Climate Vulnerability and the Cost of Debt

Gerhard Kling
University of Aberdeen Business School
Centre for Sustainable Finance, SOAS University of London

Yuen C. Lo
Guildhall School of Business and Law, London Metropolitan University
Centre for Sustainable Finance, SOAS University of London

Victor Murinde
School of Finance and Management, Centre for Global Finance, and Centre for Sustainable Finance, SOAS University of London
African Economic Research Consortium

Ulrich Volz*
Department of Economics and Centre for Sustainable Finance, SOAS University of London
German Institute of Development and Sustainability
London School of Economics and Political Science
Centre for Economic Policy Research

Abstract

We present the first systematic investigation of the impact of climate vulnerability on the cost of sovereign debt using a sample of 46 developing and advanced countries from 1996-2016. We find that a subgroup of 25 developing countries with higher exposure to climate vulnerability – all of which are members of the V20 climate vulnerable forum – exhibit, on average, a 1.174% higher cost of debt. We estimate that 40 members of the V20 paid USD 62 billion in additional interest from 2007-2016 due to their climate vulnerability. We also find that a measure of social readiness has a negative impact on bond yields, suggesting that social and physical investments in adaptation and resilience can help mitigate climate risk-related financing costs. Our findings indicate that climate vulnerability can threaten sovereign debt sustainability and cause financial exclusion, thereby undermining investment in adaptation and accelerating a vicious cycle of climate vulnerability, debt and underdevelopment.

Keywords: Climate vulnerability, cost of debt, V20 countries, climate change, financial exclusion

JEL codes: Q54, H63, G12

*Corresponding author. Email: uv1@soas.ac.uk

1. Introduction

It is well established that anthropogenic climate change has contributed to a substantial rise in the frequency and severity of extreme weather events, including droughts, extreme temperatures, floods, landslides and storms, and that the risk of climate-related disasters is bound to increase further (IPCC, 2014; Fischer and Knutti, 2015, UNDRR 2020). According to the World Meteorological Organization, the number of disasters has risen fivefold over the last five decades, driven by climate change, more extreme weather, and improved reporting (WMO 2021). Global weather-related losses have amounted to over USD 4.5 trillion over the last five decades, with a clear upward trend in annual losses (Figure 1). Developing countries suffer disproportionately from climate-related loss and damage due to their greater climate vulnerability, despite their relatively negligible contribution to climate change.

[Include Figure 1 here]

Although research into the short- and long-term economic costs of both climate change and disasters is abundant,[1] only relatively few studies have investigated the impacts of climate change on public debt. In particular, a critical missing link has been the dearth of research examining the effect of climate vulnerability on the cost of sovereign debt. This is a crucial issue because the cost at which governments can access

[1] See, for instance, Alano and Lee (2016); Batten (2018); Bouwer et al. (2007); Cabezon et al. (2015); Cavallo et al. (2013); Dellink et al. (2017); Estrada et al. (2017); Felbermayr and Groschl (2014); Ferreira and Karali (2015); Fomby et al. (2013); Gerling (2017); Hallegatte (2016); Hochrainer (2009); Kahn et al. (2021); Leimbach et al. (2017); Loayza et al. (2012); Mechler and Bouwer (2015); Mendelsohn et al. (2015); Raddatz (2007); Tol (2018).

finance affects governments' ability to invest in climate mitigation and adaptation. It also constrains investments in infrastructure, education and public health and has ramifications for investments undertaken by the private sector.[2] While prior empirical work has shown that sovereign risk is a critical variable affecting the weighted average cost of capital (Ameli et al., 2017, 2021), a crucial variable for investment appraisal, until recently the literature did not investigated the relationship between climate vulnerability and the cost of sovereign debt. We define climate impacts as the physical manifestations of man-made climate change, for example, increased frequency of floods and droughts. Climate vulnerability encompasses both sensitivity to climate change and the capacity to absorb and adapt to it. Finally, climate risks include the adverse financial outcomes of anthropogenic climate change. The latter is multidimensional, spanning transition costs as societies switch to a low-carbon economy, to physical risks such as losing fisheries when ocean temperatures change.

This analysis, published initially as a working paper in 2018 (Kling et al., 2018), presents the first systematic effort to address the aforementioned knowledge gap by investigating the impact of climate vulnerability on sovereign bond yields. This paper extends our original analysis by including new robustness checks and additional insights on the impact of climate vulnerability on market access.

We constructed a comprehensive database comprising indices from the Notre Dame Global Adaptation Initiative (ND-GAIN), sovereign bond yields, and various macroeconomic control variables for a sample of 46 developing and advanced countries

[2] See Kling et al. (2021) for an analysis of the impact of climate vulnerability on the cost of corporate capital and access to finance.

spanning the period from 1996 to 2016. Our sample includes data for 25 climate-vulnerable developing countries that are members of the Vulnerable Twenty Group (V20).[3] We employ a panel ordinary least squares (POLS) methodology to estimate a linear model that aims to explain sovereign bond yields in terms of climate vulnerability, social preparedness measures, and macroeconomic control variables. We also apply principal component analysis to account for the inherent multicollinearity between measures of climate vulnerability. Our models confirm the positive and significant impact of climate vulnerability on sovereign bond yields while social preparedness reduces them. The climate vulnerability variable encompasses structural weaknesses, such as dependence on imported energy and food, indicating a higher sensitivity to climate change. The social preparedness variable encompasses education and internet access measures, which are effectively non-GDP measures of development and infrastructure.

The empirical results of our base model yield an estimate of 12.4% as the average predicted cost for a V20 country, based on control variables such as debt-to-GDP ratio and government revenue and expenditure. Our results show that climate vulnerability, as measured by the ND-GAIN sub-indices for climate sensitivity and capacity, increases the cost of debt by 1.17 percentage points. This represents the average partial impact of climate vulnerability on the cost of debt for the V20 countries. This increase can be partially offset by investments in social and physical infrastructure, which reduces the cost of debt by an average of 0.67%. The coefficient on this preparedness index suggests that investments in adaptation and resilience can mitigate higher debt costs arising from

[3] The V20 Group of Finance Ministers of the Climate Vulnerable Forum was established in 2009 as an international partnership of countries that are highly vulnerable to a warming planet. The membership of the V20 has expanded from its 20 founding members to 55 countries with a combined population of 1.4 billion people.

higher climate vulnerability. Multiplying this incremental cost (adjusted for average V20 climate vulnerability) and historic external public and private debt for 40 members of the V20 group of climate-vulnerable countries implies a USD 62 billion higher cost of debt over the period from 2007 to 2016. We consider this a lower bound based on direct effects for a subset of climate vulnerabilities and a subset of countries with limited access to finance.

Our analysis also indicates that climate vulnerability can lead to financial exclusion of sovereigns. Overall, our findings indicate that climate vulnerability can threaten developing countries' access to international capital markets and worsen sovereign debt sustainability. This could undermine the ability of these countries to invest in adaptation and resilience, making them even more vulnerable in the face of intensifying human-induced climate change. All this could contribute to an accelerating vicious cycle of climate vulnerability, unsustainable debt and underdevelopment.

The rest of the paper is structured as follows. Section 2 provides the research context, including a review of prior empirical studies and those that have built upon our research since the initial publication of our findings in a working paper (Kling et al. 2018). Section 3 explains the data and variables. Section 4 highlights the methodology underlying our empirical model. Section 5 provides our empirical findings and climate vulnerability cost estimates. We provide a variety of robustness checks in Section 6. We conclude by discussing our findings, highlighting our limitations and directions for future research.

2. Literature review

When we first circulated the working paper of this study (Kling et al. 2018), there was no research on this topic. In the following, we will first review the broader literature on the macroeconomic impacts of climate change before describing the literature that has emerged on the nexus between climate vulnerability and sovereign debt since we published our working paper. As we will show, the studies that have replicated and built on our work corroborate and strengthen our results.

A growing body of research has studied the macroeconomic impacts of climate change. Yet, a systematic analysis of the nexus between climate change, sovereign risk, and the cost of capital has evolved relatively slowly, despite its potentially profound implications. In a recent literature review, Zenios (2024) describes the nexus between climate change, sovereign risk and cost of capital as a 'climate-sovereign debt doom loop'. While transition risks can also have major impacts on sovereign risk (Volz et al. 2020), our literature review focuses on research on disasters and climate vulnerability.

The economic and financial impacts of disasters are crucial in establishing a vector connecting climate and debt, which may lead to an increase in the frequency and severity of disasters due to climate change. Cantelmo et al. (2019) demonstrate that climate-related disasters have inflicted the greatest damage in small, disaster-prone countries, while Cabezon et al. (2015) find that these countries also exhibit higher volatility in public revenue. Consequently, disaster-prone economies face considerably higher public debt levels than those less exposed to disasters (Cabezon et al. 2015; Munevar 2018).

Macroeconomic risks related to climate-related disasters include risks of a disruption of economic activity, which may reduce tax income and other public revenues and raise spending on social transfers (e.g. Schuler et al. 2019); commodity price changes that may affect revenue or increase public spending on fossil fuel or food subsidies; supply or demand shocks that affect inflation and interest rates (e.g. Batten 2018); and exchange rate revaluations (e.g. Farhi and Gabaix 2016). Lo and Volz (2024) add an analysis of balance of payments capital flows to exchange rates to examine the second-order financial effects of disasters more holistically. They find that for a sample of World Bank International Development Association (IDA) borrowers, major disasters cause a decline in the real effective exchange rate as well as outflows of portfolio investment and other investment (e.g., bank deposits and loans).

