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Implications for Climate Change Preparation

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Abstract[*]

Climate change adaptation efforts are heavily dependent on a country's fiscal capacity and the associated costs of undertaking adaptation policies. The current accumulation of high debt levels in emerging and low-income developing countries, which are disproportionately affected by climate change, raises significant concerns. This study shows that sovereign risk, and hence funding costs for governments, exhibits significantly asymmetric reactions to its determinants across the conditional distribution of credit spreads. This aspect, previously overlooked in the literature, has relevant policy implications. Countries with elevated risk levels are disproportionately vulnerable to climate change compared to their lower-risk counterparts, especially in the short term. Notably, investing in climate change preparedness proves effective in mitigating vulnerability to climate change, in terms of sovereign risk, particularly for countries with low spreads and long-term debt (advanced economies), where readiness and vulnerability tend to counterbalance each other. However, for countries with high spreads and short-term debt, additional measures are essential as climate change readiness alone is insufficient to offset vulnerability effects in this case. Results also demonstrate that the actual occurrence of natural disasters is less influential than vulnerability to climate change in determining spreads.

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1. Introduction

Climate change poses a considerable threat to countries' macroeconomic and financial stability, as well as to development efforts of emerging and low-income economies. The ability of these economies to adapt is closely tied to their fiscal capacity and the cost of adaptation. Countries with high fiscal capacity are better positioned to implement effective mitigation and adaptation strategies. Conversely, limited fiscal capacity, prevalent in emerging markets and low-income developing economies, hinders their adaptation efforts, amplifying their vulnerability to climate change—a vulnerability that surpasses that of advanced economies (Bolton et al., 2022). This study examines how sovereign risk spreads and, consequently, the cost of national funding, respond to vulnerability and preparedness to climate change, while recognizing the different dynamics expected from emerging, low-income, and advanced economies.

Sovereign debt determinants, as outlined in the existing literature, encompass macroeconomic, institutional, external sector, and fiscal factors, along with natural disasters and climate change-related fundamentals. We present a novel and comprehensive empirical framework that makes it possible to evaluate the effects of these variables across the entire conditional spread distribution, thereby facilitating a more precise analysis of debt dynamics, which are inherently nonlinear. The nonlinearity primarily stems from the fact that the impacts of vulnerability, preparedness, and other determinants are not uniform across the spread distribution. This is evident, as we anticipate that the adverse effects of climate change will disproportionately affect countries with initially higher spreads and reliance on mainly short-term debt.

As anticipated, our findings indicate that climate change vulnerability becomes notably significant for shorter maturities, especially those equal to or less than two years. This impact is particularly pronounced for countries with a high-risk profile that experience elevated borrowing costs in the global debt market. Our results highlight the importance of international efforts aimed at addressing the repercussions of climate change, where such initiatives should recognize the distinct impact of climate change on interest payments for debt, especially for emerging and low-income countries, as the world undergoes a global ecological transition.

This study expands the existing body of research that empirically models sovereign risk and sovereign yields and, in particular, the recent literature that investigates the impact of climate change and natural disasters in sovereign risk. Literature in the former set typically emphasizes the significance of fiscal discipline and long-term growth in mitigating sovereign risk and reducing spreads, especially over the long run. According to this literature, in the long term, fundamental factors such as the debt-to-GDP ratio significantly shape market sovereign bond spreads, whereas in the short term, financial volatility becomes a dominant determinant (Bellas et al., 2010; Poghosyan, 2014). Other traditional factors influencing sovereign yields include local and foreign monetary policy conditions, local inflation rates, deficit-to-GDP ratios, terms-of-trade and their volatility, fiscal variables and political factors, alongside the quality of domestic institutions, among others (see, for instance, Afonso and Jalles, 2019; Arora and Cerisola, 2001; Beqiraj, Patella, and Tanzioni, 2021; Brooks, Cunha, and Mosley, 2022; Caggiano and Greco, 2012; Chatterjee and Eyigungor, 2019; Dailami, Masson, and Padou, 2008; De Santis 2020; Eichler, 2014; Hilscher and Nosbusch, 2010; Krishnamurthy, Nagel, and Vissing-Jorgensen, 2018; Liu and Spencer 2013; Mati, Baldacci, and Gupta, 2008; Matsumura and Machado, 2010).

Our contribution to this literature is straightforward. We are the first to consider a nonlinear relationship between the explanatory factors outlined above and the sovereign spreads, governed by the level of the spread, that is, according to the level of sovereign risk itself. Although our postulate is innovative, it firmly aligns with the established tradition in the field of distinguishing emerging (and low-income) economies from developed economies when analyzing sovereign risk. Notably, when sovereign risk is examined in advanced economies, the spread is termed as a "convenience yield" (Du and Schreger, 2016; Du, Im, and Schreger, 2018), as the dynamics of spreads are anticipated to diverge when they are high compared to when they are low. Addressing this distinction directly, we employ panel quantile models, demonstrating that certain determinants of spreads hold more relevance for different segments of the spread distribution, while others are virtually unimportant at specific quantiles. At the same time, our model refrains from establishing arbitrary distinctions between countries, particularly in terms of categories like “advanced,” “emerging,” or “low income,” which lack solid economic grounds. In short, we postulate that the different dynamics observed in the data are associated with the level of risk, rather than with some ambiguous country characteristics.

Given the predominant role of external influences on sovereign risk, a subset of research has probed the impact of financial and trade openness on sovereign spreads (Maltritz, 2012; Maltritz and Molchanov, 2014) and the importance of considering the high commonality in international debt markets when modeling sovereign spreads (Gilchrist et al., 2022; Gomez-Gonzalez, Uribe, and Valencia, 2023a; Liu and Spencer, 2013; Longstaff et al., 2011). To this literature we own the inclusion of a common international factor in our models. We empirically assess the impact of external factors on country-specific risk and demonstrate that this factor, which we estimate ourselves, remains consistently significant, irrespective of the segment of the spread distribution analyzed or the maturity of the spread. To the best of our knowledge, we are the pioneers in undertaking such an analysis.

Our research also is related to a branch of the literature that explores how different maturities of sovereign yields and spreads respond to economic shocks. Theoretically, long-term interest rates reflect expectations about a government’s future solvency and financing needs, while short-term rates indicate concerns about liquidity and short-term performance outlooks (Eichler and Maltritz, 2013; Freixas and Rochet, 2008). The composition of long-term and short-term debt is crucial, especially for emerging market economies, with long-term debt acting as a safeguard against interest-rate spread fluctuations and short-term debt encouraging prompt repayment (see Arellano and Ramanarayanan, 2012; Sánchez, Sapriza, and Yurdagul, 2018). Notably, Eichler and Maltritz (2013) delve into the factors influencing government bond yield spreads. Their findings indicate that low economic growth and greater economic openness amplify default risk across all maturity levels, while heightened indebtedness exclusively heightens short-term risk. We conduct our analysis for different maturities as well and find that the effects of most of the variables are greater in short-term maturities, especially for the highest quantiles of the spreads.

The second set of studies to which we contribute, which analyzes the impacts of climate change preparation and vulnerability and natural disasters on sovereign risk, is still in its infancy. Notable contributions have recently been made by Bolton et al. (2022) and Klusak et al. (2023) from a policy-oriented perspective and Mallucci (2022) from a theoretical standpoint that explicitly incorporates natural disasters and climate change risk into a traditional framework of sovereign debt price determination in the vein of Hatchondo and Martinez (2009) and Chatterjee et al. (2023).

Bolton et al. (2022) offer a comprehensive overview of the literature linking sovereign debt and climate change risk, examining various dimensions of the interplay between climate and debt. Their analysis involves an exploration of the financial costs associated with climate adaptation and potential fiscal constraints that may impede the implementation of such adaptation measures. Additionally, they investigate the role of green bonds in financing climate adaptation and assess whether a premium, known as a "greenium," exists in the sovereign debt market for environmentally friendly initiatives. Notably, their findings reveal the absence of a greenium. From the policy perspective, several other organizations, including the Inter-American Development Bank, the International Monetary Fund, and the United Nations, have contributed substantially to this body of work (e.g., Aligishiev, Massetti, and Bellon, 2022; Buchner et al., 2021; Buhr et al., 2018; Delgado, Eguino, and Lopes, 2021; Powell and Valencia, 2023; Voltz et al., 2020). In a nutshell, these reports shed light on the challenges and opportunities faced by both developed and emerging economies as they grapple with the consequences of climate change through fiscal and policy measures. They employ diverse research methodologies, including interviews, surveys of finance ministers and other key stakeholders, and data from a wide array of sources, including national statistics on emissions, energy sources, and fiscal revenue derived from fossil fuel sales. Subsequently, this information is harnessed to project potential scenarios of GDP and fiscal losses due to climate change risks, both from physical impacts and transition-related changes.

Together, these reports offer an ample understanding of fiscal policies and global initiatives addressing climate change. However, it is important to note that these recommendations can at times be overly broad and may not fully recognize the asymmetrical fiscal constraints faced by countries, especially the most vulnerable ones, as highlighted by Kose et al. (2022). In contrast, our models enable a detailed exploration of the impact of climate change preparation and mitigation strategies, alongside the countries' vulnerability, on the determination of borrowing costs in international debt markets for specific levels of risk. Our results also encompass a substantial set of countries, considerably larger than in most previous studies (N=68). This significantly extends previous research in this realm, notably Beirne et al. (2021), by providing comparative estimates of the effects conditional on various spread levels as explained before, and by incorporating the role of international commonality, economic complexity, and natural disasters in the analysis, alongside other relevant factors. Those factors, although crucial in theory, have thus far been absent from both the academic and the policy literature on sovereign yield determination.

Our analysis reveals distinct responses of sovereign spreads to their determinants, particularly in relation to their preparedness and vulnerability to climate change. These responses vary significantly based on whether the spreads are situated at the upper end (0.9 quantile of the spread distribution) or the lower end (0.1 quantile of the spread distribution). For instance, an increase (of a one-unit standard deviation) in the climate vulnerability index of the Notre Dame Global Adaptation Initiative (ND-GAIN) is associated with a proportional rise of 27 percent (14 percent) in the 90^{th} quantile of the 2-year spread (1-year spread). In contrast, the same increment only leads to a 7 percent increase in the 10^{th} quantile, where low-risk countries are concentrated, for both the 2-year and 1-year spreads.[1] Interestingly, this trend reverses for longer maturities. The same increment does not impact the spreads at the 90^{th} and 50^{th} percentiles but influences only the 10^{th} percentile, resulting in an approximately 13-14 percent increase in each case, for the 5-year and 10–year maturity, respectively. This suggests that climate change vulnerability is predominantly factored into short-term considerations for high-risk

[1] All effects have been scaled to allow for meaningful comparisons. In the text, percentages in the spreads are assessed as a proportion of a one-unit standard deviation of the spreads, spanning between 70 and 100 basis points based on maturity. Reverting to the original units magnifies the described effect in absolute terms, as the 2-year spread houses the highest variance of all spreads in our sample (Table 1).

countries (and high-risk periods), whereas it becomes a structural consideration for low-risk countries (and low risk- periods).

All in all, our results point to a highly asymmetric impact of climate change on emerging and low-income developing countries compared to developed countries, without imposing the distinction to start with. Essentially, our findings highlight that the effects of vulnerability to climate change disproportionately impact high quantiles of the spread distribution, representing countries facing significant credit restrictions during periods of scarce credit supply in international sovereign debt markets. Furthermore, we establish that asymmetric responses across the spread distribution to determinants extend beyond those associated with climate change. Factors such as inflation, terms of trade, the debt-to-GDP ratio, economic complexity (a measure of export quality and diversified productive structures), natural resource rents, and institutional quality all exert distinct impacts on government borrowing costs, contingent on the spread level or, in other words, the level of sovereign risk.

Our models also incorporate the occurrence of natural disasters into the determination of sovereign spreads. We demonstrate that, overall, spreads predominantly react to vulnerability and readiness to climate change as a general concept, rather than the actual occurrence of natural disasters. Nevertheless, including variables accounting for natural disasters enhances the overall model fit, aligning with theoretical expectations, particularly at longer maturities, such as 5 and 10 years. When significant, the effects of natural disasters vary based on how they are measured. Specifically, economic losses resulting from natural disasters increase spreads, while the number of people exposed to disasters reduces the spreads. We conjecture that natural disasters associated with substantial human losses are generally linked to international humanitarian aid, increasing resource flows to affected countries and mitigating credit risk concerns. Conversely, when disasters primarily entail economic losses, the risk outlook consistently increases, leading to larger spreads. In all cases, the effects of natural disasters are relatively modest compared to those of vulnerability and readiness to climate change indicators.

Our results complement those reported by Klusak et al. (2023), who focused on the effect of climate change on sovereign risk through the macroeconomic environment. In contrast, our study is specifically concerned with the direct impact of natural disasters on sovereign debt, controlling for macroeconomic conditions, institutional and fiscal variables, to isolate the direct effects of natural disasters on sovereign debt.

The remainder of this document is structured as follows. Section 2 outlines our empirical strategy, which centers around a novel panel quantile regression framework. While widely used in statistical medicine, it is a pioneering approach in economics. We enhance this model by incorporating common unobservable factors typical in macroeconomics, labeling it a factor-augmented panel quantile regression. Additionally, in this section, we introduce the random forest, a machine learning algorithm utilized for imputation, enabling a substantial expansion of our sample size compared to prior literature. Section 3 details our data, and Section 4 presents our main results, including imputation outcomes, main results, and models that account for the incorporation of natural disasters. Section 5 concludes.

2. Empirical Strategy

Our methodology consists of two parts. The first is the Random Forest (RF) (Breiman, 2001), the machine-learning algorithm employed for the analysis of missing values in the yield spreads. Our RF utilizes an extensive dataset encompassing macroeconomic, institutional, and debt-related variables, all of which are theoretically expected to be associated with sovereign yield spreads. These variables are fed to the model, enabling the accurate and theoretically consistent forecasting of missing data points. The data section includes detailed descriptions of the variables used in the imputation results, along with information about the imputed spreads and the subset of variables used to model the quantiles of the spreads in the main results section.

