

Sovereigns: climate performance and the cost of capital

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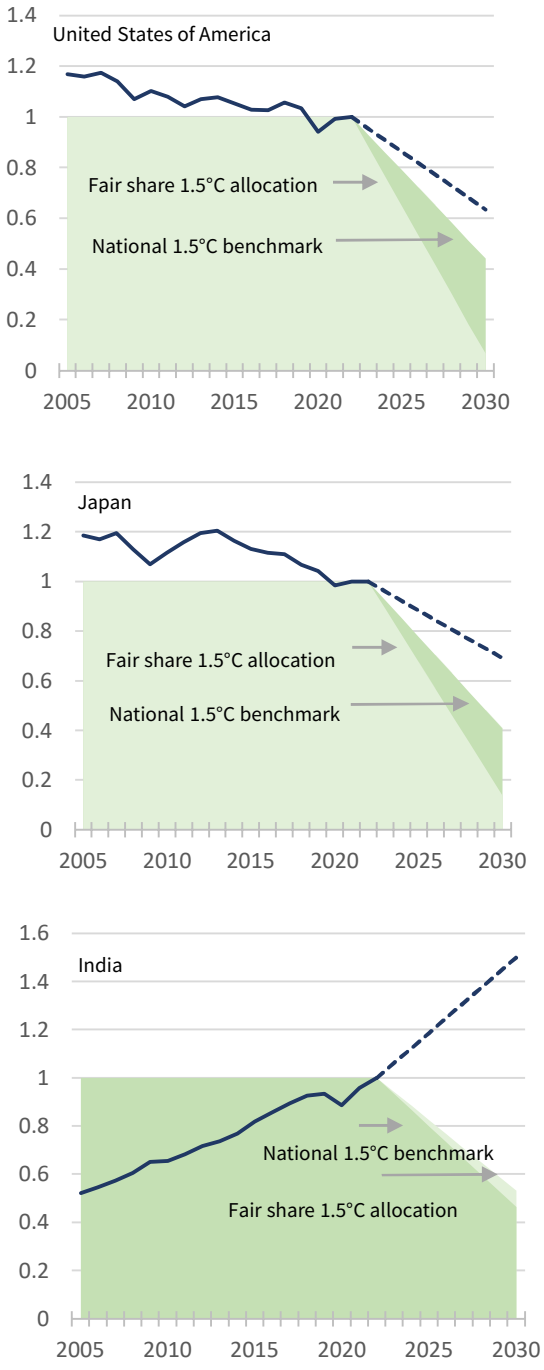
Governments sit at the core of the climate transition. Their policy decisions influence how climate risk will unfold, and their role bearing the costs of climate damage also make them vulnerable to this risk. With the global average surface temperature already around 1.2°C above pre-industrial levels,[1] much progress is needed to lower emissions in line with the Paris Agreement. (Figure 1 shows some example pathways from Transition Pathway Initiative).

It is not straightforward to forecast the relationships between the credit risks of sovereigns and their exposures to climate risks, yet it is important to lower the cost-of-capital for the necessary investments.[2]

This report presents an advanced regression model to deepen the understanding of the relationship between government bond yields and climate performance. **Strengthening this relationship should help sovereigns raise capital for risk-reducing climate investments.**

- Climate readiness and vulnerability are significant drivers of bond yields, although secondary to credit and technical factors. The significance of climate factors as a driver of bond yields has risen since 2018, with a temporary break during pandemic markets.
- For ASEAN countries, including climate factors increases the explanatory power of the model much more than for other regions. However, unintuitive relationships suggest potential mispricings.
- Europe, as relatively well progressed on climate alignment, exhibits different dynamics where higher emissions correlate with higher yields.

Figure 1. Sovereign emissions trajectories versus benchmarks. Source: ASCOR/TPI, AFII.



[1] "World Energy Outlook 2023", IEA, Oct 2023.

[2] "Emerging Economies Need Much More Private Financing for Climate Transition", IMF, 2 Oct 2023.

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Introduction

Climate change presents physical and transition risks to sovereigns.[3] Climate-driven extreme weather events and long-term changes can displace populations, damage critical infrastructure, and render certain regions uninsurable.[3] Efforts to shift economies to a low-carbon model can disrupt critical industries and inject volatility to asset valuations.