Governments are also exposed to fiscal risks through both explicit and implicit contingent liabilities (Mitchell et al., 2014; Hochrainer-Stigler, 2018; Schuler et al., 2019). Climate-related disasters frequently damage or destroy government assets and public infrastructure, resulting in expenditures for damage repair or reconstruction. Climate-related disasters may also impact the assets or operations of state-owned enterprises (SOEs), reducing their asset value or affecting dividend payments to the government. Governments may also have to realise contingent liabilities and step in to bail out SOEs impacted by a disaster. Disasters can damage or destroy private property, requiring government support for households and corporations to rebuild their homes and businesses. To the extent that disasters cause instability in the financial sector, they may force governments to bail out ailing financial institutions. Disasters can trigger a humanitarian crisis, which may necessitate public emergency measures, including rescue missions, temporary relocation of people, provision of food, clean water, and shelter, as well as medical treatment. Such crisis response measures can be costly and significantly impact public spending. Analysis of contingent liability realisations by Bova et al. (2019) with a sample of 80 advanced and emerging economies for the period 1990 to 2014 revealed that disasters (including geophysical events) are among the major sources of contingent liabilities, and can cause large fiscal distress if realised.

The economic and fiscal losses caused by a disaster depend on its intensity, the vulnerability of the population and key economic sectors, the resilience of infrastructure and buildings, the quality of the crisis response, and the speed of recovery. After a disaster, public expenditure depends on the extent of infrastructure the government rebuilds or repairs, the emergency support it provides to affected households and corporations, and the support it receives from the international community. The impact on public finances also depends on how much of the public and private assets and economic activities are insured. The empirical evidence suggests that the uninsured portion of catastrophe-related losses drives the macroeconomic costs, while insurance boosts financial resilience and supports the speed of recovery (Von Peter et al., 2012; Cebotari and Yousseff, 2020).

Acevedo's (2014) VAR model finds that public debt increases following major floods, but this only applies to a subset of the storm events covered in the study. Cabezon et al. (2015) employ a panel VAR model to identify a deterioration in fiscal balance for small Pacific island states in the first year following a disaster. Also, using a panel VAR framework with data for 81 middle-income and high-income countries from 1975 to 2008, Melecky and Raddatz (2011) find that public expenditures increased by 15% while revenue fell by 10% over the five years following a disaster. Moreover, they find that fiscal deficits worsen, especially in countries with low insurance penetration. In a follow-up paper, Melecky and Raddatz (2014) demonstrate that countries with more sophisticated debt markets experience smaller real consequences from disasters, but their deficits expand further. This emphasises the positive role financial markets can play in ameliorating the effects of disasters. Using synthetic control analysis and data for 163 countries from 1971 to 2014, Koetsier (2017) find that, on average, government debt rises by 11.3% of GDP after what they classify as particularly damaging disasters compared to a synthetic control group, with a median effect of 6.8% of GDP. Some disasters lead to a 20% or greater increase in the debt-to-GDP ratio.

Glass et al. (2015) review Standard & Poor's observation that it is rare for a country's debt rating to be downgraded due to a disaster. An example of such an exceptional case is Grenada in 2004, following Hurricane Ivan. A major reason put forward is that often the countries most affected do not have a sovereign rating or that ratings are already very low. Glass et al. (2015, 4) conclude: 'We believe that sovereigns most vulnerable to natural hazards are likely to be small island states with next to no geographical diversification and a narrow economic base'. Mallucci (2022) extends a sovereign default model to include disaster risk and finds that hurricane risk reduces the ability of Caribbean countries to raise financing. Recent analysis by Dryden and Volz (2025) identifies 1,087 'large' disasters between 1980 and 2021,[4] including 118 instances (or 11% of cases) where the sovereign experienced a one-notch or more rating downgrade in the year following the disaster.

Overall, the available empirical evidence suggests that disasters can pose a significant risk to sovereign debt sustainability through both macroeconomic and contingent liability risks. Recent studies have also highlighted that, beyond disaster risk, countries face additional risks to public finances and debt sustainability through the slow-onset effects of climate change, as well as transition risks and spending needs for climate adaptation and mitigation (Jones et al. 2013, Volz et al. 2020, Agarwala et al. 2021).

[4] Large disasters are defined as meeting at least one of the following conditions: the domestic government calls for international assistance or declares a state of emergency following the event; the total damages incurred by the disaster are in excess of 1% of GDP; or the impacted population is in excess of 2% of the total population (Dryden and Volz 2025).

Taking a step back, at the time of the initial publication of our findings as a working paper (Kling et al. 2018), there was essentially no empirical evidence on the cost of debt as it relates to climate risk and vulnerability, climate-related catastrophes, and how climate vulnerability may be increasing the cost of debt capital. An exception was the PhD thesis by Ozcan (2005) on catastrophe risk and sovereign borrowing, which follows an event study methodology.

Following the publication of our working paper, several studies have built upon our research with follow-up investigations. These findings largely confirm the positive effect of physical climate vulnerability on the cost of sovereign debt that we find in this paper. Research by the International Monetary Fund (IMF), which analysed data for 98 advanced and developing countries over the period 1995-2017, replicated the methodology and measures employed in this paper and corroborated our findings (Cevik and Jalles, 2022).

Using refined measures of climate risk and resilience, along with a higher data frequency for 40 advanced and emerging economies, Beirne et al. (2021a) also confirm our finding of a climate risk premium. Furthermore, Beirne et al. (2021a) estimate a set of panel structural VAR models, which suggest that the reaction of bond yields to climate risk shocks becomes permanent after approximately 18 quarters (4.5 years), with high-risk economies experiencing the largest permanent effects on yields. Beirne et al. (2021b) examine the nexus between climate change and sovereign risk in Southeast Asia, one of the regions most severely affected by climate change. Conducting country-specific and panel modelling for six Southeast Asian countries with monthly data from 2002 to 2018, their findings suggest that greater climate vulnerability has a significant positive effect on sovereign bond yields, while greater resilience to climate change has an offsetting effect, although the latter is smaller. More recently, Boitan and Marchewka-Bartkowiak

(2022) utilise new climate proxy metrics from Germanwatch on EU sovereign bond yields and spreads, and find that countries with higher climate vulnerability pay a premium.

Going beyond indices, a regression analysis of data from 17 MENA countries by Giovanis and Ozdamar (2022) reveals that temperature changes exacerbate fiscal deficits and increase public debt. Using monthly data for 54 emerging markets between 1994 and 2018, Böhm (2022) calculates temperature deviation from historical averages. It finds that for warmer countries, higher temperature anomalies significantly lower sovereign bond performance, i.e. increase sovereign risk. The estimates thus suggest that countries with tropical climates are likely to experience significant increases in their sovereign borrowing costs as temperatures continue to rise due to climate change.

Bingler (2022) differentiates between transition, physical, and innovation aspects of climate risks and climate performance, and estimates the pricing effects on sovereign bond yields for a sample of 29 countries for the period 2008-2021. Confirming our findings, her results suggest that greater exposure to physical risk and impacts is associated with higher bond yields at longer-term maturities for lower-rated countries. Bingler finds that these are associated with lower bond yields for countries with higher credit ratings with respect to transition risk exposure and innovation opportunities.

Combining climate-economic models with observed sovereign credit ratings and a random forest model for 108 sovereigns, Klusak et al. (2021) estimate the effects of physical climate impacts on sovereign credit ratings and the resulting additional cost of sovereign debt resulting from climate-driven downgrades under multiple warming scenarios. Their results suggest that climate change will exert downward pressure on ratings as early as 2030, with an increasing magnitude throughout the 21st century, with significant implications for the cost of public debt. Sun et al. (2023) use an ordered logit model to credit ratings using ND-GAIN indices. Their work finds that climate vulnerability has a significant negative impact on ratings, and that readiness has a considerable positive impact.

The most recent literature increasingly focuses on policy. Bolton et al. (2022, 2023), who also conduct econometric analyses confirming the impact of climate vulnerability on the cost of sovereign capital, provide an overview of the challenges faced by various financial tools for addressing the climate challenge, such as carbon offsets and green bonds, and the conditions for their success. Zenios (2022) juxtaposes an analysis of the impact of climate change on GDP, debt and debt sustainability with a call to combine integrated assessment models (IAMs) with debt sustainability analysis (DSA). He argues that these techniques can better address the risks, ambiguity, and mis-specifications inherent in the problem. In Calcaterra et al. (2025), this analytical IAM plus DSA process is applied to six countries to calculate stress tests of sovereign debt under alternative climate narratives and policy assumptions. Ten Bosch et al. (2022) examine a specific set of policy objectives, the Sustainable Development Goals (SDGs). In three out of four of their model specifications, they find a statistically significant negative coefficient on country SDG indices used to predict five-year credit default spreads (CDS). This implies that SDG-aligned policies can lower debt costs. Together, these papers suggest that policymakers can mitigate the financial effects of climate change, although they may incur upfront costs.

Overall, several studies have followed up on our original contribution, confirming our main findings. In the following sections, we first present our original analysis and then provide some additional robustness checks in response to critiques that we have received.