Regarding the latter, from a methodological standpoint, we build upon existing literature proposing longitudinal quantile models that incorporate fixed effects, that is, country/individual specific effects (e.g., Alfó et al., 2017; Geraci and Bottai, 2007, 2014; Koenker, 2004; Marino, Tzavidis, and Alfò, 2018). Our approach offers greater flexibility than employing dummy variables for each individual effect and allows for efficient estimation via maximum likelihood using mixture-distributions with fixed unobserved effects developed by the previous literature in statistical medicine.

In addition to the traditional specification, we augment our model with a time-varying market factor recovered from the observed cross-section of the yield spreads. This inclusion aims to capture the macroeconomic forces that simultaneously impact all spreads over time. This step is of utmost importance, as neglecting this general factor may result in biased estimates, as demonstrated in previous literature on global vector autoregressions (see Chudik and Pesaran, 2014; Pesaran et al., 2004) and in the case of quantile models, as indicated by Harding et al. (2020). Our factor is constructed using principal component analysis (PCA) following the insights from the dynamic factor models literature instead of cross-sectional averages (see Bai and Ng, 2008, and Bai and Wang, 2015, for reviews). This is more flexible because it allows us to test the sensitivity of our results to the inclusion of more than one factor, which can be used as if they were purged from measurement error in subsequent regressions once they are estimated (Bai and Ng, 2002, Stock and Watson, 2002, 2011).

2.1. Model for Imputation

Sovereign yields are readily accessible for numerous countries over the years, through sources like Bloomberg or Refinitiv. However, datasets encompassing yields for diverse maturities across a broad set of countries often house a considerable number of missing observations. This issue manifests in some countries having information for certain maturities but lacking it for others, while others may lack information entirely for specific years.

The conventional approach in economics involves excluding countries with missing observations and working exclusively with the remaining subset. Notably, previous literature on constructing currency-adjusted credit risk statistics, such as Du and Schreger (2016) and Du, Im, and Schreger (2018), limits its focus to a subset of countries with relatively complete data, restricting the inclusion to no more than 28 countries in their analysis.

A crucial aspect is that the missing values in such datasets are not distributed at random. Consequently, developed countries are overrepresented in datasets restricted to those with high-quality data. This presents a challenge in credit risk analysis, as countries lacking full information are essential for drawing conclusions regarding default risk and credit stress episodes. This motivates the original authors to refer instead to "convenience yields" with respect to the United States instead of credit spreads. However, the main motivation in the vast majority of studies, like ours, continues to be the study of credit risk.

Recognizing the importance of maximizing the dataset size for our sovereign risk models, which aim to examine various segments of the sovereign spread distributions from high-risk to low-risk markets, we follow a machine learning approach, RF. RF is a versatile ensemble learning model widely popular in artificial intelligence (AI) for both classification and regression tasks. During training, it constructs numerous decision trees, and the ensemble output is the mode (classification) or mean (regression) prediction of the individual trees. The randomness stems from each tree being trained on a random subset of features and a random subset of the training data. This randomness diminishes correlation among the trees, resulting in a more robust and accurate ensemble model.

Notably, RF has demonstrated strong performance compared to more sophisticated alternatives such as Deep Learning (LeCun, Bengio, and Hinton, 2015), in economic-financial datasets. This is particularly due to the prevalence of tabular data in economics which, moreover, is distinct from the considerable larger datasets typically encountered in AI applications in computer vision and natural language processing (Gu, Kelly, and Xiu, 2020).

Our RF is trained on an extensive dataset encompassing rich information on various variables for numerous countries throughout the sample period, from 2000 to 2019. Leveraging the well-established high correlation of credit risk across countries, we incorporate previously identified variables from the literature that exhibit correlations with spreads. In summary, we meticulously select 66 variables aimed at describing spread dynamics in time and across countries. These variables include dummy variables indicating a country's adherence to a fiscal rule, the existence of a fiscal or output crisis in a given year, and the quality of the fiscal rule, among others. Additionally, continuous variables such as real GDP growth rate, inflation, consumption share, the VIX in international markets, and an extensive array of debt-related variables (e.g., revenues, fiscal balances, interest paid by debt, and credit ratings by international agencies) are considered. The inclusion extends to various institutional variables, such as the rule of law, regulatory quality, voice and accountability, and political factors that potentially influence spreads, such as fractionalization or polarization indices. A comprehensive list of these variables can be found in the Appendix, Table A1.

In essence, these selected variables are expected not only to accurately characterize spreads for countries in years with some missing data points but also to predict spreads entirely in cases where data are absent for certain maturities. Within the same dataset, we incorporate information on all available maturities (beyond 10 years) and the spreads estimated by Du et al. (2016, 2018), capitalizing on the documented high correlation among sovereign risk measurements in international markets, as previously explored by the literature (see, for instance, Gomez-Gonzalez, Uribe, and Valencia, 2023a).

Random Forest

Using RF to complete missing values in a dataset involves employing the algorithm in a predictive modeling framework, where the missing values are treated as the target variable. We follow the approach exposed by Stekhoven and Bühlmann (2012). The strength of the RF algorithm lies in its ability to effectively handle complex and nonlinear relationships within the data. Its ensemble nature not only mitigates overfitting but also makes it versatile and less susceptible to noise. In comparison to recent algorithms like the Tall-Wide estimator by Cahan, Bai, and Ng (2023) or the latent factor model by Xiong and Pelger (2023), which are based on linear factor models and PCA, RF stands out. The former, due to its construction, cannot preserve the nonlinear features of data relationships, a crucial aspect in our case. Our interest lies in different fragments of the sovereign yield spreads distributions, and RF's ability to capture nonlinear features makes it a valuable alternative to these linear-based models. The inclusion of both categorical and continuous variables in our dataset further advocates for the use of RF over the factor-based alternatives.

We assume $\mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_\mathrm{p})$ to be a $\mathrm{n} \times \mathrm{p}$ dimensional data matrix. Following Stekhoven and Bühlmann (2012), we directly predict the missing values using RF estimated on the observed variables present in the dataset. For any arbitrary variable x_s, including missing points at entries $\mathrm{i}_\mathrm{s}^{\mathrm{NA}} \in \{1, \dots, \mathrm{n}\}$ the dataset can be split into four parts: (1) the non-missing values of x_s, denoted $\mathrm{y}_\mathrm{s}^{\mathrm{obs}}$; (2) the missing observations, $\mathrm{y}_\mathrm{s}^{\mathrm{NA}}$; (3) variables different from s, with observations $\mathrm{i}_\mathrm{s}^{\mathrm{obs}} = \{1, \dots, \mathrm{n}\} \backslash \mathrm{i}_\mathrm{s}^{\mathrm{NA}}$ denoted as $\mathrm{x}_\mathrm{s}^{\mathrm{obs}}$, and (4) the variables other than x_s with observations $\mathrm{i}_\mathrm{s}^{\mathrm{NA}}$, denoted by $\mathrm{x}_\mathrm{s}^{\mathrm{NA}}$.

The RF model first makes an initial conjecture for the missing values in x, in our case the mode value. Then, it sorts the variables x_s, $s = 1, \dots, \mathrm{p}$ according to the number of missing observations. For each variable x_s the missing values are filled in by estimating a RF model with response variable $\mathrm{y}_\mathrm{s}^{\mathrm{obs}}$ and predictors the rest of the variables in a given year, $\mathrm{x}_\mathrm{s}^{\mathrm{obs}}$. Then, the algorithm proceeds by predicting the missing values $\mathrm{y}_\mathrm{s}^{\mathrm{NA}}$ by applying the estimated RF to the $\mathrm{x}_\mathrm{s}^{\mathrm{NA}}$. This procedure is repeated until a pre-specified stopping criterion is met. This stopping criterion is met when the difference between the newly imputed data matrix and the previous one increases for the first time with respect to both continuous and discrete variables. For the N continuous variables, that is:

$$\Delta_\mathrm{N} = \frac{\sum_{\mathrm{j} \in \mathrm{N}} \left(\mathrm{x}_{\mathrm{new}}^{\mathrm{imputed}} - \mathrm{x}_{\mathrm{old}}^{\mathrm{imputed}}\right)^2}{\sum_{\mathrm{j} \in \mathrm{N}} \left(\mathrm{x}_{\mathrm{new}}^{\mathrm{imputed}}\right)^2}, \tag{1}$$

while for F discrete variables it takes the form:

$$\Delta_\mathrm{F} = \frac{\sum_{\mathrm{j} \in \mathrm{F}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{I}_{\mathrm{x}_{\mathrm{new}}^{\mathrm{imputed}} \neq \mathrm{x}_{\mathrm{old}}^{\mathrm{imputed}}}}{\#\mathrm{NA}}, \tag{2}$$

where #NA is the number of missing entrances in the categorical variables.

2.2. Factor-Augmented Panel Quantile Model

Once we have completed the data for the spreads, we used the completed vectors as the response variable in a panel-quantile framework for four different maturities, 1 year, 2 years, 5 years and 10 years, separately, which become $y_{it}^{maturity}$ in the following presentation, where we will omit the superscript to avoid unnecessary notation. Abrevaya et al. (2008) and Koenker (2004), among others, have extended panel quantile models to longitudinal contexts. In their approach, the dynamics of the τ-quantile of the dependent variable are characterized by the following equation:

$$Q_\tau(y_{it}|b_i, \beta, x_{it}) = b_i + x_{it}'\beta_\tau, \tag{3}$$

where, for a given quantile $\tau \in (0,1)$, β_τ summarizes the relationship between the explanatory variables x and the τ-th response quantile, for a country whose spread baseline level is equal to b_i. x consists of some key indicators previously identified by the literature on sovereign risk, including the inflation rate, real growth, the terms of trade of the country, the economic complexity indicator, the debt-to-GDP ratio, natural resource rents as a percentage of GDP, and the Rule of Law indicator. Crucially, x also contains vulnerability and readiness indicators, which both add up to the ND-GAIN indicator, which assess a country's exposure to and socio-economic capacity to face climate change and will be explained in detail in the next data section. The model in equation 3 is akin to traditional panel data models of the yield spreads and can be equivalently written as:

$$y_{it} = b_i + x_{it}'\beta_\tau + \varepsilon_{it}, \tag{4}$$

where, $Q_\tau(\varepsilon_{it}\,|b_i, \beta, x_{it}) = 0$. There are two distinct approaches to estimate such (conditional) quantile regression in longitudinal data, with a distinction between distribution-free methods and likelihood-based methods. In the distribution-free approach, fixed individual-specific intercepts are considered, treated as location shift parameters common to all conditional quantiles. This implies that the conditional distribution for each individual has the same shape but different locations, as long as the b_i's are different. Koenker (2004) introduced fixed effect quantile regression for longitudinal data in this vein. In contrast, within the likelihood framework, individual-specific parameters b_i's are assumed to be independent and identically distributed random variables. This framework effectively allows for explaining differences in the response variables across individuals (countries) and quantiles (different spread levels, associated with varying degrees of sovereign risk). It also allows us to introduce into our model, in the last section of our results, dummy variables that measure different dimensions of the occurrence of natural disasters in a given country, in a given year, within our sample period, in a parsimonious and natural way.

Let $b_i = (b_{i1}, \dots, b_{i\tau})$ represent a τ-dimensional vector of individual random parameters, which density is given by $f_b(\cdot; D_\tau)$. D_τ is covariance matrix dependent on τ. In such a case, a linear quantile mixed model is defined as follows:

$$Q_\tau(y_{it}|b_i, \beta, x_{it}, z_{it}) = x'_{it}\beta_\tau + z'_{it}b_i, \quad (5)$$

where z_{it} denotes an additional set of variables. In the simplest case, followed in our baseline model, z_{it} can be set to a vector of ones, which specifies time fixed effects per country, defined over the mixture densities $f_b(\cdot; D_\tau)$. Or z_{it} may account for the natural disaster variables as well, like in our final model specification (section 4.3).

The random structure of b_i in equation 5 enables the consideration of between-individual heterogeneity without necessitating orthogonality between the observed and omitted covariates (Geraci and Bottai, 2014; Marino and Farcomeni, 2015). Alternatively, the equation above can be written as follows:

$$y_{it} = x'_{it}\beta_\tau + z'_{it}b_i + \varepsilon_{it}, \quad (6)$$

where, $Q_\tau(\varepsilon_{it}\, |b_i, \beta, x_{it}, z_{it}) = 0$. Recall that b_i is a vector of country- and quantile-specific random coefficients which account for unobserved heterogeneity that is not captured by the elements in x_{it} and describe the dependence between repeated measurements from the same country/unit over the time. Moreover, for a given quantile level τ, y_{it} is assumed to have an Asymmetric Laplace Density (ALD) (e.g., Yu and Moyeed, 2001) given by:

$$f_{y|b}\left(y_{it}|b_{i,\tau}; \tau\right) = \left[\frac{\tau(1-\tau)}{\sigma_\tau}\right] \exp\left\{-\rho_\tau\left[\frac{y_{it}-\mu_{it,\tau}}{\sigma_\tau}\right]\right\}. \quad (7)$$

where, $\rho_\tau(\cdot)$ denotes the quantile asymmetric loss function (Koenker and Bassett, 1978), while σ_τ, and $\mu_{it,\tau}$, stand for the scale location parameters of the distribution, respectively. All in all, the ALD facilitates maximum likelihood estimation. Furthermore, the location parameter $\mu_{it,\tau}$ is modeled as follows:

$$\mu_{it,\tau} = x'_{it}\beta_\tau + z'_{it}b_i. \quad (8)$$

The modeling strategy is completed by the mixing distribution $f_b(\cdot; D_\tau)$ introduced before. At this point, instead of specifying a distribution parametrically, Alfó, Salvati, and Ranalli (2017) and Geraci and Bottai (2014) proposed estimating it directly from the data via a Non-Parametric Maximum Likelihood approach (NPML). This leads to the estimation of a quantile-specific discrete mixing distribution defined over the set of locations $\{\zeta_1, \dots, \zeta_{g,\tau}\}$, with mixture probabilities

$\pi_{g,\tau} = Pr(b_i = \zeta_{g,\tau})$, $i = 1,\ldots,n$, $g = 1,\ldots,G_\tau$, and $G_\tau \leq n$. Following this proposal, the location parameter of the ALD in equation (8) becomes $\mu_{it,\tau} = x_{it}'\beta_\tau + z_{it}'\zeta_{g,\tau}$, and the likelihood for estimation is defined accordingly as follows:

$$L(\cdot|\tau) = \prod_{i=1}^{n} \sum_{g=1}^{G_\tau} \left[\prod_{t=1}^{T_i} f_{y|b}\left(y_{it}|b_{i,\tau} = \zeta_{g,\tau};\tau\right)\right] \pi_{g,\tau}. \quad (9)$$

Left to include are the time-varying common factors that measure global macroeconomic forces that are expected to influence all debt maturities and spreads for all countries at the same time, but in a distinctive fashion. Doing so equation 6 above can be written as follows:

$$y_{it} = a_i f_t + x_{it}'\beta_\tau + z_{it}'b_i + \varepsilon_{it}, \quad (10)$$

where, f_t has dimensionality $k = 1$ in our baseline model, and it is estimated via PCA in a preliminary step. Note that the inclusion of this time-varying factor is a valid and parsimonious alternative to explicitly including in the model general macro-forces such as the VIX, oil prices, uncertainty, world interest rates, TED spreads, and other proxies for global financial cycles, inflation cycles, or commodity cycles, as far as this single factor adequately captures the variation in the common dynamics affecting sovereign credit spreads globally. While this is trivially true when $k = n_{countries}$, it holds only approximately when $k = 1$. The quality of this approximation is determined by the percentage of variance explained by the first principal component in the factor model of credit spreads. In our case, the first factor accounts for 42.8 percent of the variability in the 272 series of spreads (4 for each of the 68 countries), demonstrating a remarkably high explanatory power and validating our factor-based approach. We also assess the sensitivity of our model to the inclusion of a second factor and other modeling choices. Our results remain unaltered in this case.

