weighted by the economy's domestically generated value added content:

$$\mathrm{NCE}_{i,t} = (1 - \sum_{y} \mathrm{FVAD}_{i,y,t})\, \mathrm{CR}_{i,t} \tag{5}$$

4.2.2 Baseline specification

We deploy this novel TCE metric to disentangle countries' direct and indirect (spillover) climate impacts. This allows us to explore whether sovereigns' financing conditions deteriorate (or improve) due to its own climate stress or because counterpart countries experience climate stress which propagates through the global value chain.

$$\mathrm{Y}_{i,t} = \tilde{\beta}_0 + \underbrace{\tilde{\beta}_1\, \mathrm{NCE}_{i,t-1}}_{\text{Domestic impact}} + \underbrace{\tilde{\beta}_2\, \mathrm{TCE}_{i,t-1}}_{\text{Spillover impact}} + \tilde{\beta}_3\, Z_{i,t-1} + \gamma_t + \alpha_i + \varepsilon_{i,t} \tag{6}$$

The model sheds light on whether climate impacts in other countries matter for sovereign ratings, and also reveals the relative importance of local versus global climate risk. For instance, when $\tilde{\beta}_1$ (domestic impact) is relatively large, direct physical impacts drive vulnerability of financing conditions, thus developing strategies enhancing domestic adaptation and resilience is key. If, on the other hand, $\tilde{\beta}_2$ (spillover impact) is relatively large, vulnerability from foreign sources dominates, suggesting that diversification away from climate-sensitive trade partners is important for weather-proofing public finances.

4.2.3 Advanced specification with heterogeneous climate sensitivities

Importantly, the previous specification implicitly assumes that all countries are equally sensitive to climate change. While a useful simplification, in reality countries have different levels of vulnerability. To estimate the effect of domestic and foreign climate exposure on sovereign credit ratings accounting for such differences in vulnerability, we employ a panel regression framework that simultaneously estimates country-specific climate sensitivities.[8] The baseline specification is given by:

[8] In this context, we use the term climate sensitivity describing the relationship, or elasticity, between a country's climate risk and credit rating. It does not refer to climate sensitivity as defined in climate science, describing the Earth's global surface temperature increase from doubling atmospheric carbon dioxide concentration.

$$Y_{i,t} = \tilde{\beta}_0 + \sum_{y=1}^{N} \tilde{\beta}_{1,y}\, E_{i,y,t-1} + \tilde{\beta}_2\, Z_{i,t-1} + \gamma_t + \alpha_i + \varepsilon_{i,t} \tag{7}$$

with

$$E_{i,y,t} = \begin{cases} NCE_{i,t} & \text{if } i = y, \\ FVAD_{i,y,t} \times CR_{y,t} & \text{if } i \neq y, \end{cases}$$

where $Y_{i,t}$ denotes the sovereign credit rating of country i in year t, $E_{i,y,t-1}$ country i's climate exposure originating from country y, $Z_{i,t-1}$ is the vector of control variables, γ_t captures time- and α_i country-fixed effects, and $\varepsilon_{i,t}$ is the error term.

The key innovation of our approach stems from the construction of the climate risk exposure variable, which takes two distinct forms depending on whether the climate exposure originates domestically or from foreign countries. When $y = i$, the exposure term captures domestic climate exposure through $NCE_{i,t}$, which is the product of country i's domestic value-added share and its own level of climate change, operationalized as local temperature anomalies. When $y \neq i$, the exposure term reflects foreign climate exposure (i.e., spillovers) through the interaction of country i's value-added dependence on country y and country y's level of climate change (i.e., temperature anomalies). This structure allows us to trace how climate shocks in other countries propagate through global value chain linkages to affect sovereign creditworthiness.