3. Data and variables

For our econometric analysis, we utilise data from a sample of 46 developing and advanced countries spanning the period from 1996 to 2016. The data for the dependent variables, sovereign bond yields (YIELD), are based on weekly bond yield data collected from Bloomberg. The dataset includes marketable debt for 17 of the V20 group of climate-vulnerable countries: Bangladesh, Burkina Faso, Colombia, Costa Rica, Dominican Republic, Ghana, Guatemala, Kenya, Lebanon, Mongolia, Morocco, Philippines, Rwanda, Senegal, Tanzania, Tunisia, and Vietnam. In addition, we use annual multilateral bond yield observations, recorded by the IMF, for eight V20 countries: Ethiopia, Fiji, Honduras, Malawi, the Maldives, Nepal, Papua New Guinea, and Vanuatu. This IMF debt category is typically contracted at concessional rates through multilateral or bilateral agreements. Estimation of our model is conducted with and without an IMF dummy to isolate this effect. We also assembled data on 21 countries outside the V20: the seven countries of the G7 group of advanced economies and 14 other middle to less-developed countries. Most bond yield data refer to 10-year benchmark rates; however, this is not the case for all countries. For example, data for Burkina Faso refer to the average yield from 5-year government bond auctions, whereas for Guatemala, it is a benchmark weekly yield on 20-year government debt. We select benchmark debt time series according to the longest period available, maximising the number of observations. Local currency benchmarks are preferred over foreign currency bonds. Multilateral debt is usually denominated in USD or IMF special drawing rights. A list of all countries included in the empirical model can be seen in Appendix A. To be clear, the lack of bond data restricts the methodology that can be used to isolate the impact of climate vulnerability on the sovereign cost of debt. The methodology section outlines these limitations in detail.

The set of controls chosen is drawn from the prior literature on the drivers of sovereign bond yields (e.g. Beirne and Fratzscher 2013). Our control variables are sourced primarily from the IMF. The per capita income variable (PCY) refers to GDP per capita at purchasing power parity in US dollars. DEBT is gross government debt to GDP. REV is the government revenue to GDP. EXP is the government expenditure to GDP. PBA is the government's primary balance to GDP. CPI refers to inflation measured by the end-of-period consumer price indices. The FDI variable is sourced from the United Nations Conference on Trade and Development (UNCTAD) and is expressed as a percentage of GDP. The three dummies of the model are: (i) V20, representing the climate-vulnerable countries of the V20 group; (ii) G7, indicating the seven major economies of the G7; and (iii) IMF, representing V20 bond yield observations linked to multilateral debt and recorded by the IMF.

The climate vulnerability and readiness data are from the Notre Dame Global Adaptation Index (ND-GAIN), which gathers 74 variables to form 45 core indicators to measure the sensitivity and readiness of over 180 countries. As implied by the word adaptation, the headline index is a measure of how countries are dealing with the risks they face. Changes to a country's headline index measure a country's efforts at addressing climate risk. We focus on three sub-indices that reflect micro-level measures of vulnerability and preparedness: (i) NDS is a sensitivity index that incorporates factors such as food import dependency, the population living under five meters above sea level, dependency on natural capital, and dependency on imported energy; (ii) NDC is a capacity index based on components such as dam capacity, medical staff, quality of trade and transport-related infrastructure, paved roads, electricity access, and disaster preparedness; (iii) NDSR is a social readiness index based on measures of social inequality, information and communications technology (ICT) infrastructure, education, and innovation. ND-GAIN constructs its sub-indices by scaling each variable to a 0 to 1 score relative to a benchmark level. We decided to exclude the ND-GAIN exposure component, as it is based on climate change projections rather than actual data. We also forgo the ND-GAIN sub-index for economic readiness, which is based on the (now-discontinued) World Bank's Doing Business Index. A table of all the variables can be found in Appendix B.

Additionally, we assess the robustness of our results using alternative metrics, such as the Climate Risk Index (CRI) provided by Germanwatch and agricultural value-added as a proportion of GDP, as reported by the World Bank.[5] We also considered other indices, such as the World Risk Index, for our analysis. Unfortunately, many of these indices are available only for relatively short periods. A further issue is that purely physical climate indices are poorly suited to our methodology, as they show little variation over time, which means they cannot explain the observed variation in our dependent variable. Using actual weather events (as captured, for instance, in the EM-DAT Emergency Events Database) is also problematic because the losses count. Weather events in areas with limited economic activity are unlikely to significantly impact the economy and, consequently, bond yields. Including country-level data on financial losses due to climate-related weather events in our econometric analysis would have been

[5] Agriculture is generally considered a sector that is particularly vulnerable to climate change, although regional impacts are projected to differ (Wiebe et al., 2015).

desirable, but was not possible due to data limitations. This may be a direction for future research.

For the estimation of historic incremental debt costs due to climate vulnerability, we use total external debt stocks from the World Bank Development Indicator Databank with the series code DT.DOD.DECT.CD (downloaded 30 March 2018). It is defined as debt owed to non-residents repayable in currency, goods, or services. Total external debt is the sum of public, publicly guaranteed, and private non-guaranteed long-term debt, use of IMF credit, and short-term debt. Short-term debt includes all debt with an original maturity of one year or less and interest in arrears on long-term debt. This data series is in current US dollars.

4. Methodology

Theoretically, sovereign bond yields incorporate three main components: a risk-free rate (usually proxied using US government bonds when analysing less developed economies), a credit spread and a liquidity risk component. The credit spread accounts for the expected default risk of a country. Moreover, investors demand a premium for holding illiquid assets, resulting in a liquidity component (Huang and Huang, 2012; Huang, 2003). Studies for emerging markets such as BRICS countries suggest that liquidity risk is higher than in developed markets (Bekaert and Harvey, 1997; Lesmond, 2005). There has been no research to date on the less developed market, including V20 countries, due to a lack of available data. Using CDS, models can decompose the bond yield into a default and liquidity component Longstaff et al. (2005). Yet, CDS data are only available for a limited number of countries, making this approach unviable for answering our research question.

Our focus is on quantifying the alleged impact of climate vulnerability on the sovereign cost of debt. Whether the effect affects the credit spread by increasing default risk or the liquidity component, or both, is beyond the scope of our study. Furthermore, isolating the risk-free component, e.g., by matching the maturities of US bonds (the benchmark) and bonds issued by V20 countries, is challenging because some countries do not issue bonds with certain maturities. The robustness section tries to address this issue. Accordingly, our empirical models try to explain bond yields using measures of climate vulnerability and a set of countries. In particular, the weekly bond observations are converted into annual figures to perform the panel ordinary least squares regression (1).

$$y_{it} = \alpha + \boldsymbol{\beta}^{\mathbf{T}}\mathbf{x_{it}} + \boldsymbol{\gamma}^{\mathbf{T}}\mathbf{z_{it}} + \varepsilon_{it} \tag{1}$$

Where y_{it} denotes bond yields of country *i* at time *t*; α is a constant; β is a $k \times 1$ coefficient vector; x_{it} is a $k \times 1$ vector of climate-related variables; γ is a $p \times 1$ coefficient vector; z_{it} is a $p \times 1$ vector of control variables, and is an error term with mean zero and constant variance. All intercepts are assumed to be identical within this framework. This assumption is relaxed using the fixed effects model (2), where each country *i* has its own intercept. We conducted multiple regressions to test the significance of the climate variables and controls.

$$y_{it} = \sum_{i}^{N} \theta_i D_i + \boldsymbol{\beta}^{\mathbf{T}}\mathbf{x_{it}} + \boldsymbol{\gamma}^{\mathbf{T}}\mathbf{z_{it}} + \varepsilon_{it} \tag{2}$$

In equation (2), D denotes country dummy variables, and θ is a $N \times 1$ coefficient vector. Unfortunately, because some countries had very few usable annual data points, such a framework risks over-specifying the model. Additionally, other variables exhibit country effects due to their low temporal variability.

Our model is a linear regression model, and hence all the standard assumptions apply (OLS assumptions of linearity, spherical error terms, exogeneity). A linear prediction of the base cost of debt for the average V20 country, taking into account climate vulnerability and social preparedness, is estimated by calculating conditional expected values of the dependent variable. We can then observe the mean, median and standard deviation values for members of the V20 group of climate-vulnerable countries. The base effect is the predicted cost of debt minus the partial climate vulnerability and social preparedness effects.

Essentially, the average of the V20 sub-sample of explanatory variables is used to derive estimates of climate vulnerability cost. Further, we assume that parameters are constant, i.e. the partial impact of climate vulnerability on the cost of debt does not change over time. Specifically, our model only identifies the direct effect of climate vulnerability on the cost of debt; indirect effects through macroeconomic variables are not modelled. For example, we do not capture interventions such as IMF support, which is assumed to be exogenous, i.e. independent from climate vulnerability.

5. Empirical findings

5.1. Descriptive analysis

Table 1 shows descriptive statistics for all countries. Table 2 focuses on the V20 countries. Government bond yields are higher in V20 countries on average, and there is a considerable gap in GDP per capita, government revenues and expenditures. Extreme observations for both groups highly skew the mean of the CPI indicator.

[Insert Table 1 here]

We recommend exercising caution when interpreting these averages, as many of these time series are unbalanced. For example, the bond yield data for France covers the period 1998-2018, whereas the bond yield data for Senegal is only available for 2013 and 2014. We note that the measures of climate vulnerability, NDS and NDC, are higher for the V20 countries, and the measure of social readiness, NDSR, is lower. From this preliminary description of the data set, the question arises whether the chosen set of explanatory variables can explain the observed difference in cost of capital.

[Insert Table 2 here]

The data on debt yields are not normally distributed, exhibiting positive skewness due to the large positive outliers shown in Figure 2. Accordingly, a log transformation is applied to ensure a symmetric distribution of the dependent variable.