We conclude this section by underlining the essential role of panel quantile models in estimating the direct effects of economic and climate-related determinants on spreads, similar to traditional panel models. In a longitudinal setting, panel-like structures enable the modeling of unobserved heterogeneity between countries. Ignoring this heterogeneity would lead to biased estimates of quantile effects. The inclusion of the factor structure is driven by the need to tailor the methodology from a statistical medicine context to an international macroeconomic setting. This adjustment is essential given the well-documented presence of risk commonality across countries not only in terms of sovereign risk, but also across any given economic fundamental.

3. Data

This study uses two datasets. The first dataset, which we call the main dataset, is the one used in our main regression results in Section 5.2. This section contains the panel-quantile models explained in Section 3.2. The second dataset consists of 66 additional variables in three dimensions, macroeconomic, debt-related and institutional/political variables which help us to train the RF, as explained in Section 3.1. The results of this imputation exercise are described in detail in Section 5.1 of the results.

3.1. Main Regression Variables

Table 1 shows the variable description, variable short-name, source of information, mean, median standard deviation, maximum and minimum values of our main variables, while Table 2 consists of the country names, ISO-3 codes, and whether a country is considered to be advanced or otherwise. Only the spreads contain imputed observations in Table 1. The yields for different maturities were downloaded from Bloomberg. As the table shows, there is significant variability in the spreads, as highlighted by the substantial disparities between the maximum and minimum spread values across various maturities. The broad spread variation reflects the diversity among the countries included in the sample.

Table 1. Summary of Main Variables Statistics

Indicator	Abreviation	Source	Mean	Median	Std.Dev	Max.	Min.
Value sovereign spread with respect to the US 1 year maturity	ValSpread_1Y	Bloomberg- own elaboration	4.78	3.22	6.95	90.51	-5.88
Value sovereign spread with respect to the US 2 years maturity	ValSpread_2Y	Bloomberg- own elaboration	5.47	2.79	10.62	108.47	-5.86
Value sovereign spread with respect to the US 5 years maturity	ValSpread_5Y	Bloomberg- own elaboration	4.72	2.87	7.4	95.7	-5.08
Value sovereign spread with respect to the US 10 years maturity	ValSpread_10Y	Bloomberg- own elaboration	4.4	2.51	7.31	92.62	-4.22
The number of people affected > 100.000 a year	ndisaster1	EMDAT	0.22	0	0.42	1	0
The number of deaths > 1,000 a year	ndisaster2	EMDAT	0.03	0	0.17	1	0
Economic damage is > 2% of GDP	ndisaster3	EMDAT	0.01	0	0.1	1	0
At least one of the three conditions above is met	ndisaster	EMDAT	0.23	0	0.42	1	0
ndisaster 1 is met and there are weather disasters	ndisaster1_weather	EMDAT	0.22	0	0.41	1	0
ndisaster 1 is met and there are geophysical disasters	ndisaster1_geophysical	EMDAT	0.08	0	0.28	1	0
ndisaster 2 is met and there are weather disasters	ndisaster2_weather	EMDAT	0.03	0	0.17	1	0
ndisaster 2 is met and there are geophysical disasters	ndisaster2_geophysical	EMDAT	0.02	0	0.13	1	0
ndisaster 3 is met and there are weather disasters	ndisaster3_weather	EMDAT	0.01	0	0.09	1	0
ndisaster 3 is met and there are geophysical disasters	ndisaster3_geophysical	EMDAT	0.01	0	0.09	1	0
At least one of the three conditions above is met for weather ndisaster#_weather	ndisaster_weather	EMDAT	0.23	0	0.42	1	0
At least one of the three conditions above is met for weather ndisaster#_geophysical	ndisaster_geophysical	EMDAT	0.08	0	0.28	1	0
Natural resources rents as % of GDP	rents	WEO-IMF	2.66	0.4	5.48	43.08	0
Rule of law	rle	World Bank	0.54	0.52	0.93	2.13	-1.43
Terms of trade change in %	tot	WEO-IMF	102.35	100	15	183.84	30.73
Real GDP growth	growth	WEO-IMF	3.65	3.59	3.49	28.08	-15.1
Inflation rate,	inf_avg	WEO-IMF	4.32	2.9	5.01	55.04	-4.87
Gross debt as % of GDP, general government	debt	WEO-IMF	56.02	46.35	36.81	260.96	3.82
Readiness Indicator	readiness	ND-Gain Web Page	0.5	0.48	0.14	0.81	0.2
Vulnerability Indicator	vulnerability	ND-Gain Web Page	0.39	0.38	0.08	0.6	0.25
Economic Complexity Indicator	eci	Harvard Growth Lab Web Page	0.58	0.58	0.9	2.82	-2.34

Note: The table shows the main variables used in this study, the variables' description, sources of information, and summary statistics in the five right-hand columns.
Source: Authors' elaboration.

Table 2. Countries Included in the Sample

#	Country name	ISO3	Advanced	Emerging/ low-income	#	Country name	ISO3	Advanced	Emerging/ low-income
1	Australia	AUS	1	0	35	Korea	KOR	1	0
2	Austria	AUT	1	0	36	Lebanon	LBN	0	1
3	Belgium	BEL	1	0	37	Sri Lanka	LKA	0	1
4	Bangladesh	BGD	0	1	38	Lithuania	LTU	1	0
5	Bulgaria	BGR	0	1	39	Latvia	LVA	1	0
6	Brazil	BRA	0	1	40	Morocco	MAR	0	1
7	Botswana	BWA	0	1	41	Mexico	MEX	0	1
8	Canada	CAN	1	0	42	Mauritius	MUS	0	1
9	Switzerland	CHE	1	0	43	Malaysia	MYS	0	1
10	Chile	CHL	0	1	44	Namibia	NAM	0	1
11	China	CHN	0	1	45	Nigeria	NGA	0	1
12	Colombia	COL	0	1	46	Netherlands	NLD	1	0
13	Costa Rica	CRI	0	1	47	Norway	NOR	1	0
14	Cyprus	CYP	1	0	48	New Zealand	NZL	1	0
15	Czech Republic	CZE	1	0	49	Pakistan	PAK	0	1
16	Germany	DEU	1	0	50	Panama	PAN	0	1
17	Denmark	DNK	1	0	51	Peru	PER	0	1
18	Egypt	EGY	0	1	52	Philippines	PHL	0	1
19	Spain	ESP	1	0	53	Poland	POL	0	1
20	Finland	FIN	1	0	54	Portugal	PRT	1	0
21	France	FRA	1	0	55	Qatar	QAT	0	1
22	United Kingdom	GBR	1	0	56	Romania	ROU	0	1
23	Greece	GRC	1	0	57	Russia	RUS	0	1
24	Croatia	HRV	0	1	58	Singapore	SGP	1	0
25	Hungary	HUN	0	1	59	Slovak Republic	SVK	1	0
26	Indonesia	IDN	0	1	60	Slovenia	SVN	1	0
27	India	IND	0	1	61	Sweden	SWE	1	0
28	Ireland	IRL	1	0	62	Thailand	THA	0	1
29	Iceland	ISL	1	0	63	Turkey	TUR	0	1
30	Israel	ISR	1	0	64	Uganda	UGA	0	1
31	Italy	ITA	1	0	65	Ukraine	UKR	0	1
32	Japan	JPN	1	0	66	Vietnam	VNM	0	1
33	Kazakhstan	KAZ	0	1	67	South Africa	ZAF	0	1
34	Kenya	KEN	0	1	68	Zambia	ZMB	0	1

Note: The table shows the countries included in our sample, with their respective ISO3 codes and a dummy variable of whether they are advanced or otherwise in terms of development. They appear in alphabetical order according to the ISO3 codes.
Source: Authors' elaboration.

The minimum spread is negative across all maturities. This phenomenon is primarily due to the inclusion of countries such as Germany, Japan, and the United Kingdom, which have sometimes exhibited lower sovereign spreads than those of the United States throughout the sample period. Most of the remaining countries have consistently maintained positive spreads, with some emerging nations exhibiting high spreads. The average spreads are notably higher in the short term (especially the 2-year spreads) compared to the medium (5-year) and long-term (10-year) maturities.

As can be seen in Table 2, our sample consists of 68 countries, roughly 44 percent of which are advanced and the remaining 56 percent are emerging or low-income developing nations. Our country sample is larger than the previous samples. It represents an increase of 70 percent compared to the 40 countries in Beirne et al. (2021), and 1.4 times the dataset available from Du and Schreger (2016) and Du, Im, and Schreger (2018). It also includes earlier years, as it starts in 2000. Our analysis excludes the years 2020 and 2021, for most data are readily available due to the extraordinary disruptions caused by the COVID-19 pandemic, which significantly influenced international debt market dynamics in a way orthogonal to our interests (see, for example, Candelon and Moura, 2023).

3.1.1. Macroeconomic, Fiscal, Institutional Covariates, and Natural Disasters

Consistent with prior research, we address potential confounding factors by incorporating several macroeconomic, fiscal, and institutional covariates into our empirical model. Table 1 also provides descriptive statistics for these variables, presenting information such as their source, mean, median, standard deviation, maximum, and minimum values.

We additionally incorporate binary variables that take the value of 1 when a country experiences a natural disaster in a specific year, according to a variety of criteria. This set of variables offers valuable insights, as countries that have endured natural disasters could be more susceptible to climate risk vulnerabilities. Moreover, the repeated exposure to such disasters may incentivize a country to enhance its preparedness for future occurrences.

The variables measuring the occurrence of weather disasters were retrieved from the EMDAT (or EM-DAT), the international disasters database. The rents resulting from natural results exploitation, real growth, inflation, terms of trade, and debt-to-GDP ratio were obtained in different public datasets by the International Monetary Fund, among them the World Economic Outlook, 2019. The Rule of Law estimate was extracted from the World Development Indicators of the World Bank. The Economic Complexity Indicator (ECI) comes from the Harvard Growth Lab, which reports the ECI index developed by Hidalgo and Hausmann (2009).

3.1.2. Measuring Climate Vulnerability and Readiness For Adaptation

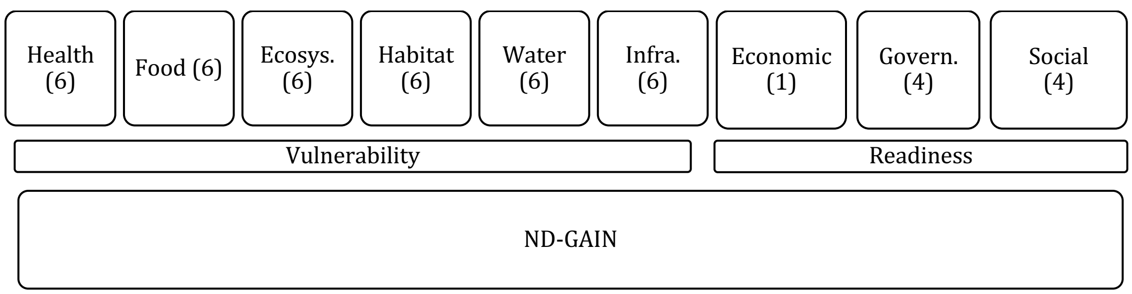
Regarding the indexes to measure vulnerability and exposure to climate change, we used those provided by the Notre Dame Global Adaptation Initiative (ND-GAIN). We employ the ND-Gain index, along with its constituent elements, to assess both climate vulnerability and the capacity for adapting to climate change. According to the ND-GAIN website, the ND-GAIN Country Index is designed to consolidate a country's susceptibility to the consequences of climate change, as well as its readiness to bolster resilience in the presence of climate-related challenges.

The primary index can be dissected into two fundamental dimensions, namely vulnerability and readiness, as illustrated in Figure 1. Vulnerability pertains to a country's predisposition to being adversely affected by climate-related hazards, while readiness signifies the nation's level of preparedness to undertake adaptive measures, incorporating responses from both the public and the private sectors.

Vulnerability indicators can be further subdivided into six life-supporting sectors: health, food, ecosystems, habitat, water, and infrastructure. Each of these is evaluated across three key dimensions: exposure, sensitivity, and adaptive capacity. Readiness, on the other hand, can be broken down into three distinct categories: economic, social, and governance. This division can be extended to yield highly actionable indicators tailored for policymakers, with the exception of exposure indicators, which lack actionable aspects.

Figure 1 presents a visual representation of the ND-GAIN country index and its constituent elements. Summary statistics for ND-GAIN indicators and their components are provided in Table 1. The readiness and vulnerability components of the ND-GAIN index are expressed on a scale from 0 to 1. A higher value on the readiness index signifies better preparedness for climate events, whereas a higher value on the vulnerability index indicates a greater likelihood of climate event occurrence. These two indexes also exhibit substantial variation. The readiness index spans from 0.20 (Nigeria in 2014) to 0.81 (Singapore in 2014) within our sample, while the vulnerability index ranges from 0.25 (Switzerland in 2015) to 0.60 (Uganda 2004). Broadly, there is a positive correlation between both the ND-GAIN and the readiness index and a country's level of development, while the correlation between the vulnerability index and development is negative.