The coefficient $\tilde{\beta}_{1,y}$ represents the climate sensitivity parameter for country y, capturing how climate in country y translates into rating impacts. Crucially, this parameter plays a dual role in our framework. When country y appears as the home country ($i = y$), the sensitivity parameter measures how country y's own rating responds to its domestic climate conditions. When country y appears as a trading partner ($i \neq y$), the same sensitivity parameter governs how country y's climate risk spills over to its trading partners' ratings. That is, we identify each country's intrinsic climate-rating elasticity once, and this determines both its domestic vulnerability and its capacity to transmit climate risk internationally. This simultaneity is a central feature to accommodate countries' heterogeneous climate-rating elasticities in our spillover estimation strategy. The approach implies that climate sensitivity reflects fundamental country characteristics that are time-invariant (at least over the short- to medium-term) such as geographical exposure, economic structure, and adaptive capacity, that determine both how a country's own rating responds to climate shocks and how consequential those shocks can be for its trading partners. By imposing this structure, we ensure that if country A is highly sensitive to climate risk domestically, our framework recognizes that climate shocks in country A should also have commensurately large spillover effects on countries exposed to A through trade linkages. Operationally, we then implement the heterogeneous sensitivities by estimating total climate impact on country i's rating, decomposed into domestic and foreign components. The domestic climate impact is calculated as $\hat{\beta}_{1,i} \times NCE_{i,t-1}$, reflecting how country i's own climate conditions affect its rating. The foreign climate impact is computed as $\sum_{y \neq i} \hat{\beta}_{1,y} \times \text{FVAD}_{i,y,t-1} \times CR_{y,t-1}$, aggregating the spillover effects from all trading partners weighted by their respective climate sensitivities and value added shares. This decomposition allows us to quantify the relative importance of domestic versus international climate transmission channels in determining sovereign credit risk. However, this also comes with restrictions that merit acknowledgment. First, implicitly we assume that the transmission mechanism, how climate risk in country y affects ratings, operates identically whether y is experiencing the shock domestically or transmitting it as a trading partner. In reality, domestic and spillover channels may differ in magnitude or timing, though both should be governed by the underlying climate vulnerability of country y. Second, for simplification, we assume climate sensitivity remains constant over our sample period. While this is reasonable for structural adaptive capacity or climate resilience which usually evolve slow-moving over long-term horizons, it does not allow for the possibilities that countries undergo rapid transformation within a short time period.

Our identification strategy exploits both cross-sectional and temporal variation in climate exposure, leveraging three key sources of exogeneity. First, our measure of climate risk, temperature anomalies, is plausibly exogenous to short- and medium-term economic and political developments. While countries may impose long-term climate trajectories through emissions, year-to-year temperature deviations are determined by climate system dynamics that cannot be influenced. Second, we lag all independent variables by one year, ensuring that they temporally precede the rating outcomes. This lag structure reflects the transmission mechanism through which climate conditions affect economic outcomes before manifesting in credit rating adjustments. This provides additional protection against reverse causality, as current ratings cannot cause past climate conditions. Third, the inclusion of country and time fixed effects addresses several potential confounders. Country fixed effects absorb all time-invariant factors, such as socio-economic characteristics, political environments, or geographical characteristics. Time fixed effects control for unobserved global trends that are homogeneous across countries. Despite these mitigation steps, certain identification challenges remain. While temperature anomalies are plausibly exogenous, value added linkages through which climate risk propagates are potentially endogenous, as countries may adjust their trade relations in response to economic conditions correlated with creditworthiness. We address this concern by using lagged value added shares, though we acknowledge that slow-moving changes in trade patterns could still reflect anticipatory climate responses. Additionally, our macroeconomic controls are assumed to adequately capture the main confounding pathways. This is justified by deploying explanatory variables widely used in well-established rating models. Nevertheless, unobserved time-varying factors such as changes in monetary policy regimes could introduce omitted variable bias if correlated with both climate exposure and ratings.

5 Preliminary results

5.1 Local climate

Table 2 presents the baseline results examining whether climate affects sovereign credit ratings. Findings provide clear evidence that climate conditions matter for sovereign credit ratings. Temperature anomaly shows a negative relationship with ratings ($p<0.01$), indicating that countries experiencing higher deviations from historical temperature means receive systematically lower sovereign ratings. A one-degree Celsius increase in temperature anomaly is associated with a rating downgrade of approximately 0.19 notches, holding other factors constant. This suggests that rating agencies recognize climate change, here represented by temperature deviations, as a material risk factor for sovereign creditworthiness. Temperature variability shows a marginally significant positive coefficient, which appears counterintuitive, and may indicate that this standard deviation metric captures aspects that operate through non-linear channels not fully captured in this specification. The SPEI demonstrates a positive relationship with ratings ($p<0.10$), consistent with conceptual logic: higher SPEI values indicate positive water balance (less drought stress), which supports higher creditworthiness. This aligns with the expectation that water availability is important for economic resilience. Notably, precipitation measures (total precipitation, extreme precipitation, wet days, precipitation deviation) do not exhibit statistically significant relationships with sovereign ratings. Among all climate variables tested, temperature anomaly stands out as the most clearly identified and economically meaningful climate-related driver of sovereign ratings. This suggests that rating agencies are particularly attentive to, or that economies are particularly vulnerable to, persistent warming trends (and/or its implications) rather than other dimensions of climate change. Of course, the prominence of temperature as a key metric in global climate policy, and climate-economy modeling may play a role here. The coefficients of control variables are aligned with theoretical expectations and validate the soundness of our data and model specification. GDP per capita (log) is strongly positively associated with ratings, reflecting the importance of income levels for fiscal capacity. While one could expect the same for GDP growth, we find a positive but not significant relationship. This could be explained by the fact that many emerging economies tend to grow faster than advanced economies, but this growth comes with other economic trade-offs and institutional constraints that put pressure on ratings. Debt-to-GDP ratios, inflation, and unemployment have a negative impact on ratings, highlighting that higher indebtedness, monetary and price instability, and labor market weakness raises default risk and undermines creditworthiness. Political stability emerges as an important institutional factor that elevate ratings.