[Insert Figure 2 here]

5.2. Multivariate analysis

Table 3 shows our initial regression model using POLS with robust standard errors. We present nominal yields in the descriptive statistics above; however, as noted, the multivariate analysis specifies the natural logarithm of our annual bond yield observations as the dependent variable.

[Insert Table 3 here]

The explanatory power is satisfactory, with an adjusted R-squared of approximately 75% (see Table 3). We observe a positive coefficient on our key climate sensitivity measure NDS, implying that higher sensitivity is correlated with higher bond yields. This index includes measures such as food import dependency, slum population and dependency on imported energy. The coefficient on NDC is positive but generally not statistically significant. The negative and significant result of our NDSR measure of social readiness confirms the importance of investments in innovation, social equality, ICT infrastructure and education in reducing the cost of debt and mitigating the risks of climate change. Using a per capita income PCY variable controls the inherent correlation of many of these measures with gross domestic product. Robustness checks examine the relationship between climate vulnerability measures and macroeconomic conditions in greater detail.

Fixed-effects models can be used, and the results are qualitatively similar. However, we decided against using fixed-effects models, as the model fit does not improve considerably, justifying the inclusion of a substantial number of country dummies. Moreover, the fraction of variance due to the country-level error term is only around 10%. Given the relatively modest sample size, adding many dummies risks overfitting.

Finally, using dummies based on a set of countries such as the G7, V20, and IMF dummies seems to be a more efficient use of explanatory variables.

We note the high degree of correlation between NDSR, NDS and NDC, leading to high variance inflation factors above the critical value of 10. The matrix of correlation coefficients is presented in Appendix C. We observe that although the acronyms are ND-Sensitivity, ND-Capacity and ND-Social Readiness, sensitivity and capacity are positively correlated at 0.611. In contrast, social readiness is negatively correlated with sensitivity at -0.515, and with capacity at -0.886. We suggest that although capacity includes measures such as dam capacity, its effect is to map out the relative paucity of such capacity.

We conduct a principal component analysis (PCA) of the NDS and NDC variables to address the multicollinearity inherent in our climate vulnerability indicators. Note that NDSR is a preparedness indicator. This statistical methodology allows us to reduce the number of variables by formulating them as two uncorrelated linear combinations of the variables, the first containing the majority of the variance. We determine the number of components appropriate to our model by using a scree plot. Eigenvalues are below one after considering each component individually, suggesting that a single component is sufficient.

[Insert Table 4 here]

We define our own climate vulnerability index (SCORE) based on the ND-GAIN sensitivity and capacity indices based on the PCA model. Table 4 demonstrates that the SCORE variable has a positive and significant impact on yield, particularly after controlling for multilateral IMF debt yields based on concessionary rates. Although country dummies are statistically significant, they are also subject to strong selection biases related to access to financial markets. In summary, our findings suggest that climate vulnerability has a positive impact on the cost of debt, while developmental indicators reflected in the NDSR have a negative impact on the cost of debt.

5.3. Estimated additional costs due to climate vulnerability

We estimate the additional cost of debt that arises directly from climate vulnerability. This figure is based on statistics for the external public, publicly guaranteed and private debt from the World Bank Development Indicator Databank for 40 members of the V20 group of climate-vulnerable countries. The number of countries is determined by data availability. This figure adds up to USD 768 billion in 2016 and USD 5.4 trillion over the ten years 2007 to 2016. The estimated climate vulnerability impacts for V20 countries are shown in Table 5. The V20 countries included in the empirical model reflect 86% of the external debt reported by the World Bank for the wider V20 group.

[Insert Table 5 here]

Multiplying external debt by our estimated climate vulnerability impact of 1.17% (adjusted for log yields and the V20 average climate vulnerability SCORE) generates an estimate of a ten-year historical cost exceeding USD 62 billion. This estimate of direct effects connects with many related issues beyond this paper's scope. External debt for this sample of V20 countries rose by over 5% in 2016. The percentage of the equity to capital required typically increases with perceived risk (e.g. sovereign debt rating), which would be more of an issue in V20 countries as (1) equity is generally scarce in less developed, largely domestic financial systems and (2) any increase in equity can dramatically increase the weighted average cost of capital. The higher debt cost and increased equity requirements would decrease the number of positive net present value investment opportunities relative to required hurdle rates. Similarly, higher hurdle rates and worse sovereign credit ratings may reduce the supply of international private sector capital.

To the extent that the cost of debt limits investment in key sectors, it would then change the profile of such investment. This might potentially reflect a bias towards conventional investments over sustainable or climate-resilient investments with higher initial capital expenditures requirements.

6. Robustness checks

6.1. Additional controls

In Table 6, we present three checks of the robustness of our earlier findings. Specification [C1] is the empirical result from our reference model B2 shown in Table 4. Model [C2] highlights how some controls have negatively impacted the number of observations, specifically concerning a number of V20 countries. Model [C3] introduces a risk-free rate (RFR) control based on US 10 year Treasury yields. The number of observations declines as the United States is no longer included in the model as observations of the dependent variable.

[Insert Table 6 here]

Specification [C4] addresses the differences in maturity by introducing a polynomial of maturity. Because the cost of debt data is limited for many countries of our sample group, and many choose to issue bonds primarily at maturities other than ten years, we have selected the most comprehensive time series available for each. Maturities vary from 5 years, 8 years, 9 years, 10 years and 20 years, with 10 years being the most common. This is a non-optimal way to address differences in maturity as it estimates a yield curve, assuming that there is a universal yield curve that is unlikely to exist. Bond yield observations on IMF concessionary debt is not included in the model [C4] as their maturity is undefined in the data.

These robustness checks confirm the original result of a positive and statistically significant coefficient on the climate vulnerability measure SCORE and a negative and statistically significant coefficient on the social readiness measure NDSR, at the 99.9% significance level.

6.2. Endogeneity of the climate vulnerability measure

The climate vulnerability measure (NDS) is an index based on a set of variables, which include climate-related and economic measures (e.g., infrastructure). By construction, the NDS is correlated with macroeconomic variables, which may cause endogeneity in models that attempt to explain financial variables, such as yields. To address the endogeneity of the NDS, we follow Kling et al. (2021) and construct a new index that consists of factors less correlated with macroeconomic variables. Accordingly, the instrument refers to a newly composed index with special statistical properties: a high correlation with the NDS and a low correlation with the error term of the regression equation. By design, the validity is high, and there is no risk of overidentification.

Table 7 shows the partial impact of the climate vulnerability measure (NDS) in specification [D1] without adjustment. Model [D2] utilises the newly constructed climate vulnerability index as an instrument to assess the impact of the original index, as outlined in Kling et al. (2021). The instrumental variable regression exhibits a similar partial impact on log bond yields, illustrating that endogeneity issues are not a major concern in this context.

By default, climate-related variables, such as annual rainfall and temperature, exhibit low levels of correlation with macroeconomic conditions compared to the ND-GAIN indices. Table 7 reports two alternative specifications using yearly averages and standard deviations of rainfall (M RAIN, SD RAIN) and temperature (M TEMP, SD TEMP) based on World Bank data. The results indicate that climate change, i.e., an increase in average temperatures, has a similar positive impact on log bond yields to the climate vulnerability measure.

[Insert Table 7 here]

6.3. Exclusion from capital markets

Thus far, our empirical model focuses on countries for which yield data is observable and available via the data provider Bloomberg. This implies that our regression analysis operates under the condition that countries can issue sovereign bonds (and that debt issues are sufficiently large and liquid to warrant recording by Bloomberg). This is not the case for all V20 countries. Our POLS model is valid as a second-stage model. Hence, we determine the conditional expected value of bond yields influenced by climate vulnerability and other factors, assuming countries have access to capital markets. The first-stage problem becomes understanding the underlying factors that enable governments to issue bonds. Climate vulnerability and other control variables may also play a role in this selection stage. Accordingly, there is a possibility that climate vulnerability reduces a country's access to capital markets, in addition to the direct yield effect we analysed earlier.

Table 8 presents our results based on a logistic regression, where access to capital markets, proxied by observable sovereign bond yields, is the dependent variable. Specification [E1] focuses exclusively on climate vulnerability, indicating a pseudo-R-squared of 0.163, which is relatively high for a single explanatory variable. Model [E2] includes all controls used in the first-stage model, as well as a V20 country dummy, indicating a general group-specific disadvantage in accessing capital markets. Both specifications reveal that climate vulnerability, once again, negatively affects V20 countries. The likelihood of being excluded (coded as one) increases with climate vulnerability throughout all specifications. Moreover, investments in social and physical infrastructure (NDSR) can reduce the likelihood of exclusion. This effect is even more substantial for V20 countries, as shown in the model [E3], as the interaction term is highly significant; in fact, the sign of the variable NDSR switches from negative to positive. As a check of robustness, model [E4] excludes dummies and the interaction term, confirming prior findings for all countries.

[Insert Table 8 here]

We use specification [E3], with a pseudo-R-squared of approximately 56%, as our reference model. It would be more appropriate to use model [E4] to illustrate the impact of climate vulnerability. Figure 3 plots the predicted probability of difficulties raising capital from debt markets, distinguishing between the sample countries based on their membership in the V20 group and the G7 or G24. A clear pattern emerges, where V20 countries, after controlling for all other factors, exhibit a high risk of exclusion, and climate vulnerability further complicates access to capital markets. Each dot represents a country-year and the estimated probability that the specific country-year is not associated with a cost of debt observation within our empirical model.