Figure 1. Graphical Description of the ND-GAIN Country Index and Its Components



Note: This figure was adapted from the webpage of ND- GAIN. It shows the components of the ND-GAIN indicator, vulnerability and readiness, and the subcomponents of each: six sectors in the former case, and three dimensions in the latter. It also shows the number of original series that are used to construct each of the sectors and dimensions in brackets.
Source: Authors' elaboration.

3.2. Auxiliary Variables for Imputation

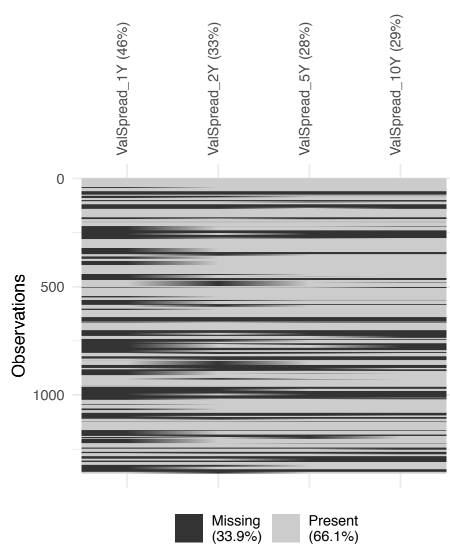
Table A1 of the Appendix displays the variables used in the RF that we train to impute the missing observations of spreads in the first part of our results. We include 66 variables, in addition to the variables unrelated to climate change from Table 1, that is, the ND-GAIN indexes and the EMDAT natural disasters dummy variables. These variables can be broadly categorized as related to debt or fiscal management, macroeconomic indicators, external sector indicators, or variables measuring the countries' institutional frameworks. The dataset also includes all maturities in our sample and the spreads available from Du et al. (2016, 2018).

4. Results

4.1. Imputation Results

We employ an RF consisting of 100 trees in each forest, sampling the square root of the number of variables (≈9) at each split, as suggested by Stekhoven and Bühlmann (2012). In Figures 2, A1, and A2 (the latter two in the Appendix), we illustrate the missing patterns in our original dataset. As depicted in Figure 1, the percentage of missing observations for spreads at various maturities ranges from 28 to 46 percent, with shorter maturities exhibiting a higher prevalence of missing values. Notably, more developed nations show almost no missing values, as evident in Figure A1. Conversely, countries such as Botswana (BWA), Mauritius (MUS), or Peru (PER) exhibit a substantial number of missing values, particularly at shorter maturities. Furthermore, the missing values are more frequently observed at the beginning of the sample period, with certain maturities in the years 2000 and 2001 lacking information for more than half of the sample.

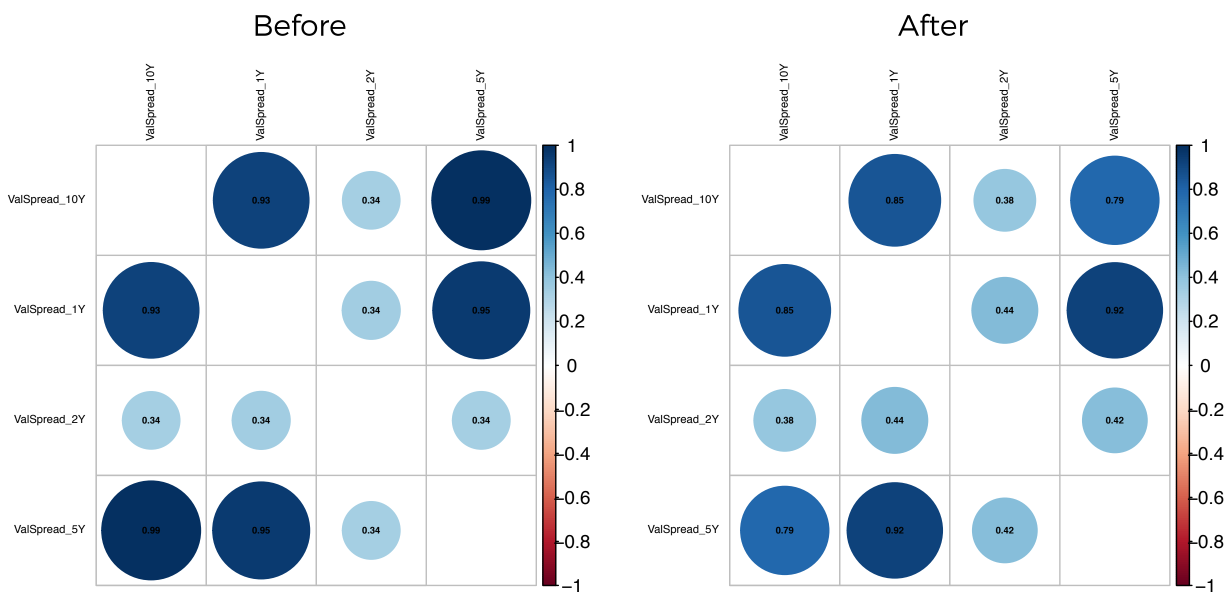
Figure 2. Missing Patterns in the Spreads Data



Note: The figure shows the frequency of missing observations for 1-year, 2-year, 5-year and 10-year maturities. Maturities with a larger amount of missing data were excluded from the analysis. The sample consists of 68 countries, and the number of years is 20, from 2000 to 2019.
Source: Authors' elaboration.

Figure 3 depicts the correlation between spreads at various maturities both before and after imputation. It is evident that the signs of the correlations remain consistently preserved. The magnitudes exhibit a slight reduction for larger correlations, such as those between spreads at 5 and 10 years, while tending to slightly increase for lower correlations, such as those between short-term maturity spreads at 1 and 2 years. Overall, the correlations suggest that the dynamics between the spread series are effectively preserved throughout the imputation process.

Figure 3. Correlation among Spreads Before and After Imputation

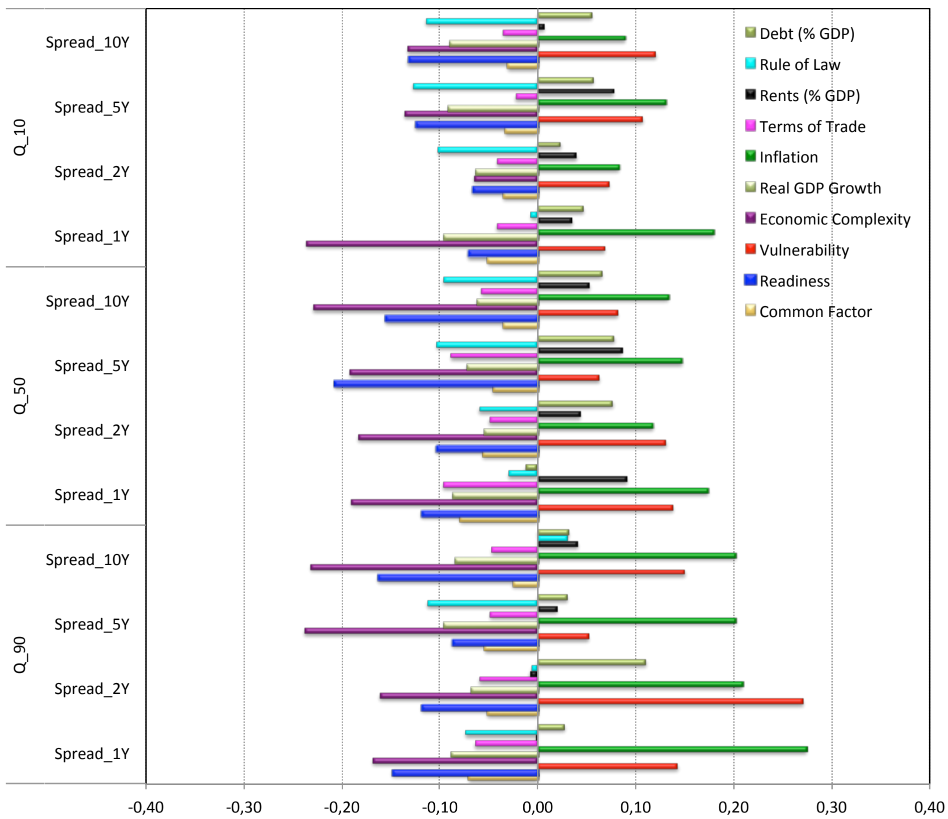


Note: The figure shows the correlation among sovereign spreads with respect to the United States for 1-year, 2-year, 5-year, and 10-year maturities, from 2000 to 2019, for a sample of 68 countries, before and after imputation of missing observations by RF.
Source: Authors' elaboration.

4.2. Main Results: Panel Quantile Factor Model

In Figure 3 and Table 3, we present our main results. Figure 3 depicts the impacts of the determinants of sovereign spreads in our model across various maturities and quantiles of the spreads distribution. Table 3 presents these effects and offers an evaluation of their statistical significance. The table includes standard errors, z-values, and p-values, computed through a block-bootstrap procedure following Alfó et al. (2023). For ease of presentation, Table 3 is divided into three panels (A to C). Panel A presents the results for short-term maturities in our sample (1 and 2 years), and Panel B for longer term maturities (5 and 10 years). Panel C contains some of the mixture distribution parameters that model the idiosyncratic effects in our panel of countries.

Figure 4. Summary of the Impact of Determinants on Sovereign Yield Spreads



Note: The figure summarizes the effects of all determinants across spreads quantiles and maturities.
Source: Authors' elaboration.

All variables were scaled to have zero mean and unitary variance before estimation, enabling a comparison of effects across variables, akin to a beta-coefficient model but for the quantiles. The variables incorporated into our model align with a broad consensus in the literature and maintain a direct connection to economic intuition and theoretical foundations, which will be explained in the following exposition of the results. Indeed, all variables demonstrate the expected signs in accordance with theoretical expectations. In summary, a higher debt-to-GDP ratio, inflation, and, notably, increased vulnerability to climate change contribute to higher spreads across all maturities. Conversely, improved institutions, measured by the

World Bank's Rule of Law estimate, higher terms of trade, greater economic complexity, and importantly, heightened preparedness for climate change adaptation (as measured by the readiness indicator of the ND-Gain), all contribute to lower spreads across all maturities.

The most pronounced effects of explanatory variables manifest in short-term maturities, particularly within the highest quantiles of spreads, as depicted in the figure and evident in the comparison of Panel A and B of Table 3. In general, the model's variables demonstrate significance across quantiles and maturities. Notably, for shorter maturities, individual variables exhibit greater explanatory power for the center and left tail of the distribution. Conversely, for longer maturities, these variables exert a more notable influence on the center and right tail. This observation is based on the identification of significant variables in each case.

The common factor consistently proves significant, underscoring the importance of incorporating the common market shocks it represents. This aligns with existing literature, which emphasizes the importance of considering the high correlations among the cross-section of sovereign debt markets (Gomez-Gonzalez, Uribe, and Valencia, 2023a). Although the effects are statistically significant, their magnitude is relatively small, ranging between -3 and -6 percent, with a slightly larger impact at the center of the distribution. The negative sign should not be construed as indicative, given that the factor was constructed using PCA. In this context, the factor is identified up to a column sign rotation, and it could be reversed without necessitating additional justification (Bai and Ng, 2008). Therefore, we interpret it merely as evidence of common market trends that must be accounted for in our model. Notably, within these maturities and quantiles, the most substantial positive effects are those associated with vulnerability to climate change and inflation.

Inflation and Debt-to-GDP Ratio

The impact of inflation on a country's sovereign risk is well documented, particularly in its erosion of the real value of bonds, with longer-term debt instruments being more significantly affected. Countries with higher inflation rates are anticipated to offer greater compensation to investors holding their government bonds, as indicated by previous literature (Buraschi and Jiltsov, 2005; Camba-Méndez, 2020; Camba-Méndez and Werner, 2017; D'Amico et al., 2018; Gürkaynak, et al., 2010; Hördahl and Tristani, 2012). Our findings support this view and expand it across all quantiles of the spread distribution, as detailed in Tables 3A and 3B. Importantly, the impact of inflation is not only consistently significant but also more pronounced at longer maturities within each quantile.

Increases in inflation often lead to an immediate improvement in debt-to-GDP ratios, potentially mitigating the overall positive causal effect of inflation on sovereign yields—a phenomenon colloquially known as "inflating debt away." Interestingly, the effect associated with the debt-to-GDP ratio, frequently emphasized in the literature (e.g., Gill 2018; Liu and Spencer 2013; Poghosyan, 2014; Wang et al., 2021), is generally non-significant at short maturities in most of our specifications. When significant, the effect is relatively modest, ranging between 8 and 11 percent (of one standard deviation in the debt-to-GDP ratio) for the median and the 90th quantile of the 2-year spread.

In this regard, our findings are the first to highlight the asymmetric effect of higher inflation on sovereign risk across different quantiles of spreads. Specifically, the impact of inflation on 1-year spreads falls from 0.27 to 0.17-0.18 when transitioning from the 90th quantile to the 50th and 10th quantiles. For the 2-year spread, this phenomenon is even more pronounced, decreasing from 0.21 to 0.12 to 0.08. In Panel B, focusing on longer maturities, the asymmetry in the effects of inflation persists, particularly evident in the 10-year maturity. The effects diminish from 0.20 to 0.13 to 0.09 as we transition from the 90th quantile to the 50th and, finally, to the 10th quantile. For these longer maturities, the influence of the debt-to-GDP ratio remains relatively modest, ranging between 6 and 8 percent of one standard deviation in spreads for the lower quantiles, when significant. This means that increments in the inflation rate of countries always increase sovereign risk, but the effect is even more pronounced when the sovereign risk is very high (90th quantile) to start with. For low-risk countries increments of the same magnitude are not equally important, in terms of risk compensation.