Because temperature anomaly is found to be the climate variable with the highest predictive power of ratings, we now provide a more in-depth quantile analysis to explore whether the temperature impact varies across levels of creditworthiness (Table 3). Findings describe the impact of temperature anomaly on ratings at different points of the dependent variable's distribution, ranging from the 10th percentile to the 90th percentile. This yields conditional estimates and a richer heterogeneous

Table 2: Aggregate regression results - Local climate

	Dependent variable: Sovereign credit rating						
T Anom.$_{t-1}$	−0.185***						
	(0.070)						
T Variability$_{t-1}$		0.343*					
		(0.179)					
P Total$_{t-1}$			0.000				
			(0.000)				
P Extreme$_{t-1}$				−0.001			
				(0.001)			
P WetDays$_{t-1}$					0.000		
					(0.002)		
P Dev.$_{t-1}$						0.046	
						(0.099)	
SPEI$_{t-1}$							0.205*
							(0.106)
log GDP percap$_{t-1}$	2.889***	2.870***	2.897***	2.896***	2.895***	2.896***	3.003***
	(0.682)	(0.684)	(0.681)	(0.681)	(0.681)	(0.681)	(0.702)
GDP growth$_{t-1}$	0.019	0.022	0.019	0.019	0.019	0.019	0.023
	(0.026)	(0.027)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Debt/GDP$_{t-1}$	−0.045***	−0.045***	−0.045***	−0.045***	−0.045***	−0.045***	−0.047***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Curr.acc./GDP$_{t-1}$	−0.014	−0.013	−0.014	−0.014	−0.014	−0.014	−0.013
	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
CPI$_{t-1}$	−0.034**	−0.035**	−0.034**	−0.034**	−0.034**	−0.033**	−0.036**
	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Unemployment$_{t-1}$	−0.184***	−0.182***	−0.181***	−0.181***	−0.181***	−0.181***	−0.181***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.040)	(0.041)
Political stability$_{t-1}$	1.071***	1.073***	1.083***	1.089***	1.085***	1.083***	1.030***
	(0.336)	(0.334)	(0.337)	(0.339)	(0.338)	(0.338)	(0.347)
FE (time)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE (country)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1340	1340	1340	1340	1340	1340	1275
R^2	0.57	0.57	0.57	0.57	0.57	0.57	0.58

Notes: Averages with country-clustered standard errors in parentheses. All explanatory variables are lagged by one year. Significance levels: * p<0.1; ** p<0.05; *** p<0.01