[Insert Figure 3 here]

7. Discussion and conclusion

This paper fills a critical knowledge gap by investigating the impact of climate vulnerability on sovereign bond yields. It provides the first evidence that measures of climate vulnerability have a positive effect on the cost of sovereign debt. This statistically significant result highlights one channel of financial cost that the V20 climate-vulnerable countries bear due to their higher exposure to vulnerabilities, such as a higher dependency on natural capital or a greater water dependency ratio. Due to higher climate vulnerability, we estimate that the debt cost has exceeded USD 62 billion over the past decade. All these results are after controlling for conventional macroeconomic and fiscal factors that influence the cost of debt. Our results also draw attention to how the adverse impact of climate vulnerability can be mitigated by investments that enhance social readiness, comprising investment in education, innovation, social equality, and ICT infrastructure for those countries which are most in need.

Apart from sovereign bond yields, our logistic models indicate a negative impact of climate vulnerability on countries' ability to raise capital. Consequently, climate vulnerability affects market access, leading to financial exclusion. Limiting access to affordable finance undermines investment in resilience and adaptation, trapping countries in high-risk settings. Underinvestment in adaptation and resilience will make countries even more vulnerable in the face of intensifying anthropogenic climate change. All this could contribute to an accelerating vicious cycle of climate vulnerability, unsustainable debt and underdevelopment. To reverse this vicious cycle, it will be critical to address the cost of capital problem and enhance access of vulnerable countries to affordable climate finance. Importantly, our analysis reinforces calls for fair mechanisms to address loss and damage associated with the impacts of climate change in developing countries particularly vulnerable to the adverse effects of climate change. It also underscores the need for a fair and efficient sovereign debt restructuring mechanism that will provide debt relief to overindebted countries trapped in the vicious cycle.

The publication of this research as a working paper in 2018 has motivated several follow-up studies, as discussed in the literature review. Future directions of this work could examine the interrelation between rating changes, bond yields and climate vulnerability using a qualitative short panel vector auto-regression model. This could reveal whether ratings drive markets or vice versa. Secondly, it would be interesting to explore the direct and indirect effects of climate vulnerability using a structural equation model. This could help determine whether climate vulnerability acts directly or indirectly by affecting macroeconomic variables, taking into account the cost of capital.

Conflict of interest: None

Data availability: Upon request.

Funding: MAVA Foundation.

References

Acevedo, S. (2014), 'Debt, growth and natural disasters: A caribbean trilogy', IMF Working Paper No. 14/125, Washington, DC: International Monetary Fund.

Alano, E. and Lee, M. (2016), 'Natural disaster shocks and macroeconomic growth in Asia: Evidence for typhoons and droughts', ADB Economics Working Paper No. 503, Manila: Asian Development Bank.

Ameli, N., Biancardi, A., Drummond, P., Leonidas, P., Grubb, M., Vrontisi, Z., Kostas, F., Panagiotis, F. and Mandel, A. (2017), 'Stylized models of relative rates of return, technology co-benefit / spillover effects for key sectors', mimeo, London: University College London.

Ameli, N., Dessens, O., Winning, M., Cronin, J., Chenet, H., Drummond, P., Calzadilla, A., Anandarajah, G. and Grubb, M. (2021), 'Higher cost of finance exacerbates a climate investment trap in developing economies', *Nature Communications* 12, 4046.

Agarwala, M., Burke, M., Klusak, P., Mohaddes, K., Volz, U. and Zenghelis, D. (2021), 'Climate change and fiscal sustainability: Risks and opportunities', *National Institute Economic Review*, 258, 28–46.

Batten, S. (2018), 'Climate change and the macro-economy: A critical review', Bank of England Staff Working Paper No. 706, London: Bank of England.

Beirne, J., and Fratzscher, M. (2013), 'The pricing of sovereign risk and contagion during the European sovereign debt crisis', *Journal of International Money and Finance* 34(C), 60–82.

Beirne, J., Renzhi, N. and Volz, U. (2021a), 'Feeling the heat: Climate risks and the cost of sovereign borrowing', *International Review of Economics and Finance* 76, 920–936.

Beirne, J., Renzhi, N. and Volz, U. (2021b), 'Bracing for the typhoon: Climate change and sovereign risk in Southeast Asia', *Sustainable Development* 29(3), 537–551.

Bekaert, G. and Harvey, C. R. (1997), 'Emerging equity market volatility', *Journal of Financial Economics* 43(1), 29–77.

Bingler, J.A. (2022), 'Expect the worst, hope for the best: The valuation of climate risks and opportunities in sovereign bonds', CER-ETH Economics Working Paper No. 22/371, Zurich: Center of Economic Research at ETH Zurich.

Böhm, H. (2022), 'Physical climate change and the sovereign risk of emerging economies', *Journal of Economic Structures* 11, 31.

Boitan, I. A., and Marchewka-Bartkowiak, K. (2022), 'Climate change and the pricing of sovereign debt: Insights from European markets', *Research in International Business and Finance* 62, 101685.

Bolton, P., Buchheit, L., Galati, M., Panizza, U., Weder di Mauro, B., and Zettelmeyer, J. (2022), 'Climate and Debt'. Geneva Reports on the World Economy 25. London: CEPR Press.

Bolton, P., Buchheit, L., Galati, M., Panizza, U., Weder di Mauro, B., and Zettelmeyer, J. (2023), 'On Debt and climate', *Oxford Open Economics* 2, 1–6.

Bouwer, L. M., Crompton, R. P., Faust, E., Hoppe, P. and Pielke, R. A. (2007), 'Confronting disaster losses', *Science* 318(5851), 753–753.

Bova, E., Ruiz-Arranz, M., Toscani, F.G. and Elif Ture, H. (2019), 'The impact of contingent liability realizations on public finances', *International Tax and Public Finance* 26(2), 381–417.

Cabezon, E., Hunter, L., Tumbarello, P., Washimi, K. and Wu, Y. (2015), 'Enhancing macroeconomic resilience to natural disasters and climate change in the small states of the pacific', IMF Working Paper No. 15/125, Washington, DC: International Monetary Fund.

Calcaterra, M., Consiglio, A., Martorana, V., Tavoni, M., and Zenios, S. A. (2025), 'Sovereigns on thinning ice: Debt sustainability, climate impacts, and adaptation', Bruegel Working Paper No. 06/2025, Brussels: Bruegel.

Cantelmo, A., Melina, G. and Papageorgiou, C. (2019), 'Macroeconomic outcomes in disaster-prone countries', IMF Working Paper No. 19/217, Washington, DC: International Monetary Fund.

Cavallo, E., Galiani, S., Noy, I. and Pantano, J. (2013), 'Catastrophic natural disasters and economic growth', *The Review of Economics and Statistics* 95(5), 1549–1561.

Cebotari, A. and Youssef, K. (2020), 'Natural disaster insurance for sovereigns: Issues, challenges and optimality', IMF Working Paper No. 20/3, Washington, DC: International Monetary Fund.

Cevik, S. and Tovar Jalles, J. (2022), 'This changes everything: Climate shocks and sovereign bonds', *Energy Economics* 107, 105856.

Dellink, R., Chateau, J., Lanzi, E. and Magné, B. (2017), 'Long-term economic growth projections in the shared socioeconomic pathways', *Global Environmental Change* 42, 200–214.

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

Estrada, F., Tol, R. S. and Botzen, W. J. (2017), 'Global economic impacts of climate variability and change during the 20th century', *PLOS ONE* 12(2), e0172201.

Farhi, E., and Gabaix, X. (2016), 'Rare disasters and exchange rates', *Quarterly Journal of Economics* 131(1), 1–52.

Felbermayr, G. and Groschl, J. (2014), 'Naturally negative: The growth effects of natural disasters', *Journal of Development Economics* 111, 92–106.

Ferreira, S. and Karali, B. (2015), 'Do earthquakes shake stock markets?', *PLOS ONE* 7(10), e0133319.

Fischer, E.M. and Knutti, R. (2015), 'Anthropogenic contribution to global occurrence of heavy-precipitation and high-temperature extremes', *Nature Climate Change* 5, 560–564.

Fomby, T., Ikeda, Y. and Loayza, N.V. (2013), 'The growth aftermath of natural disasters', *Journal of Applied Econometrics* 28(3), 412–434.

Gerling, K. (2017), ‘The macro-fiscal aftermath of weather-related disasters: Do loss dimensions matter?’, IMF Working Paper No. 17/235, Washington, DC: International Monetary Fund.

Giovanis, E., and Ozdamar, O. (2022), ‘The impact of climate change on budget balances and debt in the Middle East and North Africa (MENA) region’, *Climatic Change* 172, 3-4.

Glass, B., Kraemer, M., Mrsnik, M. and Petrov, A. (2015), *Storm alert: Natural disasters can damage sovereign creditworthiness*, New York: NY: Standard and Poor’s.

Hallegatte, S. (2016), Natural disasters and climate change. An economic perspective, New York: Springer.

Hochrainer, S. (2009), ‘Assessing the macroeconomic impacts of natural disasters. Are There any?’, Policy Research Working Paper No. 4968, Washington, DC: World Bank.

Hochrainer-Stigler, S., Keating, A., Handmer, J. and Ladds, M. (2018), ‘Government liabilities for disaster risk in industrialized countries: A case study of Australia’, *Environmental Hazards* 17(5), 418–435.

Huang, J.-Z. and Huang, M. (2012), ‘How much of the corporate-treasury yield spread is due to credit risk?’, *Review of Asset Pricing Studies* 2(2), 153–202.