Governments ultimately bear the cost of these risks. These have the potential to undermine their financial and economic stability, which in turn could prompt credit rating downgrades.[4] In general, the lower a sovereign's credit rating, the higher their cost-of-funding. A sovereign downgrade also has ramifications for corporate and private sector capital allocation, reducing inbound investment by 9% and debt issuance in the region by 5%.[5]

Studies show a correlation between credit ratings and climate data,[6] although credit rating agencies are not yet explicit about the extent to which they use climate-related data to inform their decisions. They also suggest the impact of climate change on sovereign credit risk is asymmetric.[7] Research from the University of London and the Inter-American Development Bank finds that countries with higher yields (typically developing countries) have more adverse climate impacts. ASEAN nations, in particular, face high physical risks —such as extreme heat and flooding — and transition risks due to the higher carbon footprint of their exports.[4]

Research also shows that sovereigns can mitigate these risks through impactful climate policies and innovative financing mechanisms. For example, 'green' financial policies aimed at improving the pricing of climate risk can offset asset valuation risk in high-carbon sectors.[8] Innovative financial tools are also being proposed to drive sovereign climate action. These include AFII's contingent resilience-linked bonds[9] and partial or full guarantees linked to certain sustainability indicators, which can enhance the credit ratings of the target countries.[10]

In this study we hope to expand on existing research, focusing on the market price of sovereign credit risk. Our approach decomposes bond yields into different categories of potential drivers to produce insights on the climate-sovereign relationship. We aim to add to the body of analysis in this space, specifically reviewing more recent moves in bond pricing and looking at how the significance of climate factors has changed with time. We also consider two sub-populations,

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[3] "The Link between Physical Climate Risk and Sovereign Default", ICE Sustainable Finance, 3 March 2024.
[4] "Climate Change and Sovereign Risk", SOAS University of London, 2020.
[5] "The Real Effects of Credit Ratings: The Sovereign Ceiling Channel", The Journal of Finance, 2017.
[6] "Sovereign Ratings Change under Climate Risks", Research in International Business and Finance, 1 Oct 2023.
[7] "Asymmetric Sovereign Risk: Implications for Climate Change Preparation", Inter-American Development Bank, Gomez-Gonzalez et al., Mar 2024.
[8] "Do Green Financial Policies Offset the Climate Transition Risk Penalty Imposed on Long-Term Sovereign Bond Yields?", Research in International Business and Finance, 1 Apr 2023.
[9] "Contingent Resilience-Linked (CORL) bonds: combining public and private capital for resilience", AFII, Oct 2023.
[10] "The Role of Credit Enhancement in Sovereign Sustainability- Linked Debt Issuance", Sustainability-linked Sovereign Debt Hub, Willems et al., Jan 2022.

ASEAN (Association of Southeast Asian Nations) and Western Europe, which appear to exhibit different dynamics.

Furthermore, we extend recent research into sovereign yields and ND Gain data, a data set from Notre Dame University that considers sovereign climate readiness and vulnerability, to determine how much climate risk is impacting yields and the evolution of this relationship over time.[11] We differ from existing research by using monthly yield data for countries instead of yearly or quarterly data. This allows us to analyse more granular market prices. We also provide a more comprehensive explanatory framework, using SHAP analysis.[12] This quantifies the climate risk that is being priced in the market as a % of importance over all the variables considered.

In common with other studies, we explicitly rely on credit ratings as one of the control variables. As sovereign credit ratings aggregate a vast array of macroeconomic factors, we expect rating changes to reflect historic improvements or deteriorations of a given sovereign's economic conditions. This data is readily available for credit investors and thus eases the macro data controls typically used in existing research.

We also provide an extended literature review on sovereign yields and climate impact, together with details on the data and methods used, in Appendix 1: Extended literature review.

Objective

The objective of this paper is to quantify the importance of climate risk factors in explaining government bond yields, and to comment on the patterns discerned over time and within subpopulations. We consider this a starting point for understanding the relationships between climate data and bond yields, and intend to follow up with case studies and more specific analysis in the near future.

We have opted to make our model as simple as possible, to promote easy comprehension, even if this has meant including correlated datasets.

There will always be limitations with such studies and their interpretation. For example, they use historic data, which may be incomplete. Moreover, they investigate correlations but can say nothing about causality. Nevertheless, we believe they are useful for understanding the relationships between data.

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[11] "This Changes Everything: Climate Shocks and Sovereign Bonds", Energy Economics, Cevik et al., 1 Mar 2022.

[12] SHAP calculates the relative importance of all variables in a regression analysis. SHAP borrows methods from game theory and measures the performance of the model with all possible combinations of the variables, thus quantifying the importance of each variable. For more details please refer to "A Unified Approach to Interpreting Model Predictions", Advances in Neural Information Processing Systems, Lundberg et al., 2017.