understanding that goes beyond standard regression models' average effects and allows us to test whether climate affects highly-rated and poorly-rated sovereigns differently, a question with important implications for risk assessments and thus financing. The pattern of coefficients reveals two main findings. First, confirming aggregate results, estimates across all parts of the distribution are consistently negative, implying that temperature increases are detrimental to ratings independent of countries' level of creditworthiness. Second, there is relevant heterogeneity across quantiles, with the effect being about 9.8 times larger at the 10th percentile (-0.157) compared to the 90th percentile (-0.016). Temperature anomalies exhibit strong negative impacts on ratings at the lower end of the distribution (Q10 to Q50), with coefficients ranging from -0.163 to -0.131 (all $p<0.05$). This indicates that countries with lower credit ratings experience economically meaningful rating downgrades in response to rising temperatures. The magnitude of the effect is relatively stable across these lower quantiles, suggesting a persistent climate penalty for public financing of less creditworthy sovereigns. In contrast, the effect becomes statistically insignificant and economically negligible at higher quantiles (Q60 to Q90), with coefficients between -0.037 and -0.016. This finding suggests that higher-rated sovereigns, predominantly advanced economies with healthy investment grade status, appear largely insulated from temperature-related impacts. This differential picture likely reflects several underlying mechanisms. Lower-rated countries often have economies more dependent on climate-sensitive sectors like agriculture, weaker institutional capacity to manage climate shocks, tighter fiscal space to fund climate adaptation measures, and less diversified economic structures. These structural vulnerabilities make their creditworthiness more susceptible to climate deterioration. Conversely, higher-rated sovereigns tend to possess stronger adaptive capacity, more diversified economies, more resilient infrastructure, and greater financial resources to buffer climate impacts. In addition, this pattern could reflect that rating agencies may be more responsive to climate signals when evaluating already vulnerable economies, while giving less weight to climate concerns for countries with strong fundamental creditworthiness. This distinction between actual economic resilience and rating agency perception merits further investigation. Overall, results show that climate change poses a non-linear heterogeneous downward pressure on ratings across the sovereign landscape, underlining the importance of obtaining conditional estimates across quantiles.

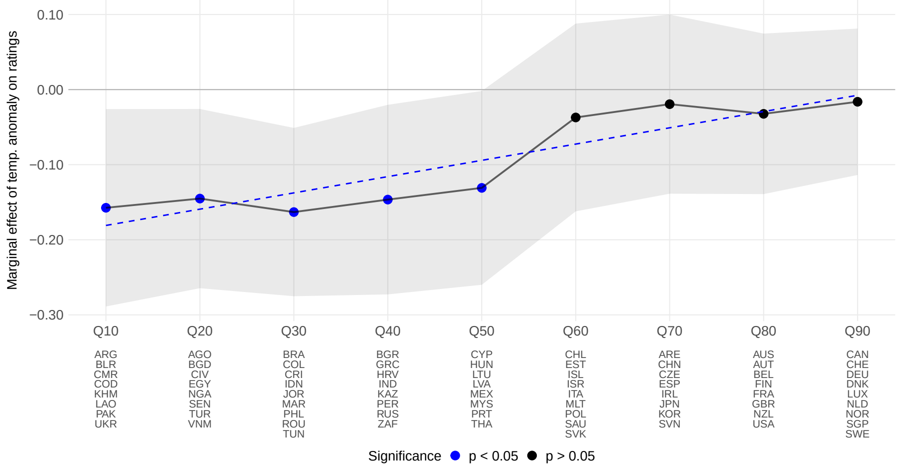
Table 3: Quantile regression results - Local climate

	Dependent variable: Sovereign credit rating								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
T Anom.$_{t-1}$	−0.157**	−0.145**	−0.163***	−0.147**	−0.131**	−0.037	−0.019	−0.032	−0.016
	(0.064)	(0.059)	(0.059)	(0.062)	(0.066)	(0.067)	(0.058)	(0.057)	(0.052)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE (time)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE (country)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1340	1340	1340	1340	1340	1340	1340	1340	1340
R^2	0.84	0.83	0.83	0.83	0.82	0.83	0.83	0.83	0.81

Notes: Averages by quantiles with country-clustered bootstrapped standard errors in parentheses. Significance levels: * p<0.1; ** p<0.05; *** p<0.01

To examine whether the temperature anomaly effect varies across individual countries, Figure 2 presents country-specific regression coefficients. This granular perspective allows us to identify which countries' ratings are most sensitive to temperature changes, moving beyond pooled averages to reveal cross-country heterogeneity. The pooled estimate (vertical red line with shaded 95% confidence interval) provides a full sample benchmark for comparison, but individual country point estimates range from approximately -1.3 to +1.4, with 60% of sample countries showing a negative value. However, when only considering coefficients that are significant at the 5% level, all of these estimates are negative. Brazil displays the strongest negative sensitivity, followed by Mexico, Indonesia, Spain, and Italy. Additional countries showing significant negative effects include Bulgaria, the Slovak Republic, and Hungary. This suggests that rating agencies, or the underlying economic fundamentals, respond strongly to temperature increases in these sovereigns, re-