Huang, M. (2003), ‘Liquidity shocks and equilibrium liquidity premia’, *Journal of Economic Theory* 109(1), 104–129.

IPCC (2014), Climate change 2014: Synthesis report. Contribution of working groups i, ii and iii to the fifth assessment panel on climate change, Technical report, Intergovernmental Panel on Climate Change.

Jones, B., Keen, M. and Strand, J. (2013), 'Fiscal implications of climate change', *International Tax and Public Finance* 20, 29–70.

Kahn, M. E., Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M. and Yang, J.-C. (2021), 'Long-term macroeconomic effects of climate change: A cross-country analysis', *Energy Economics* 104, 105624.

Kling, G., Lo, Y. C., Murinde, V., and Volz, U. (2018), 'Climate vulnerability and the cost of debt', Centre for Global Finance Working Paper No. 12/2018, London: SOAS University of London.

Kling, G., Volz, U., Murinde, V. and Ayas, S. (2021), 'The impact of climate vulnerability on firms cost of capital and access to finance', *World Development* 137, 105131.

Klusak, P., Agarwala, M., Burke, M., Kraemer, M., and Mohaddes, K. (2023), 'Rising temperatures, falling ratings: The effect of climate change on sovereign creditworthiness', *Management Science, 69*, 7468–7491.

Koetsier, I. (2017), 'The fiscal impact of natural disasters', Utrecht School of Economics Discussion Paper No. 17-17, Utrecht: Utrecht University.

Leimbach, M., Kriegler, E., Roming, N. and Schwanitz, J. (2017), 'Future growth patterns of world regions – a GDP scenario approach', *Global Environmental Change* 42, 215–225.

Lesmond, D. A. (2005), ‘Liquidity of emerging markets’, *Journal of Financial Economics* 77(2), 411–452.

Lo, Y.C., and Volz, U. (2025), ‘The impacts of disasters on capital flows, international reserves and exchange rates: implications for public sector financial risk management and development lenders’, SOAS Economics Working Paper No. 265, London: SOAS University of London.

Loayza, N. V., Olaberra, E., Rigolini, J. and Christiaensen, L. (2012), ‘Natural disasters and growth: Going beyond the averages’, *World Development* 40(7), 1317–1336.

Longstaff, F. A., Mithal, S. and Neis, E. (2005), ‘Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market’, *The Journal of Finance* 60(5), 2213–2253.

Mallucci, E. (2022), ‘Natural disasters, climate change, and sovereign risk’, *Journal of International Economics* 139, 103672.

Mechler, R. and Bouwer, L. M. (2015), ‘Understanding trends and projections of disaster losses and climate change: Is vulnerability the missing link?’, *Climatic Change* 133(1), 23–35.

Melecky, M. and Raddatz, C. (2011), ‘How do governments respond after catastrophes? Natural-disaster shocks and the fiscal stance’, Policy Research Working Paper No. 5564, Washington, DC: World Bank.

Melecky, M. and Raddatz, C. (2014), ‘Fiscal responses after catastrophes and the enabling role of financial development’, *The World Bank Economic Review* 29(1), 129–149.

Mendelsohn, R., Kerry, E., Chonabayashi, S. and Bakkensen, L. (2015), 'The impact of climate change on global tropical cyclone damage', *Nature Climate Change* 2, 205–209.

Mitchell, T., Mechler, R. and Peters, K. (2014), 'Placing disaster risk management at the heart of national economic and fiscal policy', in: Markandya, A., Galarraga, I. and de Murieta, E.S. (eds.), *Handbook on the economics of adaptation*, London: Routledge, 417–436.

Munevar, D. (2018), 'Climate change and debt sustainability in the Caribbean. Trouble in paradise', Background paper for the Intergovernmental Group of Experts on Financing for Development, 2nd Session, Geneva: United Nations Conference on Trade and Development.

Ozcan, B. (2005), *Market convergence, catastrophe risk and sovereign borrowing: An empirical analysis for emerging market countries*, PhD thesis, Medford, MA: Fletcher School of Law and Diplomacy.

Raddatz, C. (2007), 'Are external shocks responsible for the instability of output in lowincome countries?', *Journal of Developmental Economics* 84, 155–187.

Sun, X., Shen, Y., Guo, K., and Ji, Q. (2023), 'Sovereign ratings change under climate risks', *Research in International Business and Finance* 66, 102040.

Schuler, P., Edgard Oliveira, L. Mele, G. and Antonio, M. (2019), 'Managing the fiscal risks associated with natural disasters', in: Pigato, M.A. (ed.), *Fiscal policies for development and climate action*, Washington, DC: World Bank, 133–154.

Ten Bosch, E., Van Dijk, M. A., and Schoenmaker, D. (2022), Do the SDGs affect sovereign bond spreads? First evidence, CEPR Discussion Paper No. 16898, London: Centre for Economic Policy Research.

Tol, R.S. (2018), 'The economic impacts of climate change', *Review of Environmental Economics and Policy* 12(1), 4–25.

UNDRR (2020), The human cost of disasters: An overview of the last 20 years (2000-2019), Geneva: United Nations Office for Disaster Risk Reduction.

Volz, U., Beirne, J., Ambrosio Preudhomme, N., Fenton, A., Mazzacurati, E., Renzhi, N., and Stampe, J. (2020), *Climate change and sovereign risk*, London: Centre for Sustainable Finance, SOAS University of London.

Von Peter, G., S. von Dahlen, and S. Saxena. 2012. 'Unmitigated disasters? New evidence on the macroeconomic cost of natural catastrophes', BIS Working Paper No. 394, Basel: Bank for International Settlements.

Wiebe, K., Lotze-Campen, H., Sands, R., Tabeau, A., van der Mensbrugghe, D., Biewald, A., Bodirsky, B., Islam, S., Kavallari, A., Mason-DCroz, D. et al. (2015), 'Climate change impacts on agriculture in 2050 under a range of plausible socioeconomic and emissions scenarios', Environmental Research Letters 10(8), 085010.

WMO (2021), WMO atlas of mortality and economic losses from weather, climate and water extremes (1970–2019), Geneva: World Meteorological Organization.

Zenios, S. A. (2022), 'The risks from climate change to sovereign debt', Climatic Change, 172(30).

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

Table 1: Descriptive statistics: All countries

	N	Mean	Std	P25	P50	P75
YIELD	473	7.468	6.028	3.760	5.820	9.540
NDS	3762	0.403	0.098	0.332	0.396	0.477
NDC	3960	0.513	0.170	0.390	0.493	0.653
NDSR	4048	0.308	0.161	0.194	0.257	0.376
PCY	6351	8350	13659	798	2589	9505
DEBT	4104	57.256	49.904	28.400	46.250	71.250
REV	4292	29.236	13.463	18.577	26.981	38.076
EXP	4268	31.734	14.058	20.985	29.676	40.628
PBA	4065	-0.011	7.031	-2.327	-0.214	2.092
CPI	5892	35.623	359.970	2.000	4.800	10.500
FDI	6619	16.311	260.635	0.444	1.682	4.527

YIELD = Sovereign bond yield; NDS = Notre-Dame Global Adaptation Initiative (ND-GAIN) Sensitivity Index; NDC = ND-GAIN Capacity Index; NDSR = ND-GAIN Social Readiness Index; PCY = GDP per capita; DEBT = Ratio of Gross Government Debt to GDP; REV = Ratio of Primary Balance to GDP; CPI = Consumer Price Index; FDI = ratio of Foreign Direct Investment to GDP.

Table 2: Descriptive statistics: V20 countries

	N	Mean	Std	P25	P50	P75
YIELD	174	10.307	6.586	6.200	7.975	12.660
NDS	880	0.451	0.085	0.396	0.464	0.503
NDC	924	0.629	0.124	0.530	0.635	0.730
NDSR	990	0.230	0.084	0.172	0.214	0.274
PCY	1563	1931	2617	421	958	2286
DEBT	930	57.864	43.087	33.200	45.700	69.800
REV	988	21.594	13.090	13.788	18.801	25.129
EXP	985	25.002	14.051	17.015	22.198	28.746
PBA	916	-1.329	4.427	-2.881	-1.061	0.886
CPI	1459	28.914	316.806	2.900	6.300	11.800
FDI	1564	2.732	3.977	0.341	1.325	3.894

Variables as defined in Table 1.