Vulnerability and Readiness

Sovereign risk is expected to be influenced by climate change through two primary channels. These channels can be broadly categorized within the context of physical and transition risks, as outlined by the Network for Greening the Financial System (NGFS, 2019), which assesses the implications of climate change on the financial system, and which is readily extensible to analyzing the impact of climate change on public debt and its cost. On the one hand, physical risks are associated with the occurrence and severity of extreme weather events. These have the potential to devastate both commercial and private properties, inflict damage on infrastructure, reduce agricultural yields, and impede economic growth. Furthermore, the financial burden on governments, stemming from lost tax revenues and increased expenditures for relief and reconstruction, can strain fiscal budgets (Schuler et al., 2019).

On the other hand, transition risks involve the implementation of policies aimed at fostering a climate-resilient and sustainable economy. Investments in mitigation efforts can strain public finances, and climate mitigation policies, such as carbon taxes, may have implications for revenue generation (e.g., Bachner, Bednar-Friedl, and Knittel, 2019). Moreover, as noted by Pizon et al. (2020), the value of sovereign bonds is in part contingent upon how countries manage their natural capital. The pressure to align sovereign bonds with environmental sustainability is expected to intensify in the coming decade, with a growing emphasis on sovereign bonds as a unique asset class connecting macroeconomic performance and capital markets.

In examining vulnerability and preparedness in the context of climate change and its impact on sovereign risk, we observe a distinct positive relationship between vulnerability and sovereign risk, comparable in magnitude to the effect of inflation (as measured by the scaled quantile slopes of the indicators). This association is particularly pronounced at the highest quantiles of spreads. This finding aligns with the conclusions drawn by Beirne, Renzhi, and Volz (2021), who, using a smaller country sample, a different empirical approach, and focusing on exposure to climate change risk rather than the spread level itself (as in our study), similarly find that vulnerability to climate change positively influences sovereign borrowing costs.

Notably, our study diverges from Beirne, Renzhi, and Volz (2021) in highlighting the importance of climate change readiness. Contrary to their emphasis on vulnerability, our results suggest that the positive effects of vulnerability can be offset by proportionate increases in climate change preparedness. This is evident in the effects of increments in the readiness indicator, which generally mirror the magnitude (but with opposite signs) of vulnerability effects. The only exception is the 90th quantile of the 2-year spread, where vulnerability's impact is most pronounced within our sample.

Table 3. Panel A. Determinants of Yield Spreads at Short Maturities

	Spread 1 year											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)
Common factor	-0.07	0.01	-4.89	0.00	-0.08	0.01	-8.03	0.00	-0.05	0.01	-5.90	0.00
Readiness	-0.15	0.05	-2.86	0.00	-0.12	0.06	-2.11	0.03	-0.07	0.05	-1.44	0.15
Vulnerability	0.14	0.05	2.67	0.01	0.14	0.05	2.79	0.01	0.07	0.05	1.40	0.16
Economic complexity	-0.17	0.05	-3.59	0.00	-0.19	0.04	-4.93	0.00	-0.24	0.04	-5.55	0.00
Real GDP growth	-0.09	0.02	-5.25	0.00	-0.09	0.02	-4.25	0.00	-0.09	0.02	-3.96	0.00
Inflation	0.27	0.04	6.71	0.00	0.17	0.04	4.75	0.00	0.18	0.04	5.13	0.00
Terms of trade	-0.06	0.02	-3.27	0.00	-0.10	0.02	-4.10	0.00	-0.04	0.02	-2.14	0.03
Rents (% GDP)	0.00	0.03	-0.03	0.96	0.09	0.03	3.18	0.00	0.04	0.03	1.02	0.30
Rule of law	-0.07	0.06	-1.21	0.22	-0.03	0.07	-0.40	0.67	-0.01	0.07	-0.10	0.90
Debt (% GDP)	0.03	0.04	0.73	0.46	-0.01	0.02	-0.61	0.53	0.05	0.03	1.86	0.06
	Spread 2 Years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Common factor	-0.05	0.01	-3.92	0.00	-0.06	0.01	-9.75	0.00	-0.03	0.01	-5.84	0.00
Readiness	-0.12	0.06	-2.14	0.03	-0.10	0.04	-2.32	0.02	-0.07	0.04	-1.60	0.11
Vulnerability	0.27	0.07	4.14	0.00	0.13	0.04	3.13	0.00	0.07	0.03	2.34	0.02
Economic complexity	-0.16	0.06	-2.93	0.00	-0.18	0.04	-4.43	0.00	-0.07	0.02	-3.83	0.00
Real GDP growth	-0.07	0.02	-3.61	0.00	-0.05	0.01	-3.68	0.00	-0.06	0.02	-3.40	0.00
Inflation	0.21	0.03	7.69	0.00	0.12	0.02	5.23	0.00	0.08	0.01	5.69	0.00
Terms of trade	-0.06	0.03	-2.27	0.02	-0.05	0.02	-2.17	0.03	-0.04	0.01	-2.85	0.00
Rents (% GDP)	-0.01	0.04	-0.19	0.83	0.04	0.02	2.35	0.02	0.04	0.02	2.19	0.03
Rule of law	-0.01	0.10	-0.07	0.93	-0.06	0.06	-0.98	0.32	-0.10	0.04	-2.56	0.01
Debt (% GDP)	0.11	0.05	2.43	0.01	0.08	0.02	3.39	0.00	0.02	0.02	0.98	0.32

Note: The table shows the effect of the determinants of sovereign yield spreads with respect to the US at short maturities (1 year, 2 years) and three quantiles of the spreads distribution (0.1, 0.5 and 0.9). All the variables have been scaled and have zero mean and unit variance, which makes comparison of the effects easier. Significant effects in bold and shadow.
Source: Authors' elaboration.

There is an intriguing pattern in the effects of vulnerability on sovereign spreads: in Panel A, for short maturities, the impact of vulnerability is more significant at higher quantiles. That is, the substantial effects observed at the highest quantile (e.g., 0.14 and 0.27 for 1- and 2-year yield spreads) diminish to zero for 1-year maturities and 7 percent for 2-year maturities at the lowest quantile. In contrast, in Panel B, the effect is more pronounced for lower quantiles (e.g., 0.12 and 0.13 for five and ten years. respectively) than for the higher quantiles, where the effect is non-significant. This suggests that the market places a high price on climate risk for short-term maturities, particularly for countries with riskier profiles that typically incur higher funding costs. At longer terms, the effects are smaller but disproportionately penalize low-risk countries. That is, while climate change vulnerability is more of a rollover risk, for high-risk countries (typically emerging and low-income countries), it is more of a structural long-term solvency risk for advanced economies, which usually face lower borrowing costs.

All in all, our analysis reveals that climate change preparation can mitigate the exposure to climate risk. This is especially evident when focusing on longer maturities and lower quantiles of the spreads, but the attenuation provided by readiness is considerable smaller for high-quantile spreads at shorter maturities.

Table 3. Panel B. Determinants of Yield Spreads at Longer Maturities

	Spread 5 Years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)
Common factor	-0.05	0.01	-4.64	0.00	-0.05	0.01	-4.65	0.00	-0.03	0.01	-4.65	0.00
Readiness	-0.09	0.04	-2.02	0.04	-0.21	0.05	-4.30	0.00	-0.12	0.05	-2.63	0.01
Vulnerability	0.05	0.05	1.01	0.30	0.06	0.06	1.07	0.28	0.11	0.03	3.98	0.00
Economic complexity	-0.24	0.04	-6.51	0.00	-0.19	0.05	-3.64	0.00	-0.14	0.02	-6.48	0.00
Real GDP growth	-0.10	0.02	-5.16	0.00	-0.07	0.02	-2.96	0.00	-0.09	0.02	-4.92	0.00
Inflation	0.20	0.04	4.95	0.00	0.15	0.03	4.76	0.00	0.13	0.02	5.75	0.00
Terms of trade	-0.05	0.03	-1.56	0.12	-0.09	0.03	-3.33	0.00	-0.02	0.02	-1.25	0.21
Rents (% GDP)	0.02	0.04	0.55	0.57	0.09	0.04	2.12	0.03	0.08	0.02	4.66	0.00
Rule of law	-0.11	0.07	-1.73	0.08	-0.10	0.07	-1.52	0.13	-0.13	0.05	-2.50	0.01
Debt (% GDP)	0.03	0.03	1.17	0.24	0.08	0.04	2.01	0.04	0.06	0.02	2.68	0.01
	Spread 10 Years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Common factor	-0.03	0.01	-2.22	0.03	-0.04	0.01	-4.57	0.00	-0.03	0.01	-4.98	0.00
Readiness	-0.16	0.05	-3.00	0.00	-0.15	0.05	-3.22	0.00	-0.13	0.04	-3.34	0.00
Vulnerability	0.15	0.10	1.56	0.12	0.08	0.04	2.13	0.03	0.12	0.04	3.34	0.00
Economic complexity	-0.23	0.05	-4.83	0.00	-0.23	0.03	-7.11	0.00	-0.13	0.02	-5.94	0.00
Real GDP growth	-0.08	0.02	-3.93	0.00	-0.06	0.02	-3.35	0.00	-0.09	0.02	-5.45	0.00
Inflation	0.20	0.05	4.40	0.00	0.13	0.02	5.41	0.00	0.09	0.02	3.95	0.00
Terms of trade	-0.05	0.03	-1.60	0.11	-0.06	0.02	-2.39	0.02	-0.04	0.01	-2.93	0.00
Rents (% GDP)	0.04	0.05	0.87	0.38	0.05	0.03	2.07	0.04	0.01	0.02	0.38	0.69
Rule of law	0.03	0.09	0.34	0.72	-0.10	0.07	-1.42	0.15	-0.11	0.04	-2.76	0.01
Debt (% GDP)	0.03	0.04	0.73	0.46	0.07	0.02	3.56	0.00	0.06	0.02	2.57	0.01

Note: The table shows the effect of the determinants of sovereign yield spreads with respect to the US at long maturities (5 years, 10 years) and three quantiles of the spreads distribution (0.1, 0.5 and 0.9). All the variables have been scaled and have zero mean and unit variance, which makes comparison of the effects easier. Significant effects in bold and shadow.
Source: Authors' elaboration.

Our findings make a significant contribution by emphasizing the varying effects observed across the quantiles of the spreads distribution. This distinction is crucial for emphasizing the actual risks posed by climate change, especially to emerging and low-income countries, which as shown are different from those of advanced economies. Additionally, our results offer a valuable framework for contextualizing and understanding the mitigating effects of climate change preparation. They are also related to the literature that advocates for differentiating the determinants of short- and long-term maturities.

Economic Complexity and Growth

The economic complexity indicator can be understood as an index of export clusters within the international trade network. Economies characterized by higher complexity demonstrate increased productivity, innovation, and intricate production networks. These attributes facilitate specialization in the production of high-value-added goods, valued in global markets for their lower price volatility and better preparedness for future higher growth trajectories. Conversely, less complex economies often specialize in commodities and low-value-added goods, exposing them to greater market fluctuations, particularly in fiscal revenues.

A recent study by Gomez-Gonzalez, Uribe, and Valencia (2023b) establishes that economic complexity is a reliable predictor of future fiscal crises. As a result, it is expected that economies with higher complexity would also experience lower borrowing costs, indicative of a lower risk profile. This expectation is further substantiated by the results presented in Table 3. Our findings extend this understanding by revealing that the impact of economic complexity tends to be more pronounced for higher quantiles, with the exception of the very short 1-year maturity. Across various maturities and quantiles, the effects are both statistically and economically significant, ranging between -0.24 and -0.07.

These effects of economic complexity are intricately linked with structural factors, reflecting long-term productivity and growth. Accordingly, we include the annual real growth rate of economies as an explanatory variable. To proxy for short-run performance and generation of fiscal revenues. This variable consistently proves significant across all maturities and quantiles. In contrast to complexity and most other factors in our model, the effect of growth remains consistently sized in all cases, ranging between -5 and -10%.

Terms of Trade, Rents

Highlighted by Bulow and Rogoff (1989) and Hilscher and Nosbusch (2010), changes in a country's terms of trade affect its ability to generate dollar revenue from exports, thereby influencing its capacity to meet obligations on externally denominated debt in dollars. The volatility in terms of trade holds significance for the broader economy as well. Terms of trade play an essential role in explaining fluctuations in output at business cycle frequencies, as stressed by Mendoza (1995), and have adverse effects on long-term economic growth, as per Mendoza (1997).

In a related context, for countries dependent on commodities, in addition to the effects of terms of trade, the unpredictability of export revenues stemming from high volatility in commodity prices is also expected to impact sovereign yields (e.g., Céspedes and Velasco, 2012; Igan et al., 2022; Van der Ploeg and Poelhekke, 2009), demanding separate consideration. However, the expected sign of rents remains ambiguous, as more commodity-dependent countries tend to exhibit more volatile growth trajectories. On the other hand, higher rents should facilitate the repayment of sovereign obligations. Therefore, both negative and positive signs could be justified.

According to our results, a modest and negative impact, ranging between -4% and -10%, is attributable to terms of trade. This effect is consistently significant for short-term debt in Panel A, while for Panel B it holds significance, especially at the center of the distribution. The magnitude of this effect remains relatively stable across quantiles. Conversely, natural resource rents, expressed as a percentage of a country's GDP, result in a marginal increase in spreads. However, this effect consistently proves to be very slight, with most instances, as detailed in Table 3, Panel A, not reaching statistical significance.

Institutions

Institutional factors have been identified as key contributors to variations in cross-country credit risk. Notably, Eichler (2014) presents evidence suggesting that a higher level of political stability and the capacity to enforce austerity measures significantly reduce sovereign yield spreads. Cole and Kehoe (1995) explore one theoretical foundation for this association, arguing that the effectiveness of reputation in supporting debt is intricately linked to a country's institutional framework. Specifically, in cases where bankers are permitted to default on payments owed to governments, nurturing a positive relationship with bankers confers lasting benefits on the government, enabling substantial borrowing supported by its reputation. In contrast, if bankers are obligated to honor contracts, the government experiences only transient benefits from cultivating a positive relationship, and its reputation can sustain minimal (or even zero) borrowing. Following this line of reasoning, this mechanism is anticipated to influence not only the quantity of credit extended to the government but also its pricing.

In our findings, the institutional quality of a country, gauged by the Rule of Law estimate in the Worldwide Governance Indicators (Kaufmann, Kraay, and Mastruzzi, 2010), exhibits the anticipated negative sign as per theoretical expectations. However, it only proves statistically significant for long maturities and at lower quantiles. This underscores its role as a long-term structural determinant, particularly in market scenarios characterized by low volatility.