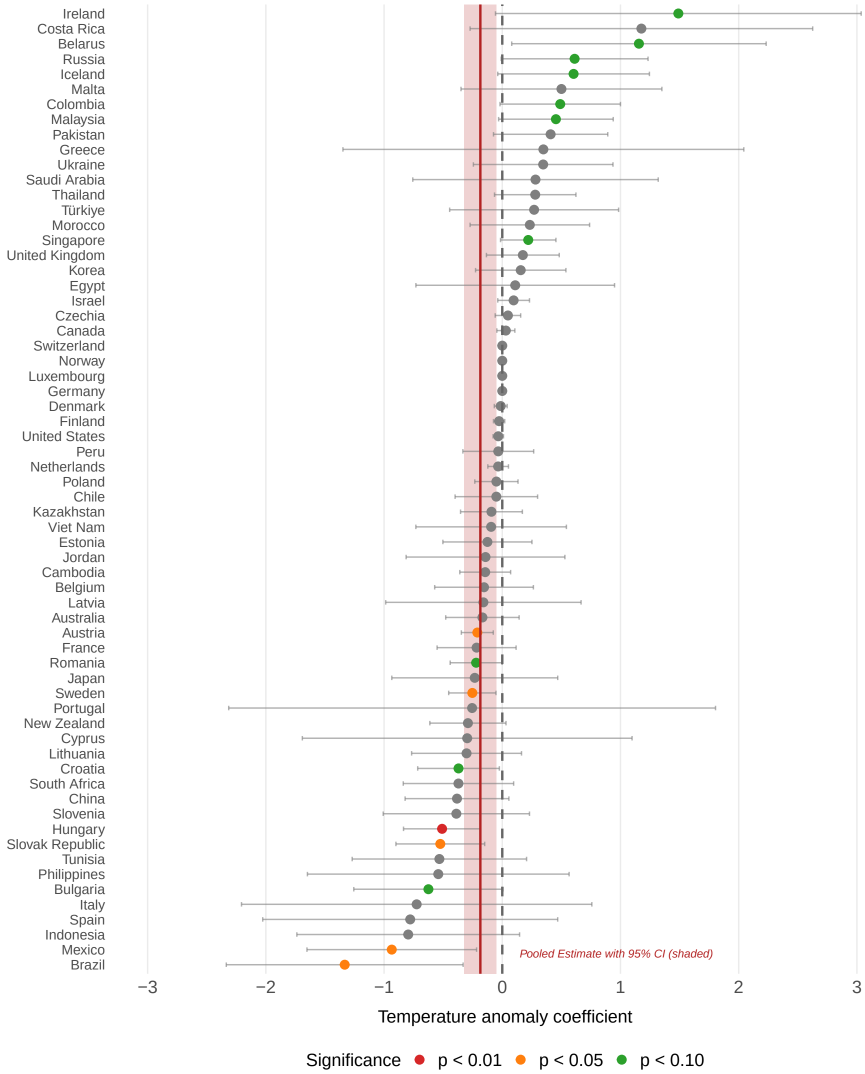
Figure 1: Quantile regression coefficients - Local climate



Notes: Relationship between temperature anomaly$_{t-1}$ and sovereign credit rating for the 10th to 90th percentile of the rating distribution. ISO3 country codes show each countries' "typical decile" based on where its observations fall in the overall rating decile distribution, using the mean of its observation-level deciles. Countries are then ranked by this typical decile position and split into nine equally sized groups, indicating which countries are more typically associated with lower versus higher parts of the rating distribution. Dashed line represents smoothed trend line. Shaded area shows the 95% confidence interval with bootstrapped standard errors.

sulting in measurable rating deterioration. Some economies show coefficients close to zero or even positive, even though they lack statistical significance. Notably, these are high-latitude sovereigns, such as Ireland, Russia or Iceland, with relatively cold climate. A limitation of this country-specific model is the underlying trade-off between statistical power and granularity, with pooled estimates leveraging the full panel structure and country-level regressions relying on time-series variation. This may explain why some coefficients lack statistical significance despite signaling economically meaningful point estimates.