Table 3: Determinants of log yields

	[A1]	[A2]	[A3]	[A4]
NDS	1.082***	0.879*	1.197***	0.775*
NDC	0.424	0.235	0.678	0.418
NDSR	-1.524***	-1.493***	-1.649***	-2.567***
PCY	0.000*	0.000*	0.000**	-0.000
DEBT	-0.010***	-0.010***	-0.009***	-0.010***
CAB	-0.005	-0.005	-0.005	-0.003
REV	-0.183***	-0.186***	-0.170***	-0.161***
EXP	0.179***	0.181***	0.170***	0.153***
PBA	0.149***	0.151***	0.140***	0.107***
CPI	0.006***	0.006***	0.006***	0.006**
FDI	0.021	0.017	0.023*	0.023*
V20		0.094		
IMF			-0.228*	-0.266**
G7				1.013***
aic	364.332	364.663	360.721	331.072
bic	411.065	415.290	411.349	385.593
R^2_a	0.738	0.739	0.742	0.762

N	363	363	363	363

All models refer to POLS using the Huber-White sandwich estimator. IMF = statistical dummy for concessional lending programmes; V20 = statistical dummy identifying members of V20 group of environmentally vulnerable countries; G7 = statistical dummy identifying G7 group of industrial countries; other variables as defined in Table 1; aic = Akaike information criterion; bic = Bayesian information criterion; N = number of observations; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 4: Determinants of bond yields based on Principal Component Analysis

	[B1]	[B2]	[B3]	[B4]
SCORE	0.137***	0.105*	0.166***	0.106*
NDSR	-1.443***	-1.383***	-1.648***	-2.559***
PCY	0.000**	0.000*	0.000**	-0.000
DEBT	-0.010***	-0.010***	-0.009***	-0.010***
CAB	-0.005	-0.005	-0.005	-0.003
REV	-0.183***	-0.187***	-0.170***	-0.161***
EXP	0.180***	0.182***	0.170***	0.153***
PBA	0.150***	0.152***	0.140***	0.107***
CPI	0.006***	0.006***	0.006***	0.006**
FDI	0.021	0.018	0.023*	0.023*
V20		0.089		
IMF			-0.228**	-0.267***
G7				1.013***
aic	362.514	363.010	358.721	329.075
bic	405.352	409.743	405.454	379.702
R^2_a	0.739	0.739	0.742	0.763
N	363	363	363	363

All models refer to POLS using the Huber-White sandwich estimator. Variables are as defined in Tables 1 and 3; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 5: Estimates of V20 incremental debt yield

	Mean	P50	SD
BASE	12.420	12.270	3.357
CLIMATE	1.174	1.213	0.198
PREPAREDNESS	-0.674	-0.686	0.092

BASE = base estimated debt yield for sample countries; CLIMATE = estimate of incremental debt yield due to climate vulnerability; PREPAREDNESS = estimate of decremental debt yield due to social preparedness; Mean = sample mean; P50 = sample median; and SD = standard deviation.

Table 6: Robustness checks

	[C1]	[C2]	[C3]	[C4]
SCORE	0.166***	0.111***	0.155***	0.191***
NDSR	-1.648***	-1.716***	-1.717***	-1.260***
PCY	0.000**	-0.000	0.000*	0.000
DEBT	-0.009***	-0.005***	-0.009***	-0.009***
CAB	-0.005	-0.014*	-0.007	-0.016*
REV	-0.170***		-0.158***	-0.164***
EXP	0.170***		0.158***	0.164***
PBA	0.140***		0.115***	0.138***
CPI	0.006***	0.008***	0.006***	0.007***
FDI	0.023*	0.015	0.017	0.017
IMF	-0.228**	-0.484***	-0.257**	
RFR			0.342***	
MAT				-0.334
MAT^2				0.024
aic	358.721	504.196	325.809	331.450
bic	405.454	539.915	375.850	381.111
R^2_a	0.742	0.626	0.759	0.756
N	363	391	347	337

All models refer to POLS using the Huber-White sandwich estimator. RFR = Risk Free Rate (US bond yield); MAT = Maturity period; MAT^2 = Quadratic maturity adjustment. Other variables as defined in Tables 1 and 3. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 7: Endogeneity of the climate vulnerability measure

	[D1]	[D2]	[D3]	[D4]
NDS	2.857***	2.249***		0.386
M_RAIN			-0.001	-0.001
M_TEMP			0.047***	0.042***
SD_RAIN			-0.000	-0.000
SD_TEMP			-0.010	-0.017
aic	844.255	.	720.472	721.774
bic	852.223	.	740.080	745.303
R^2_a	0.133	0.126	0.283	0.282
N	397	385	373	373

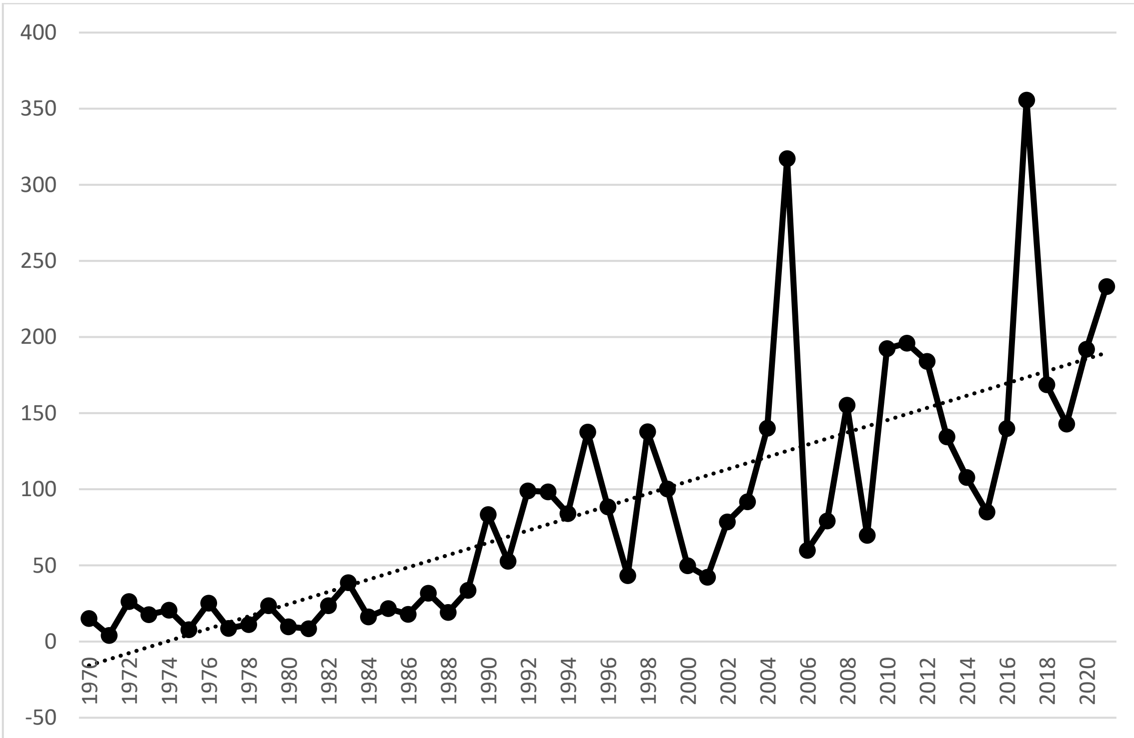
Models D1, D3-D4 refer to POLS using the Huber-White sandwich estimator. D2 is an instrumental variable regression. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Predicting exclusion from capital markets

	[E1]	[E2]	[E3]	[E4]
SCORE	0.856***	0.718**	0.748**	0.292**
NDSR		-5.785	135.824**	-7.719***
PCY		0.000*	0.000**	-0.000***
DEBT		0.035***	0.038***	0.015***
REV		0.253*	0.264*	0.215***
EXP		-0.203*	-0.215*	-0.151**
PBA		-0.083	-0.095	-0.069
CPI		0.000	-0.000	0.007
FDI		0.096*	0.097*	0.126***
V20		21.072**	117.544**	
NDSRxV20			-141.863**	
aic	1319.354	473.128	473.285	917.027
bic	1329.612	524.422	529.242	966.074
r2_p	0.157	0.583	0.585	0.314
N	1248	783	783	997

All models refer to POLS using the Huber-White sandwich estimator. Variables are as defined in Tables 1 and 3. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Figure 1: Total insured and uninsured losses due to catastrophic weather events (USD billion), 1970-2021



Source: Compiled by authors with data from Swiss Re Institute's sigma explorer (http://www.sigma-explorer.com)