Lastly, in Table 3, Panel C, we present the results associated with the idiosyncratic components in our panel quantile model. In this specification, the effects adhere to tradition, as we include only a constant in modeling the effects for all quantiles. For example, for the 1-year spreads at the 0.9 quantile, the results reveal a clear differentiation into three groups. The first group centers around spreads with a mean of zero (including those below the average value), the second encompasses countries close to spreads around 0.36 standard deviations, and a high-risk group clusters around 1.17 standard deviations. As we progress to the right in the table, the estimated location parameters consistently shift to the left, and the groups cluster around negative values at the 0.1 quantile.

The estimated parameters exhibit similarity across maturities, with one exception for a 2-year spread, where a notably high component is recorded at the 90^{th} quantile, possibly indicative of outliers. This observation further underscores the motivation behind our approach. It's essential to highlight that one of the significant advantages of quantile regressions lies in their robustness to outliers, given that they are constructed based on order statistics. In the subsequent section, we introduce additional explanatory variables for these location parameters, emphasizing the role of natural disasters in determining yield spreads.

Table 3. Panel C. Idiosyncratic Components Results

	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Spread 1 year												
	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)
Component 1	0.00	0.02	0.18	0.84	-0.28	0.03	-8.47	0.00	-0.67	0.04	-16.75	0.00
Component 2	0.36	0.05	6.95	0.00	0.05	0.03	1.48	0.14	-0.37	0.02	-15.44	0.00
Component 3	1.17	0.23	5.07	0.00	0.70	0.13	5.25	0.00	-0.06	0.08	-0.78	0.43
Spread 2 Years												
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Component 1	0.01	0.03	0.22	0.81	-0.25	0.03	-8.20	0.00	-0.56	0.03	-21.80	0.00
Component 2	0.52	0.05	10.64	0.00	0.01	0.04	0.30	0.75	-0.30	0.01	-22.35	0.00
Component 3	8.28	3.37	2.46	0.01	0.22	0.15	1.49	0.13	-0.03	0.07	-0.54	0.58
Spread 5 Years												
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Component 1	-0.06	0.04	-1.57	0.11	-0.33	0.04	-8.45	0.00	-0.68	0.03	-23.51	0.00
Component 2	0.24	0.05	5.09	0.00	-0.02	0.03	-0.61	0.53	-0.31	0.02	-19.15	0.00
Component 3	0.95	0.07	14.04	0.00	0.37	0.08	4.49	0.00	-0.08	0.08	-1.04	0.29
Spread 10 Years												
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Component 1	-0.02	0.03	-0.66	0.50	-0.30	0.05	-6.52	0.00	-0.64	0.03	-20.14	0.00
Component 2	0.23	0.05	5.09	0.00	-0.05	0.03	-1.60	0.11	-0.31	0.02	-18.02	0.00
Component 3	1.09	1.03	1.05	0.29	0.19	0.04	4.61	0.00	-0.11	0.04	-2.74	0.01

Note: The table displays the idiosyncratic components of the model, which are modeled in all specifications as a mixture of the three distributions described by the location parameters presented in the table.
Source: Authors' elaboration.

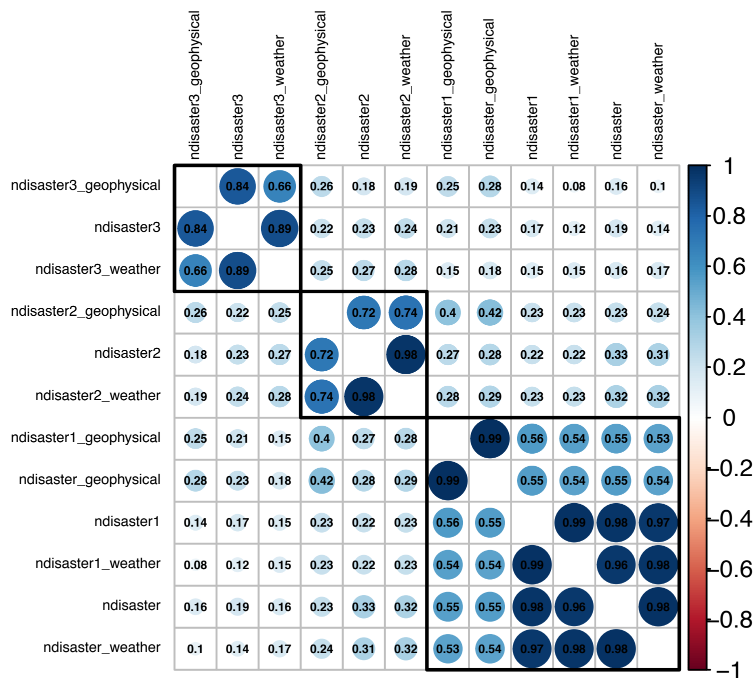
4.3. The Effects of Natural Disasters

The impact of natural disasters on sovereign risk has garnered recent attention in the literature. According to Mallucci (2022), natural disasters diminish governments' capacity to borrow from abroad and depress overall welfare. In Mallucci's framework, disasters are modeled as exogenous shocks to income and are calibrated to replicate the frequency and intensity of major hurricanes in a sample of seven small Caribbean economies. In the absence of disaster risk, sovereign spreads are lower, as disasters constrain governments' access to financial markets.

To our knowledge, we are the first to introduce natural disasters as a determinant of sovereign risk in a comprehensive sample of countries. To this end, we utilized EMDAT indicators, as explained in Table 1. These indicators present high correlation observed within the same category (from 1 to 3) and low correlation between categories. The categories represent different ways of measuring the disasters' impact (see Table 1).

Figure 5 illustrates the clustering of variables. It indicates that while the correlation within categories is high, the correlation between different ways of measuring the effects of the disasters is low. For instance, the correlation between disasters estimated as a percentage of economic loss to GDP (category 3), the number of deaths (category 2), or the number of people affected (category 1) is low. The correlation between disasters in category 1 (ndisaster1) and category 2 (ndisaster2) is 0.22; between category 2 and category 3 (ndisaster3) is 0.17 and it is 0.23 between the second and third categories.

Figure 5. Correlation among Natural Disasters Variables



Note: The figure shows the correlation among different proxies for natural disasters considered in the literature, which differ in the way that disaster intensity is measured.
Source: Authors' elaboration.

From this information we decide to incorporate the three disaster variables simultaneously into the location equation of the idiosyncratic country-specific components of our model. That is, as components of z_{it} in equation 10. In this way, our model is able to capture the heterogeneous characteristics of disaster occurrences and considers the impact on the location of the yield distribution across quantiles and maturities.

The results of the new model, following this strategy, are presented in Table 5, equivalent to Table 3 but explicitly considering the occurrence of natural disasters in determining cross-country heterogeneity in sovereign debt markets. While the overall results remain very consistent, there is a noticeable improvement in the models, particularly for 5-year maturities, with an increase in the number of statistically significant variables. Green highlights in Table 5 indicate variables that become significant compared to Table 3 in this new specification. Only a couple of variables seem to be less significant (highlighted in red in Table 3), notably the debt-to-GDP ratio, which loses its significance in two specifications and gains significance only on one occasion. The Rule of Law becomes significant on five occasions, while losing its significance in one. Overall, the model adjustment appears to improve with the incorporation of natural disasters, with no changes in the magnitudes or signs of the effects provided in Table 3 and discussed earlier.

Table 5. Models Including Natural Disasters

						Spread 1 year						
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)
Common factor	-0.06	0.02	-3.73	0.00	-0.06	0.01	-5.58	0.00	-0.04	0.01	-5.12	0.00
Readiness	-0.16	0.04	-4.51	0.00	-0.21	0.06	-3.45	0.00	-0.09	0.04	-2.15	0.03
Vulnerability	0.11	0.05	2.50	0.01	0.11	0.04	2.66	0.01	0.13	0.03	4.06	0.00
Economic complexity	-0.22	0.04	-4.98	0.00	-0.20	0.04	-4.82	0.00	-0.04	0.03	-1.65	0.10
Real GDP growth	-0.08	0.02	-3.94	0.00	-0.08	0.02	-3.97	0.00	-0.09	0.02	-3.79	0.00
Inflation	0.28	0.04	7.32	0.00	0.20	0.04	5.12	0.00	0.15	0.03	5.32	0.00
Terms of trade	-0.05	0.03	-2.05	0.04	-0.09	0.03	-3.21	0.00	-0.08	0.02	-3.96	0.00
Rents (% GDP)	-0.02	0.03	-0.57	0.55	0.10	0.04	2.77	0.01	0.07	0.03	2.41	0.02
Rule of law	-0.04	0.05	-0.88	0.37	-0.08	0.08	-1.03	0.30	-0.11	0.04	-2.85	0.00
Debt (% GDP)	0.00	0.04	0.11	0.89	0.06	0.03	2.04	0.04	0.01	0.02	0.58	0.55
						Spread 2 Years						
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Common factor	-0.06	0.01	-5.44	0.00	-0.06	0.01	-8.67	0.00	-0.04	0.01	-4.84	0.00
Readiness	-0.04	0.05	-0.90	0.36	-0.13	0.05	-2.80	0.00	-0.03	0.03	-1.06	0.28
Vulnerability	0.16	0.04	4.28	0.00	0.18	0.05	3.84	0.00	0.15	0.03	4.51	0.00
Economic complexity	-0.15	0.05	-2.86	0.00	-0.16	0.04	-4.42	0.00	-0.11	0.02	-5.70	0.00
Real GDP growth	-0.07	0.02	-3.93	0.00	-0.06	0.01	-3.99	0.00	-0.06	0.02	-3.58	0.00
Inflation	0.14	0.04	4.00	0.00	0.10	0.02	5.12	0.00	0.10	0.01	8.65	0.00
Terms of trade	-0.06	0.02	-3.04	0.00	-0.05	0.02	-2.41	0.02	-0.03	0.01	-2.93	0.00
Rents (% GDP)	0.00	0.05	-0.10	0.90	0.06	0.03	1.93	0.05	0.02	0.02	1.35	0.17
Rule of law	-0.11	0.04	-2.43	0.01	-0.01	0.05	-0.23	0.80	-0.06	0.04	-1.72	0.08
Debt (% GDP)	0.09	0.06	1.57	0.11	0.06	0.02	2.73	0.01	0.04	0.01	2.81	0.00

	Spread 5 years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Common factor	-0.04	0.01	-4.41	0.00	-0.05	0.01	-5.76	0.00	-0.04	0.01	-5.69	0.00
Readiness	-0.13	0.03	-4.20	0.00	-0.18	0.05	-3.81	0.00	-0.09	0.04	-2.12	0.03
Vulnerability	0.11	0.03	3.19	0.00	0.10	0.04	2.61	0.01	0.15	0.02	6.13	0.00
Economic complexity	-0.21	0.03	-8.27	0.00	-0.22	0.03	-7.69	0.00	-0.12	0.02	-5.78	0.00
Real GDP growth	-0.10	0.02	-5.17	0.00	-0.06	0.02	-2.85	0.00	-0.06	0.02	-3.59	0.00
Inflation	0.21	0.04	5.92	0.00	0.13	0.03	4.04	0.00	0.13	0.02	5.61	0.00
Terms of trade	-0.07	0.02	-3.90	0.00	-0.09	0.02	-4.47	0.00	-0.04	0.02	-2.00	0.04
Rents (% GDP)	0.10	0.03	3.94	0.00	0.07	0.03	2.86	0.00	0.06	0.02	3.29	0.00
Rule of law	-0.12	0.04	-3.04	0.00	-0.17	0.06	-2.92	0.00	-0.11	0.05	-2.46	0.01
Debt (% GDP)	0.03	0.02	1.48	0.14	0.06	0.03	2.07	0.04	0.06	0.02	2.65	0.01

	Spread 10 years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Common factor	-0.02	0.01	-2.31	0.02	-0.04	0.01	-3.52	0.00	-0.03	0.01	-4.93	0.00
Readiness	-0.19	0.06	-3.31	0.00	-0.09	0.03	-3.10	0.00	-0.09	0.03	-3.06	0.00
Vulnerability	0.13	0.07	1.83	0.07	0.12	0.06	2.20	0.03	0.19	0.03	7.39	0.00
Economic complexity	-0.23	0.05	-4.28	0.00	-0.18	0.03	-5.92	0.00	-0.13	0.02	-5.98	0.00
Real GDP growth	-0.08	0.02	-4.59	0.00	-0.07	0.02	-3.34	0.00	-0.08	0.01	-5.57	0.00
Inflation	0.28	0.04	6.46	0.00	0.12	0.03	4.31	0.00	0.11	0.02	6.04	0.00
Terms of trade	-0.06	0.03	-2.18	0.03	-0.08	0.02	-4.57	0.00	-0.05	0.01	-3.32	0.00
Rents (% GDP)	0.02	0.04	0.46	0.63	0.05	0.03	1.78	0.07	0.02	0.02	1.34	0.18
Rule of law	0.02	0.08	0.26	0.78	-0.17	0.04	-3.98	0.00	-0.09	0.03	-3.49	0.00
Debt (% GDP)	0.03	0.05	0.74	0.45	0.03	0.03	1.13	0.25	0.05	0.02	3.22	0.00

Note: The table shows the impact of determinants on sovereign yield spreads across all maturities (ranging from 1 to 10 years) and three quantiles of the spreads distribution (0.1, 0.5, and 0.9). All variables have been standardized to have zero mean and unit variance, facilitating the comparison of effects. Significant effects are denoted in bold and shaded. Notably, variables achieving significance in this updated model specification are highlighted in green, compared to the models in Table 3, which did not incorporate variables for natural disasters. Conversely, variables that lose significance in the new models are highlighted in red.
Source: Authors' elaboration.

Table 6 reports the modeling outcomes of the country-idiosyncratic effects, which this time consist of the traditional country-specific effects, and the variations in the location of the spread distributions resulting from the incorporation of natural disasters in z_{it}. As can be observed, by general rule, natural disasters more often than not are insignificant across quantiles and maturities. From the three variables, natural disasters in category 3, which are disasters as a GDP loss, are the most frequently significant and positive.