Regression model

We have constructed a Least Squares Dummy Variables (LSDV) regression model to answer the question of how government bond yields are related to climate factors.[13] We introduce structural, credit, and climate data to understand the relative weights of each in explaining bond yields.[14]

The universe of securities assessed consists of bullet or callable bonds issued by governments (Bloomberg classification Treasury, Government Guaranteed or Sovereign) between 2015 and 2024, with an initial size of at least $0.5bn (exchange rate as of issue date).[15] This resulted in 2,620 bonds, which includes local currency and hard currency securities in emerging markets.

Our model uses historical data to see how yields and the other potential explanatory variables shifted in the period 2015 to 2024.[16] We sampled monthly data during this period, which resulted in 106k bond-month data points.

Security data

One issue that makes an analysis of sovereign bond data more complicated than it is for corporate analyses is currency. In our earlier corporate bond analyses,[14] the securities were issued in limited currencies only, so we could compare the spreads. In our sovereign universe, currency is an important factor, both because the universe of currencies used is much broader and because we would expect debt issued in local currency to have different dynamics to hard-currency debt. For example, in local currency, the risk-free rate is the cost-of-debt for the sovereign. To capture these dynamics, we have conducted the regression on total bond yield and exposed currency as a variable in the regression.

Bond yield: This is the yield-to-worst[17] on each security at a point in time; the dependent variable in the model.

Credit data

Credit rating: This ordinal variable represents the average credit rating from the three main agencies (S&P, Moody's and Fitch). Higher values indicate higher risk and generally wider yields. We use further binary variables indicating whether an issuer is Investment Grade, High Yield, or Unrated.

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[13] For full technical details on the models used, and a comparison with models that were not used, please see Appendix 2: Regression model details and Appendix 3: Methodology review.
[14] For earlier work in this series please see "Auto manufacturers: Climate performance and the cost of capital", AFII, 15 Dec 2023 and "Oil & Gas: climate performance and the cost of capital", AFII, 6 Mar 2023.
[15] For smaller issuances the securities are often illiquid and so the pricing data cannot be relied upon. Other kinds of bonds such as convertibles or perpetual bonds have different risk metrics and so are excluded from this analysis.
[16] This time period coincides with the 2015 Paris Agreement and helps to study the evolution of yields in the years following.
[17] Yield-to-worst is the lowest possible yield that an investor can expect on the bond. It is a useful measure when there are embedded options, such as call options, in the bond which can reduce the maturity and the final price if an issuer executes them.

Coupon: This is a structural variable of the bond; however, it is representative of the market yield at the time of issuance.

Climate data

Emissions: Climate Watch country greenhouse gas emissions dataset, drawn from non-governmental sources.[18] This emissions dataset offers comprehensive and comparable emissions data for 193 countries over the 1990-2021 period.

ND Gain: For a more sophisticated assessment of countries' climate risks, we have used the Notre Dame Global Adaptation Initiative's (ND-GAIN) Country Index, an open source tool that assesses a country's vulnerability to climate disruptions and its readiness to use investments for adaptation. The ND-GAIN Country Index brings together more than 40 core indicators to measure vulnerability and readiness of 182 UN countries from 1995 to 2021.[19] To cover our full bond yield dataset we have rolled forward the 2021 figures to 2024.

The ND-GAIN Country Index is calculated by analysing a country's vulnerability to climate change and readiness to improve resilience:

$$\text{ND-Gain Score} = (\text{Readiness score} - \text{Vulnerability} + 1) \times 50$$

ND-Gain Country Index adjusted GDP: To account for the correlation between ND-GAIN scores and GDP per capita, the Notre Dame Institute introduced the 'GDP-adjusted ND-GAIN score', which measures the difference between a country's actual ND-GAIN score and its expected value based on GDP regression.

Readiness: Measures a country's ability to leverage investments and convert them into adaptation actions. It includes three components:

> **Economic readiness:** "The ability of a country's business environment to accept investment that could be applied to adaptation that reduces vulnerability (reduces sensitivity and improves adaptive capacity)."
>
> **Governance readiness:** The stability of the society and "institutional factors that enhance application of investment for adaptation."
>
> **Social readiness:** Social conditions that capture factors like "social inequality, ICT infrastructure, education and innovation that enhance the mobility of investment and promote adaptation actions."

Vulnerability: Measures a country's exposure, sensitivity, and capacity to adapt to the negative effects of climate change. It measures overall vulnerability by considering six life-supporting sectors: food, water, health, ecosystem service, human habitat, and infrastructure. This measure consists of three components:

[18] International Energy Agency (IEA), United Nations Food and Agriculture Organization (FAO), U.S. Environmental Protection Agency (EPA) and Global Carbon Project.
[19] "Country Index Technical Report", University of Notre Dame Global Adaptation Initiative, 30 Jan 2023.

Exposure: A forward-looking indicator that measures a country's exposure to significant climate change from a biophysical perspective.