Figure 2: Country-specific temperature anomaly coefficient estimates

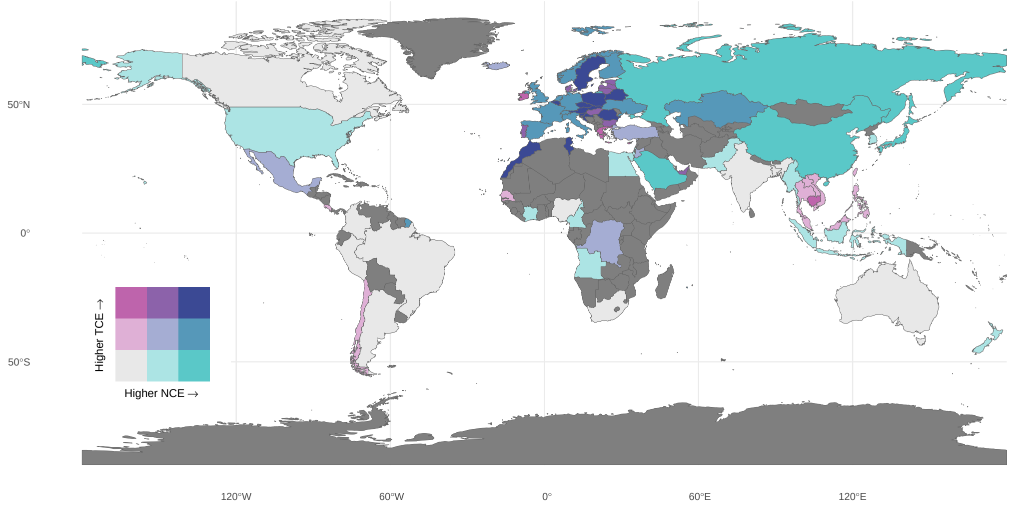


5.2 Global climate spillovers

5.2.1 Global climate risk exposure

To provide intuitive and stylised descriptive results, Figure 3 displays countries' climate exposure profiles, simultaneously capturing impacts from local (NCE) and global (TCE) sources. The color gradient indicates the joint distribution of these exposures, with darker shades representing higher exposure across both dimensions. The spatial pattern reveals heterogeneity in profiles across countries, distinguishing regions where domestic climate impacts constitute the primary source of risk from those where foreign spillovers play a dominant role. Several regions exhibit elevated local climate risk, particularly in sub-Saharan Africa and parts of South- and East Asia, consistent with observed warming patterns in these latitudes. At the same time, the geographical distribution illustrates that in addition to local impacts most countries are also exposed to transnational climate risks. For example, highly integrated economies in Europe face considerable exposure to global climate spillovers (TCE) through global value chain relationships. This simple descriptive representation highlights that focusing exclusively on domestic climate conditions provides an incomplete picture. Transnational climate exposures can constitute a significant and often underappreciated risk channel, underscoring the relevance of formally incorporating spillovers in climate-related economic analyses.

Figure 3: Country classification across national and transnational climate exposure (2022)



5.2.2 Baseline regression results

While the spatial patterns presented in Figure 3 suggest that foreign climate spillovers may be an important and unevenly distributed source of risk, they do not by themselves quantify how such exposures translate into sovereign financing outcomes. Therefore, this section econometrically analyses the relevance of these climate exposure profiles. Table 4 presents the baseline regression results deploying the NCE and TCE metrics to assess the impacts of domestic and foreign climate risks on sovereign credit ratings. In aggregate, the coefficient for the total temperature anomaly, which aggregates NCE and TCE weighted by value added dependency, is negative (-0.26) and highly statistically significant (column 1). This result aligns with the prior findings in Section 5.1, confirming that higher temperature deviations are detrimental to sovereign credit ratings. However, this coefficient is about 40% higher than the coefficient (-0.18) when only considering local impacts assuming countries are effectively unaffected by climate in other countries. Thus, on aggregate, integrating climate spillovers into temperature exposure results in a larger negative impact on ratings. A key insight on the heteregeneity of effects emerges when decomposing this total climate effect into its constituent parts and differentiating between countries' degree of economic globalization. Column 2 and 3 show results for country groups with economies that are weakly and strongly integrated into the global open economy, respectively. For highly globalized economies, the TCE coefficient alone is statistically significant and economically relevant. This suggests that for countries characterized by high openness and global integration, such as Singapore, the Netherlands, or Ireland, climate spillovers from foreign sources present a substantial risk. In fact,