Table 6. Idiosyncratic Components Results Including Natural Disasters

	Spread 1 Year											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)
Component 1	0.01	0.02	0.61	0.53	-0.38	0.04	-8.39	0.00	-0.72	0.05	-15.37	0.00
Component 2	0.33	0.05	6.13	0.00	-0.04	0.03	-1.25	0.21	-0.38	0.02	-18.18	0.00
Component 3	1.06	0.18	6.02	0.00	0.33	0.06	5.14	0.00	0.10	0.05	2.19	0.03
Natural D. 1.1	-0.01	0.01	-0.85	0.39	-0.04	0.02	-1.46	0.14	-0.10	0.03	-2.81	0.00
Natural D. 1.2	-0.04	0.06	-0.71	0.47	-0.01	0.02	-0.54	0.57	-0.01	0.03	-0.31	0.74
Natural D. 1.3	-0.15	0.06	-2.32	0.02	-0.02	0.04	-0.53	0.58	-0.03	0.03	-1.14	0.25
Natural D. 2.1	-0.01	0.01	-0.79	0.42	-0.04	0.02	-1.98	0.05	0.02	0.01	1.74	0.08
Natural D. 2.2	-0.02	0.03	-0.53	0.59	-0.02	0.02	-1.35	0.17	0.00	0.01	0.30	0.75
Natural D. 2.3	-0.02	0.08	-0.22	0.81	-0.04	0.03	-1.45	0.14	-0.01	0.02	-0.65	0.50
Natural D. 3.1	0.00	0.01	0.14	0.87	0.00	0.01	0.10	0.90	0.00	0.02	0.15	0.86
Natural D. 3.2	0.01	0.03	0.24	0.79	0.01	0.01	0.85	0.39	0.03	0.01	3.06	0.00
Natural D. 3.3	-0.08	0.05	-1.66	0.09	0.00	0.02	0.24	0.79	0.03	0.01	2.46	0.01
	Spread 2 Years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Component 1	-0.05	0.02	-2.61	0.01	-0.26	0.03	-10.26	0.00	-0.52	0.02	-26.81	0.00
Component 2	0.26	0.04	5.98	0.00	-0.04	0.04	-1.19	0.23	-0.28	0.01	-19.55	0.00
Component 3	1.09	0.64	1.69	0.09	0.20	0.10	2.03	0.04	-0.17	0.06	-3.10	0.00
Natural D. 1.1	-0.01	0.02	-0.66	0.50	-0.05	0.02	-2.64	0.01	-0.05	0.02	-2.98	0.00
Natural D. 1.2	0.02	0.02	0.89	0.37	-0.06	0.03	-1.79	0.07	0.02	0.02	0.98	0.32
Natural D. 1.3	0.16	0.40	0.39	0.68	0.03	0.05	0.50	0.60	0.03	0.04	0.73	0.45
Natural D. 2.1	0.00	0.01	0.04	0.95	0.00	0.02	-0.16	0.85	0.01	0.01	0.57	0.55
Natural D. 2.2	-0.01	0.02	-0.73	0.45	-0.03	0.02	-1.39	0.16	-0.01	0.02	-0.76	0.44
Natural D. 2.3	1.35	0.70	1.93	0.05	0.01	0.02	0.27	0.77	0.01	0.03	0.43	0.65
Natural D. 3.1	0.02	0.02	0.88	0.37	0.02	0.01	1.95	0.05	0.01	0.01	0.70	0.47
Natural D. 3.2	-0.01	0.01	-0.79	0.42	0.01	0.01	1.45	0.14	0.02	0.01	3.44	0.00
Natural D. 3.3	-0.84	0.42	-2.01	0.04	0.00	0.01	-0.01	0.97	0.00	0.01	0.37	0.70
	Spread 5 Years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)	Estimate	Std.Error	z.value	P(>|z|)
Component 1	0.02	0.02	0.96	0.33	-0.39	0.04	-11.02	0.00	-0.65	0.02	-27.22	0.00
Component 2	0.33	0.05	6.58	0.00	-0.07	0.03	-2.35	0.02	-0.33	0.02	-14.42	0.00
Component 3	0.90	0.06	14.55	0.00	0.31	0.03	8.79	0.00	-0.10	0.04	-2.52	0.01
Natural D. 1.1	-0.03	0.01	-2.39	0.02	-0.05	0.03	-1.66	0.10	-0.05	0.02	-2.61	0.01
Natural D. 1.2	-0.06	0.06	-1.01	0.31	-0.04	0.02	-1.96	0.05	0.00	0.03	-0.07	0.92
Natural D. 1.3	-0.11	0.09	-1.15	0.25	-0.01	0.03	-0.41	0.67	0.02	0.03	0.54	0.58
Natural D. 2.1	-0.03	0.01	-2.30	0.02	-0.03	0.02	-1.68	0.09	-0.01	0.01	-0.52	0.59
Natural D. 2.2	-0.02	0.03	-0.59	0.54	-0.01	0.01	-1.47	0.14	-0.01	0.02	-0.42	0.66
Natural D. 2.3	0.02	0.11	0.16	0.86	-0.03	0.02	-1.53	0.12	-0.01	0.02	-0.36	0.71
Natural D. 3.1	0.02	0.01	1.84	0.06	-0.01	0.02	-0.45	0.64	0.02	0.01	1.83	0.07
Natural D. 3.2	0.00	0.03	0.13	0.88	0.01	0.01	1.33	0.18	0.01	0.01	1.01	0.31
Natural D. 3.3	-0.08	0.06	-1.28	0.20	0.01	0.02	0.73	0.46	0.03	0.01	2.75	0.01

	Spread 10 Years											
	Quantile=0.9				Quantile=0.5				Quantile=0.1			
Component 1	0.28	0.08	3.43	0.00	-0.36	0.04	-9.44	0.00	-0.62	0.03	-22.43	0.00
Component 2	0.02	0.03	0.64	0.51	-0.12	0.02	-5.25	0.00	-0.32	0.02	-20.91	0.00
Component 3	1.12	1.98	0.57	0.56	0.15	0.04	4.23	0.00	-0.11	0.02	-5.81	0.00
Natural D. 1.1	-0.06	0.03	-1.92	0.05	-0.07	0.03	-2.23	0.03	-0.05	0.01	-3.74	0.00
Natural D. 1.2	-0.02	0.03	-0.79	0.42	-0.02	0.02	-1.15	0.25	0.04	0.02	2.65	0.01
Natural D. 1.3	-0.15	1.24	-0.12	0.89	-0.01	0.02	-0.32	0.74	0.04	0.02	2.23	0.03
Natural D. 2.1	0.00	0.03	-0.07	0.92	-0.02	0.01	-1.26	0.21	-0.03	0.03	-1.01	0.31
Natural D. 2.2	-0.02	0.01	-1.79	0.07	-0.01	0.01	-1.94	0.05	-0.04	0.03	-1.42	0.15
Natural D. 2.3	-0.21	0.10	-2.11	0.03	-0.02	0.02	-0.68	0.49	0.01	0.01	0.90	0.36
Natural D. 3.1	0.00	0.02	0.11	0.89	-0.01	0.01	-0.99	0.31	0.00	0.01	0.36	0.70
Natural D. 3.2	0.01	0.01	0.99	0.31	0.00	0.01	0.64	0.51	0.03	0.01	2.18	0.03
Natural D. 3.3	-0.02	0.04	-0.53	0.59	0.01	0.01	0.81	0.41	-0.01	0.01	-0.77	0.43

Note: The table displays the idiosyncratic components of the model, which are modeled in all specifications as a mixture of the three distributions described by the location parameters, and the country specific natural disasters variables (from 1 to 3, for three clusters of countries) presented in the table. Significant coefficients are emphasized with bold text and shading, while those specifically associated with natural disasters variables are enclosed within a box.
Source: Authors' elaboration.

Spreads are higher in six cases due to increments in disasters in the third category. Surprisingly, when the other disaster variables (i.e. in terms of deaths and population affected) are significant, the effects are negative on the spreads. This occurs on 10 (out of 12) occasions in category 1 (people exposed) and 3 (out of four) times in category 2 (deaths). There is only one notable exception to this pattern, which is a positive impact on the 2-year spreads, for the second cluster of countries, the second category of disasters and the 90th percentile. In all cases except for the latter, and for the same quantile at a 1-year maturity, first category, third cluster, the effects are small, and below 4 percent in absolute terms.

Our findings complement those presented by Klusak et al. (2023). These authors employ machine learning to simulate prospective scenarios of sovereign debt ratings and associated costs. Their research indicates that downgrades are anticipated by 2030, with noteworthy increases in funding costs posing a concern for companies and countries most vulnerable to climate change. Klusak et al.'s methodology involves assessing the impact of climate-induced changes in credit ratings and yields through their influence on macroeconomic variables. Specifically, they draw simulated climate change scenarios from prior literature to model macroeconomic conditions, subsequently utilizing these simulated variables in their sovereign risk models. In contrast, our models diverge by directly examining the impact of natural disasters while accounting for key determinants of sovereign debt, including macroeconomic, institutional, and fiscal variables. That is, unlike Klusak et al. (2023), who explore total effects inclusive of intermediate impacts stemming from the macroeconomic environment, our approach allows for a more targeted analysis of the immediate consequences of natural disasters on sovereign debt dynamics.

5. Concluding Remarks and Policy Implications

We show that sovereign spreads respond differently to economic determinants, particularly in relation to preparation for and vulnerability to climate change, depending on whether the spreads are very high (0.9 quantile of the spread distribution) or very low (0.1 quantile of the spread distribution). Through this analysis, we underscore the asymmetric risk that climate change poses to emerging and low-income developing countries, as opposed to developed countries. In essence, we highlight that the impacts of vulnerability to climate change disproportionately affect high quantiles of the spread distribution, precisely those in which one can expect to find countries facing significant credit restrictions, in times of scarce credit supply in international markets.

Furthermore, we demonstrate that asymmetric responses across the spread distribution to determinants, beyond those associated with climate change, are not exceptions but rather the norm. For instance, factors such as inflation, terms of trade, the debt-to-GDP ratio, economic complexity, natural resource rents, and institutional quality all exert distinct impacts on government borrowing costs, contingent on the spread level.

Our models also integrate the occurrence of natural disasters into the determination of sovereign spreads. We demonstrate that, on the whole, spreads predominantly react to vulnerability and readiness to climate change as a general concept, rather than the actual occurrence of natural disasters. Nevertheless, the inclusion of variables accounting for natural disasters enhances the overall model fit, aligning with theoretical expectations, particularly at longer maturities, such as 5 and 10 years.

When significant, the effects of natural disasters vary depending on how they are measured. Specifically, economic losses resulting from natural disasters increase spreads, while the number of people exposed to the disasters reduces the spreads. We posit that natural disasters associated with substantial human losses are generally linked to international and substantial humanitarian aid, thereby increasing resource flows to the affected countries and mitigating credit risk concerns. Conversely, when disasters are primarily characterized by economic losses, the risk outlook consistently increases, leading to larger spreads. In all cases, the effects of natural disasters are relatively modest compared to those of vulnerability and readiness to climate change indicators.

A note of caution is in order. Our results do not imply that natural disasters have no effect on sovereign risk. Rather, they suggest that the effect is very small or insignificant once one controls for traditional determinants of sovereign risk, including macroeconomic, institutional, and fiscal variables. In other words, the link between climate change and sovereign risk incorporates, as an intermediate effect, the macroeconomic and institutional environment. There is no direct link, at least not currently.

Our study yields a series of policy recommendations that have implications for climate change preparedness, all while maintaining a vigilant focus on sovereign risk. The readiness indicators of countries, serving as proxies for climate change preparation, highlight that efforts in this regard are most effective, in relative terms, in reducing sovereign risk at long-term maturities, specifically over 5 and 10 years, in our study sample. However, the impact diminishes notably at shorter maturities. Notably, an increase in readiness can potentially offset heightened vulnerability to climate change, particularly at the lower quantiles of the spread distribution. This is positive news for developed countries actively preparing for climate change, as they experience lower debt spreads and primarily finance through long-term debt.

By contrast, countries with high spreads, relying on short-term debt (such as emerging and low-income economies), face a distressing situation. In these cases, increments in readiness tend to be smaller than the effects of vulnerability.

Although preparation has positive effects, it is insufficient to counterbalance vulnerability impacts. In such economies, additional measures, like enhancing their productive structure to improve the quality of exports, may be essential to concurrently manage sovereign risk (considering the attenuating effect of economic complexity on the spreads).

Our findings align, for instance, with recent strategies pursued by the European Commission involving the allocation of substantial public funds to accelerate climate change preparation and digitalization of the European economies, while derisking private investment in sectors key for the ecological transition. This strategy, as recently implemented through the framework of Next Generation EU, has been predominantly aimed at countries such as Italy and Spain, which have historically had higher spreads. Considering our results, it is anticipated that this strategy will be particularly effective in mitigating sovereign risk of the region, because the effects will be targeted at short-term and high-quantile spreads that are disproportionately influenced by climate change vulnerability.

However, a caveat emerges from our results: the amplification of climate change effects may pose challenges to sustaining such funding schemes in the long term. This aspect, previously overlooked, suggests that vulnerability could lead to increased borrowing costs for European countries in general, reflecting their solvency position, particularly in maturities exceeding 5 years.

While our findings indicate a modest impact of natural disasters on sovereign risk, they are nonetheless significant across various fragments of the spread distribution. The positive relation that we document between natural disasters and economic losses to GDP implies that an uptick in such occurrences could shift the entire spread distribution upward, exacerbating sovereign risk at all maturities and spread levels. Consequently, countries should prioritize monitoring efforts to minimize the potential systemic risk arising from natural disasters due to climate change in the years ahead.