Figure 2: Kernel density of nominal yields

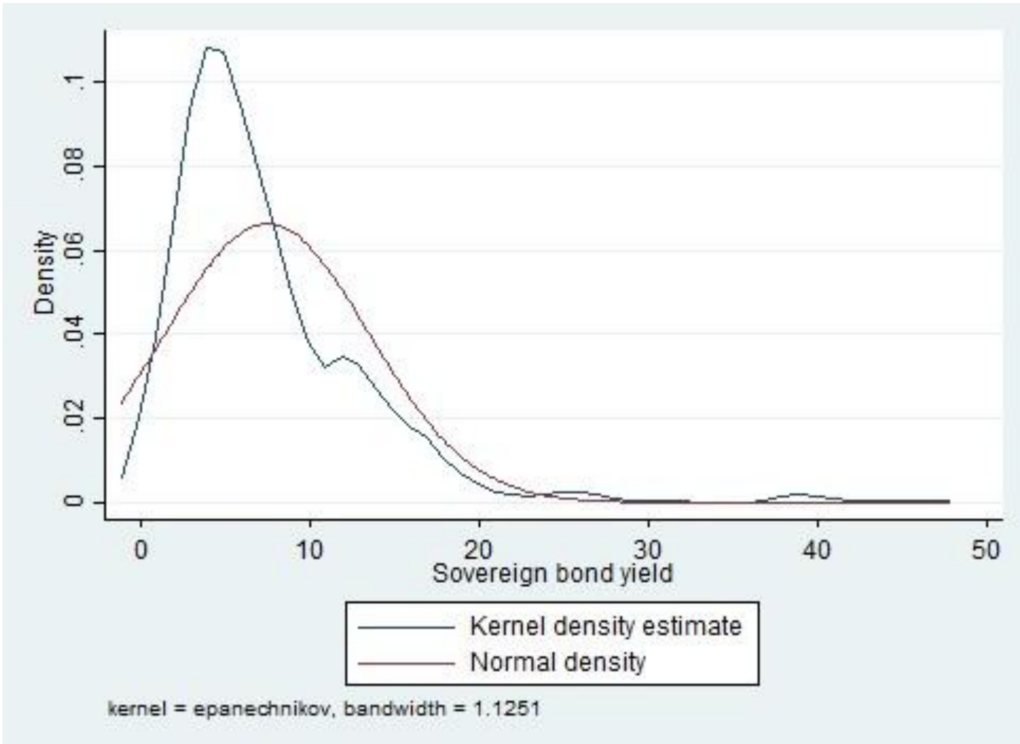
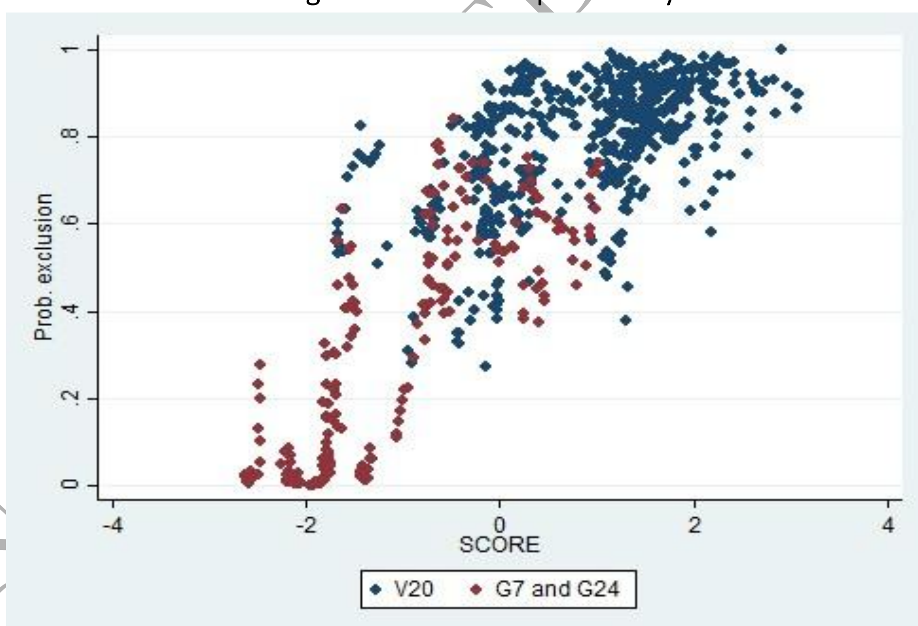


Figure 3: Predicted probability for exclusion



8. Appendix A. Countries included in panel ordinary least squares regression model

Country	Type of debt cost observation		V20 member	Outstanding debt 2016 (V20 only), in USD billions		
	Marketable	Multilateral		External total	Public & guaranteed	Multilateral
Argentina	✓					
Bangladesh	✓		✓	41.1	28.6	26.5
Brazil	✓					
Burkina Faso	✓		✓	2.8	2.5	2.5
Canada	✓					
China	✓					
Colombia	✓		✓	120.3	70.9	6.8
Costa Rica	✓		✓	25.6	11.1	1.2
Dominican Republic	✓		✓	28.0	17.2	1.8
Egypt	✓					
Ethiopia		✓	✓	23.1	21.8	15.8
Fiji		✓	✓	0.9	0.7	0.3
France	✓					
Germany	✓					
Ghana	✓		✓	21.4	17.0	8.7
Guatemala	✓		✓	21.2	8.1	1.3
Honduras		✓	✓	7.6	6.0	3.4
India	✓					
Indonesia	✓					
Italy	✓					
Jamaica	✓					
Japan	✓					
Kenya	✓		✓	22.3	18.3	12.7
Lebanon	✓		✓	32.0	27.2	0.8
Malawi		✓	✓	1.8	1.5	1.5
Maldives		✓	✓	1.2	0.9	0.7
Mexico	✓					
Mongolia	✓		✓	23.9	4.5	2.1
Morocco	✓		✓	46.3	30.1	9.0
Nepal		✓	✓	4.3	3.6	3.6
Nigeria	✓					
Pakistan	✓					
Peru	✓					
Philippines	✓		✓	77.3	33.4	8.4
Papua New Guinea		✓	✓	19.7	1.9	1.2
Rwanda	✓		✓	2.8	2.4	1.9
Senegal	✓		✓	6.6	6.1	4.9
South Africa	✓					
Tanzania	✓		✓	16.5	11.2	9.1
Thailand	✓					
Tunisia	✓		✓	28.1	18.3	5.5
UK	✓					
United States	✓					
Vanuatu		✓	✓	0.2	0.1	0.1
Venezuela	✓					
Vietnam	✓		✓	87.0	48.0	35.0
Total				661.9	391.7	164.8

Source: Compiled with data from Bloomberg and the World Bank. Multilateral debt is typically at concessionary rates. Total external debt consists of public, publicly-guaranteed, private non-guaranteed and IMF credit

Appendix B. Table of variables

Variable	Source	Definition
YIELD	Bloomberg	Up to weekly Sovereign Bond yield observations collected on 46 countries to estimate an annual bond yield. For liquid markets, this would be 52 observations of generic benchmark yields as calculated by Bloomberg. For other markets, this might reflect the average yield at a debt auction. IMF bonds are discussed below. Clean or dirty (including accrued coupons) pricing is used based on market convention. Local currency bonds are chosen over USD versions.
NDS	Notre-Dame Global Adaptation Initiative	The ND-GAIN Sensitivity index consists of 12 measures including: Food import dependency, rural population, fresh water withdrawal rate, water dependency ratio, slum population, dependency on external resource for health services, dependency on natural capital, ecological footprint, urban concentration, age dependency ratio, dependency on imported energy, and the population living under 5m above sea level. Statistics are rebased to 0 to 1, relative to a selected benchmark level.
NDC	Notre-Dame Global Adaptation Initiative	The ND-GAIN Capacity index consists of 12 measures, including agriculture capacity (fertilizer, irrigation, pesticide, tractor use), child malnutrition, access to reliable drinking water, dam capacity, medical staff, access to improved sanitation, protected biomes, engagement in international environmental conventions, quality of trade and transport-related infrastructure, paved roads, electricity access and disaster preparedness.
SCORE	PCA of NDS and NDC	Principal Component Analysis (PCA) is a mathematical tool that generates orthogonal linear combinations, in this case of our NDS and NDC indices, with the majority of the variance contained in the first vector generated.
NDSR	Notre-Dame Global Adaptation Initiative	The ND-GAIN Social Readiness index is based on four indicators. The social inequality measure is the poorest quintile's share in national income or consumption. The indicator for information and communications technology is made up of percent of individuals: using the internet, with mobile phone subscriptions, with fixed phone subscriptions and with fixed broadband subscriptions. Education is measured by enrollment in tertiary education as a percentage of gross. Innovation is estimated by patents per capita.
CRI	Germanwatch	The Climate Risk Index analyses to what extent countries have been affected by the impacts of weather-related loss events (storms, floods, heatwaves etc.) We utilise the short term i.e. annual index, for the period 2006 to 2016.
PCY	IMF WEO	Per capita income is GDP per capita at purchasing power parity in US dollars.
DEBT	IMF WEO	Gross government debt to GDP.
REV	IMF FM and PFMH	Government revenues to GDP.
EXP	IMF FM and PFMH	Government expenditures to GDP.
PBA	IMF FM and PFMH	Primary balance to GDP.
CPI	IMF FM and PFMH	Change in end of period consumer price index.
FDI	UNCTAD	Foreign direct investment to GDP.
V20	UNEP	Statistical dummy used to identify members of the V20 group of climate vulnerable countries.
G7	G7	Statistical dummy used to identify members of the G7 group of major economies.
IMF	IMF	Statistical dummy used to identify IMF bonds under concessional lending programmes. For example, Vanuatu's public external debt is mostly concessional (17.9% of GDP) and contracted from multilateral lenders such as the IMF, European Investment Bank, World Bank-IDA and Asian Development Bank, or via bilateral agreements such as with China Eximbank. Typically, the nominal interest rates of these instruments are fairly low and with long maturities over 20 years.
RFR	Bloomberg	The risk-free rate is the benchmark US 10 year Treasury yield for any given year in the sample.
M RAIN	World Bank	Annual average rainfall based on monthly data.
SD RAIN	World Bank	Annual standard deviation of rainfall based on monthly data.
M TEMP	World Bank	Annual average temperature based on monthly data.
SD TEMP	World Bank	Annual standard deviation of temperature based on monthly data.

Appendix C. Matrix of correlation coefficients

	(1)										
	YIELD	NDS	NDC	NDSR	PCY	DEBT	REV	EXP	PBA	CPI	FDI
YIELD	1										
NDS	0.367***	1									
NDC	0.664***	0.611***	1								
NDSR	-0.726***	-0.515***	-0.886***	1							
PCY	-0.698***	-0.568***	-0.835***	0.930***	1						
DEBT	-0.608***	-0.0590	-0.579***	0.577***	0.582***	1					
REV	-0.567***	-0.625***	-0.825***	0.794***	0.787***	0.402***	1				
EXP	-0.517***	-0.569***	-0.824***	0.796***	0.788***	0.495***	0.954***	1			
PBA	-0.0472	-0.199***	-0.0684	-0.0195	-0.0314	-0.208***	0.223***	-0.0432	1		
CPI	0.299***	0.00332	0.105*	-0.150**	-0.169**	-0.146**	-0.176***	-0.0602	-0.406***	1	
FDI	0.204***	-0.00639	0.0982	-0.183***	-0.156**	-0.227***	-0.0265	-0.0554	0.0943	-0.0496	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$