Table 4: Baseline regression results

	All	Low Econ. Glob.	High Econ. Glob.
	(1)	(2)	(3)
Total T Anom.$_{t-1}$	−0.260***		
	(0.089)		
NCE$_{t-1}$		−0.317	−0.093
		(0.274)	(0.170)
TCE$_{t-1}$		−0.742	−2.095***
		(1.565)	(0.727)
log GDP percap$_{t-1}$	2.892***	2.527***	1.201
	(0.681)	(0.586)	(0.891)
GDP growth$_{t-1}$	0.019	−0.010	−0.002
	(0.026)	(0.013)	(0.019)
Debt/GDP$_{t-1}$	−0.046***	−0.043***	−0.050***
	(0.005)	(0.007)	(0.006)
Curr.acc./GDP$_{t-1}$	−0.015	0.035	−0.038**
	(0.015)	(0.024)	(0.016)
CPI$_{t-1}$	−0.033**	−0.027*	−0.115***
	(0.017)	(0.015)	(0.040)
Unemployment$_{t-1}$	−0.184***	−0.097*	−0.277***
	(0.040)	(0.055)	(0.058)
Political stability$_{t-1}$	1.070***	1.215***	0.784
	(0.335)	(0.376)	(0.584)
FE (time)	Yes	Yes	Yes
FE (country)	Yes	Yes	Yes
Observations	1340	595	723
R^2	0.57	0.49	0.66

Notes: Averages with country-clustered standard errors in parentheses. Total T Anom. is total temperature exposure (NCE + TCE) weighted by value added dependency. The Low (High) Economic Globalisation columns refer to countries below (above) the median of the KOF Economic Globalisation Index, which proxies countries' degree of global economic openness and integration. All explanatory variables are lagged by one year. Significance levels: * $p<0.1$; ** $p<0.05$; *** $p<0.01$

for those countries, vulnerability to climate stress in partner countries dominate in magnitude relative to vulnerability to domestic climate stress. For countries with low economic globalization, such as Nigeria, Russia, or Egypt, the NCE nor the TCE are negative and economically sizeable but not statistically significant. Overall, this outcome highlights that ignoring climate risk spillovers by focusing on local impacts alone can lead to a systemic underestimation of total risk exposure. The findings provide evidence that climate impacts in other countries matter for sovereign ratings, particularly for highly globalized economies. This implies that for such countries, diversification away from climate-sensitive trade partners and resilience building in their value added chains can be an important risk mitigation option.

5.2.3 Advanced specification with heterogeneous climate sensitivities

Results for this section are work in progress and to be completed.

6 Conclusion

This paper contributes to the literature on climate risk and public finance by investigating how physical climate impacts, both from domestic and foreign sources, affect sovereign financing conditions. While previous research has established that local (i.e. domestic) climate vulnerability poses material risks to public finances, evidence on the cross-border transmission of climate impacts and their implications for sovereign risk remains extremely scarce. We address this gap by empirically investigating an expanded set of climate indicators and by conceptualizing, constructing, and quantifying climate spillovers transmitted through global economic linkages.

Our analysis yields three key results. First, local temperature anomalies and drought conditions exhibit significant negative relationships with sovereign credit ratings, with a one-unit increase associated with a 0.2 notch downgrade. Precipitation shows no effect, suggesting that sovereign risk assessments mainly consider economic vulnerabilities from persistent warming trends and water scarcity. Second, quantile analysis reveals pronounced heterogeneity, with temperature effects approximately ten times larger for countries at the 10th percentile than at the 90th percentile of the ratings distribution, indicating that climate risks disproportionately burden lower-rated sovereigns. Third, incorporating exposure to foreign climate through our novel climate spillover metric increases estimated effects by 40% relative to local-only specifications. For highly globalized economies, climate spillovers transmitted through global value chains can even exceed domestic impacts in magnitude. These results demonstrate that ignoring international climate risk propagation may lead to systematic - typically downward - misestimation of total climate risk, with consequences for optimal policy responses, fiscal planning, and asset valuation.

These findings carry important implications for multiple stakeholders. For financial authorities and investors seeking to integrate climate risk into regulatory frameworks, stress testing and investment decisions, our results underscore the necessity of expanding analytical tools beyond local mechanisms. For policymakers, particularly in economies with high global integration, findings suggest that effective climate risk mitigation strategies require a dual approach: strengthening domestic adaptation and resilience while simultaneously enhancing strategic trade diversification and supply chain flexibility to weather-proof public finances against both local and global climate shocks. Several avenues merit further investigation. Extending the analysis to additional transmission mechanisms beyond trade linkages such as financial contagion or migration, examining temporal dynamics and non-linearity of international spillovers, and modelling costs and benefits of adaptation investments and sector-level value chain reallocation could enable more targeted policy guidance for risk mitigation efforts.