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Appendix

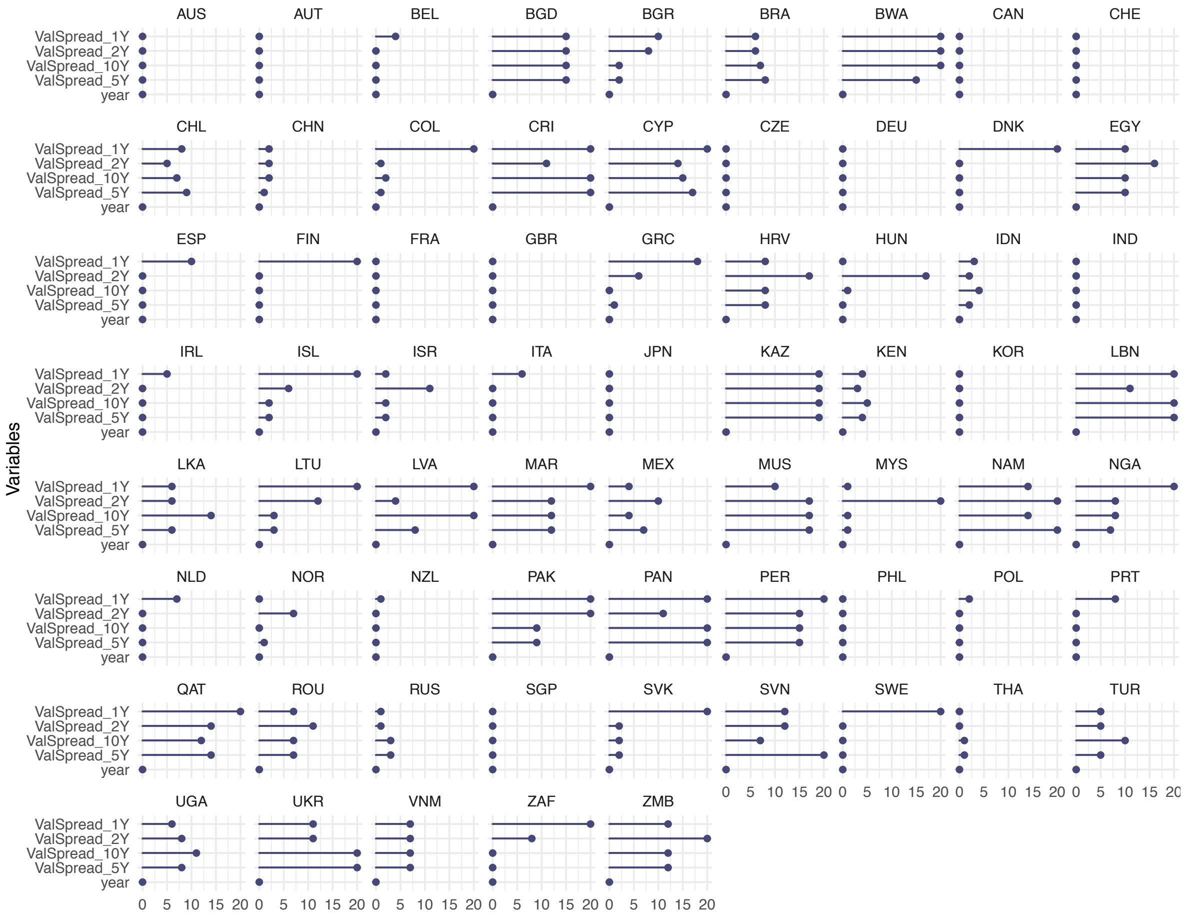
Table A1

Indicator	Abreviation	Source	Mean	Median	Std.Dev	Max.	Min.
Fiscal rule	rule	IMF; Schaechter et al. (2012)	0.27	0	0.44	1	0
population in millions	pop	World Bank	37.17	8.07	134.42	1433.78	0.04
Dummy variable that takes the value of 1 for a fiscal crisis year	fiscal_crisis	Medas et al. 2018 until 2015, from 2015 own elaboration	0.34	0	0.47	1	0
Dummy variable that takes the value of 1 for serial defaulters	serial_default	Argentina and Greece	0.02	0	0.13	1	0
Dummy variable that takes the value of 1 forresource rich economies	resource_rich_imf	Mlachila and Ouedraogo (2020)	0.39	0	0.49	1	0
Gross capital formation, % GDP	gkf	IMF	23.73	21.96	16.02	442.77	-39.73
Gross fixed capital formation, % GDP	gfkf	IMF	22.28	20.88	12.6	319.06	0
Human capital index	hc	Penn World Tables	2.28	2.25	0.72	4.35	1.01
Log of per capita real consumption	ccon	Penn World Tables	12.45	12.44	1.49	16.19	9.06
Real domestic absorption, at current PPPs (in mil. 2017US$)	cda	Penn World Tables	10.87	10.74	2.11	16.88	5.43
Expenditure-side real GDP at current PPPs (in mil. 2017US$)	cgdpe	Penn World Tables	10.82	10.7	2.17	16.85	5.19
Output-side real GDP at current PPPs (in mil. 2017US$)	cgdpo	Penn World Tables	10.83	10.7	2.17	16.84	5.21
Capital stock at current PPPs (in mil. 2017US$)	cn	Penn World Tables	11.97	11.91	2.38	18.44	5.49
Capital services levels at current PPPs (USA=1)	ctfp	Penn World Tables	0.67	0.67	0.26	1.9	0.05
Real internal rate of return	irr	Own estimates	0.11	0.09	0.08	1.1	0.01
Nominal exchange rate, end period	trm_end	Blomberg	444.65	6.47	2134.76	42000	0
Change nominal exchange rate, end period	change_trm	Own estimates	613.42	1.94	17530.56	1314185	-42773
Exchange rate, national currency/USD (market+estimated)	xr	IMF	12572.24	6.45	961340	76369942	0
Trade openness index, (exports+imports)/GDP	openness	Own estimate, data from IMF	73.35	60.14	51.41	402.32	0.14
Financial openness, Chinn-Ito index	kaopen	Chinn and Ito Web page	0.06	-0.15	1.55	2.32	-1.92
Exports Diversification Index	diversification	UNCTAD	0.67	0.71	0.15	0.94	0.23
Exports Concentration Index	concentration	UNCTAD	0.34	0.29	0.22	0.99	0.04
Interest payment % GDP, primary balance - overall balance	interest	WEO (October 2019)	1.9	1.46	2.45	17.71	-35.48
Implicit interest rate, Interest Payment / Debt	interest_rate2	Own estimate, data from IMF	3.19	3.13	3.36	11.5	-34.82
Primary balance % of GDP, general government	primary_balance	IMF	-0.56	-0.66	6.46	126.46	-186.79

Indicator	Abreviation	Source	Mean	Median	Std.Dev	Max.	Min.
Overall balance % of GDP, general government	total_balance	IMF	-2.41	-2.47	6.52	125.14	-151.31
Pop 65+/ Pop 15-65	ratio_old	World Bank	11.09	7.83	7.16	48.64	0.8
GDP constant prices, domestic currency	gdp_r	IMF	121536	522.92	939712	15112986	0.06
General government revenue, % GDP	revenue	IMF	27.88	25.06	14.01	164.05	0.04
Domestic currency debt % total debt	p_dd	IMF	45.72	41.95	29.25	100	0
Foreign currency debt % total debt	p_fd	IMF	54.28	58.05	29.25	100	0
Oil rents (% of GDP)	oil_rents	World Bank	3.55	0	9.26	71.49	0
Coal rents (% of GDP)	coal_rents	World Bank	0.3	0	2.49	69.8	0
Forest rents (% of GDP)	forest_rents	World Bank	2.08	0.32	4.17	44.6	0
Mineral rents (% of GDP)	mineral_rents	World Bank	0.78	0.01	2.45	39.67	0
Natural gas rents (% of GDP)	gas_rents	World Bank	0.37	0	2.34	68.68	0
Fractionalization Index	frac	Drazanova (2019)	0.52	0.58	0.28	1	0
Polarization Index	polariz	The Polarization Index	0.4	0	0.77	2	0
Voice and Accountability, Estimate	vae	World Bank	-0.05	-0.04	1.07	4.28	-5.78
Voice and Accountability, Percentile Rank (0-100)	var	World Bank	48.32	48.28	31.02	183.87	-85.12
Political Stability and Absence of Violence/Terrorism, Estimate	pve	World Bank	-0.08	0.05	1.35	6.5	-7.92
Political Stability and Absence of Violence/Terrorism, Percentile Rank (0-100)	pvr	World Bank	47.58	47.09	40.43	269.68	-137.77
Government Effectiveness, Estimate	gee	World Bank	-0.08	-0.17	1.11	3.92	-4.27
Government Effectiveness, Percentile Rank (0-100)	ger	World Bank	48.23	48.82	35.24	171.65	-136.25
Regulatory Quality, Estimate	rqe	World Bank	-0.09	-0.18	1.19	6.47	-5.78
Rule of Law, Percentile Rank (0-100)	rlr	World Bank	48.12	45.54	33.32	235.96	-64.68
Control of Corruption, Estimate	cce	Penn World Tables	-0.05	-0.27	1.14	5.79	-6.04
Control of Corruption, Percentile Rank (0-100)	ccr	Penn World Tables	48.74	47.81	34.68	186.46	-134.65
Regulatory Quality, Rank	rqr	Penn World Tables	47.5	47.3	36.96	331.87	-169.53
Interest payment % GDP, primary balance - overall balance	interest	IMF	1.9	1.46	2.45	17.71	-35.48
Implicit interest rate, ((debt+primary_balance)*(1+gdp_growth)/l.debt-1)	interest_rate1	IMF	10.61	7.09	22.61	202.18	-104.59
Implicit interest rate, Interest Payment / Debt	interest_rate2	IMF	3.19	3.13	3.36	11.5	-34.82
Dummy variable that takes the value of 1 for year with negative real GDP growth	crisis	Own elaboration	0.16	0	0.36	1	0
Chicago Board Options Exchange Volatility Index	vix	Bloomberg	19.49	17.1	6.15	32.7	11.09

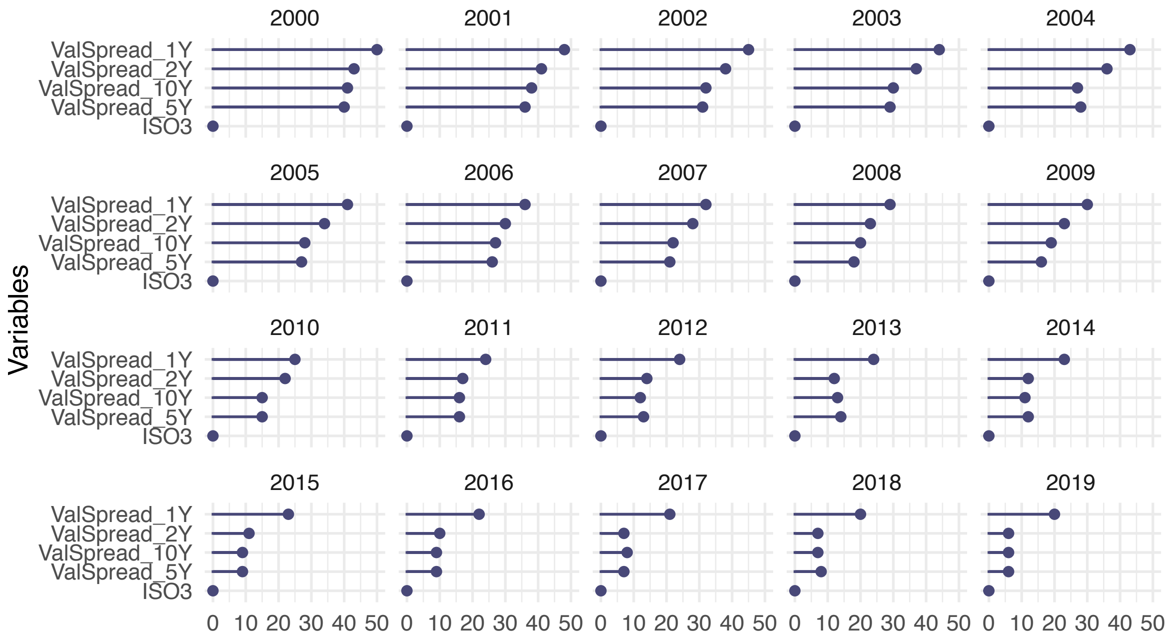
Indicator	Abreviation	Source	Mean	Median	Std.Dev	Max.	Min.
Debt spike: 1 if the 5-year change is bigger than the 80th percentile	spike	Own elaboration	0.15	0	0.36	1	0
Real GDP per capita	gdp_pc	IMF	2026463	47125	12147459	181845616	10.81
Fitch rating, numeric	rating_fitch_num	Bloomberg	11.42	11	4.95	20	1
Moodys rating, numeric	rating_moodys_num	Bloomberg	12.7	12	5.37	21	1
Sp rating, numeric	rating_sp_num	Bloomberg	13.29	13	5.46	22	1
Fiscal rule quality, all rules	quality_fr	Own elaboration based on IMF; Schaechter et al. (2012)	0.21	0	0.61	5	0
Foreign/US govt bond yield spread, end year	diff_3m_end	Du et al. 2016, 2018	2.15	1.52	3.55	19.72	-5.64
Foreign/US govt bond yield spread, end year	diff_1y_end	Du et al. 2016, 2019	2.24	1.55	3.56	18.43	-6.02
Foreign/US govt bond yield spread, end year	diff_2y_end	Du et al. 2016, 2020	2.16	1.41	3.52	16.8	-5.98
Foreign/US govt bond yield spread, end year	diff_3y_end	Du et al. 2016, 2021	2.11	1.32	3.46	17.04	-5.89
Foreign/US govt bond yield spread, end year	diff_5y_end	Du et al. 2016, 2022	1.99	1.19	3.34	16.29	-5.29
Foreign/US govt bond yield spread ,end year	diff_7y_end	Du et al. 2016, 2023	1.84	1.11	3.17	15.3	-5.15
Value sovereign spread with respect to the US 20 years maturity	ValSpread_20Y	Bloomberg, own elaboration	2.04	0.12	5.28	65.52	-4.03
Value sovereign spread with respect to the US 30 years maturity	ValSpread_30Y	Bloomberg, own elaboration	0.69	-0.02	2.88	31.78	-3.49

Figure A1. Sovereign Spreads Missing Observations by Country



Note: The figure shows the frequency of missing observations per country in our sample for 1 year, 2 years, 5 years and 10 years maturities. Countries or maturities with a larger amount of missing data were excluded from the analysis. The number of missing data per country represents years and the total number of years in the sample is 20.
Source: Authors' elaboration.

Figure A2. Sovereign spreads missing observations by year



Note: The figure shows the frequency of missing observations per year in our sample for 1 year, 2 years, 5 years and 10 years maturities. Years and maturities with a larger amount of missing data were excluded from the analysis. The number of missing data per year represents countries and the total number of countries in our sample is 68.
Source: Authors' elaboration.