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Appendix

A.1

Table 5: Credit rating converting scheme

S&P	Moody's	Fitch	Value
AAA	Aaa	AAA	21
AA+	Aa1	AA+	20
AA	Aa2	AA	19
AA-	Aa3	AA-	18
A+	A1	A+	17
A	A2	A	16
A-	A3	A-	15
BBB+	Baa1	BBB+	14
BBB	Baa2	BBB	13
BBB-	Baa3	BBB-	12
BB+	Ba1	BB+	11
BB	Ba2	BB	10
BB-	Ba3	BB-	9
B+	B1	B+	8
B	B2	B	7
B-	B3	B-	6
CCC+	Caa1	CCC+	5
CCC	Caa2	CCC	4
CCC-	Caa3	CCC-	3
CC			
C		CC	2
CI	Ca	C	
R			
SD			1
D	C	D	
NR		NR	–

A.2

Mean temperature:

$$TM_{x,y} = \frac{1}{D_y} \sum_{d=1}^{D_y} T_{x,d,y} \tag{8}$$

Temperature anomaly:

$$TA_{x,y} = T_{x,y} - \frac{1}{N_{1951:1980}} \sum_{y'=1951}^{1980} TM_{x,y} \tag{9}$$

Daily temperature variability:

$$TV_{x,y} = \frac{1}{12} \sum_{m=1}^{12} \sqrt{\frac{1}{D_m} \sum_{d=1}^{D_m} \left(T_{x,d,m,y} - \bar{T}_{x,m,y}\right)^2} \tag{10}$$

Total precipitation:

$$PT_{x,y} = \sum_{d=1}^{D_y} P_{x,d,y} \tag{11}$$

Extreme daily precipitation:

$$\mathrm{Pext}_{x,y} = \sum_{d=1}^{D_y} H(P_{x,d} - P99.9_x) \times P_{x,d} \tag{12}$$

Number of wet days (P > 1mm):

$$\mathrm{Pwd}_{x,y} = \sum_{d=1}^{D_y} H(P_{x,d} - 1\mathrm{mm}) \tag{13}$$

Standardised monthly precipitation deviations:

$$\mathrm{RM}_{x,y} = \sum_{m=1}^{12} \frac{R_{x,m,y} - \bar{R}_{x,m}}{\sigma_{x,m}} \frac{\bar{R}_{x,m}}{\mathrm{RA}_r} \tag{14}$$

Mean SPEI:

$$SPEI_{x,y} = \frac{1}{D_y} \sum_{d=1}^{D_y} SPEI_{x,d,y} \tag{15}$$

A.3

Table 6: Sample countries

Advanced economies	Emerging economies
Australia (AUS)	Angola (AGO)
Austria (AUT)	Argentina (ARG)
Belgium (BEL)	Bangladesh (BGD)
Canada (CAN)	Belarus (BLR)
Croatia (HRV)	Brazil (BRA)
Cyprus (CYP)	Bulgaria (BGR)
Czechia (CZE)	Cambodia (KHM)
Denmark (DNK)	Cameroon (CMR)
Estonia (EST)	Chile (CHL)
Finland (FIN)	China (CHN)
France (FRA)	Colombia (COL)
Germany (DEU)	Costa Rica (CRI)
Greece (GRC)	Côte d'Ivoire (CIV)
Iceland (ISL)	Dem. Rep. of Congo (COD)
Ireland (IRL)	Egypt (EGY)
Israel (ISR)	Hungary (HUN)
Italy (ITA)	India (IND)
Japan (JPN)	Indonesia (IDN)
Korea (KOR)	Jordan (JOR)
Latvia (LVA)	Kazakhstan (KAZ)
Lithuania (LTU)	Laos (LAO)
Luxembourg (LUX)	Malaysia (MYS)
Malta (MLT)	Mexico (MEX)
Netherlands (NLD)	Morocco (MAR)
New Zealand (NZL)	Nigeria (NGA)
Norway (NOR)	Pakistan (PAK)
Portugal (PRT)	Peru (PER)
Singapore (SGP)	Philippines (PHL)
Slovak Republic (SVK)	Poland (POL)
Slovenia (SVN)	Romania (ROU)
Spain (ESP)	Russia (RUS)
Sweden (SWE)	Saudi Arabia (SAU)
Switzerland (CHE)	Senegal (SEN)
United Kingdom (GBR)	South Africa (ZAF)
United States (USA)	Thailand (THA)
	Tunisia (TUN)
	Türkiye (TUR)
	Ukraine (UKR)
	United Arab Emirates (ARE)
	Vietnam (VNM)