Sensitivity: Measures the degree to which "a country is dependent upon a sector negatively affected by climate hazard, or the proportion of the population particularly susceptible to a climate change hazard."

Adaptive capacity: Measures society and its supporting sectors' ability to adjust to, and reduce damage from, climate events. It aims to capture available social resources for sector-specific climate change impacts.

We have used the component variables in our full regression model and used the composite variables in time series analysis and visualisations, as described in more detail later. A summary of the expected direction of relationships is shown in Table 1.

Table 1. Summary of climate variables and expected direction of relationship with climate risk. Source: AFII.

+ means higher number drives wider spreads	Expected relationship
Adaptive capacity (vulnerability)	+
Exposure (vulnerability)	+
Sensitivity (vulnerability)	+
Economic (readiness)	-
Governance (readiness)	-
Social (readiness)	-

Economic data

Due to the nature of sovereign creditworthiness, we have included some specific economic factors.

Gross debt: This covers the total liabilities owed by the sovereign.

Net debt: This is calculated as gross debt minus the financial assets of the sovereign.

Region: We use binary variables to identify five regions: Africa, the Americas, Asia, Europe, and Oceania.

Other data

Bond characteristics can be drivers of yields, so we included some in the full model.

Amount outstanding: This is the size of the bond in USD, thereby allowing for currency revaluations.

Currency: Here we bucket currencies into USD, other G7, or other.

Time to maturity of the bond / Age of the bond: These parameters combine the year the security was issued, its initial length, and the roll-down of maturity as time passes.

Year / Month: Financial markets exhibit trends and seasonality, so we have included the month and year as structural variables to isolate these effects.

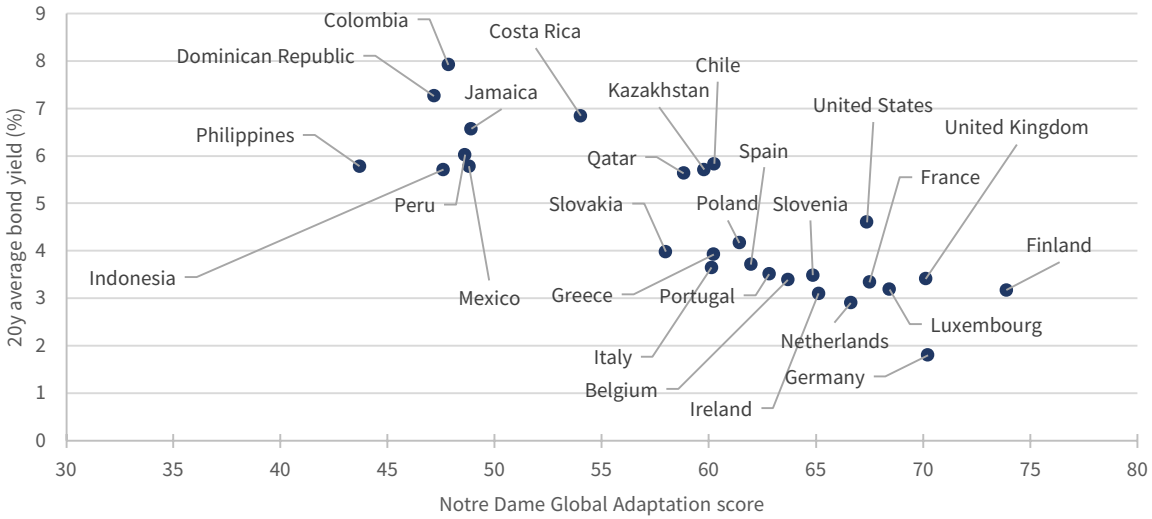
Summary visualisation

The initial basic visualisation suggests a relationship between climate adaptation and bond yields. Looking only at the latest data point in April 2024, Figure 2 shows the average yield for G7 currency bonds with maturity between 17.5 and 22.5 years plotted against summary ND Gain scores.

Considering its climate score, the United States stands out as having a relatively high yield. US treasuries have a different investor base and dynamics, so the yield may have more external dependencies than other sovereigns.

Latin American sovereigns (Colombia, Costa Rica, Chile) seem to have higher yields relative to their climate scores when compared to European issuers (Greece, Italy, Portugal, Ireland, Netherlands, Germany) which seem below the trendline.

Figure 2. ND Gain data plotted against average G7 currency bond yield for maturity between 17.5 and 22.5 years in Apr 2024. Source: Bloomberg.



This visualisation introduces our dataset and highlights the potential relationship between bond yields and climate risks. We will now present a fuller regression analysis to investigate these factors further.

Credit ratings regression

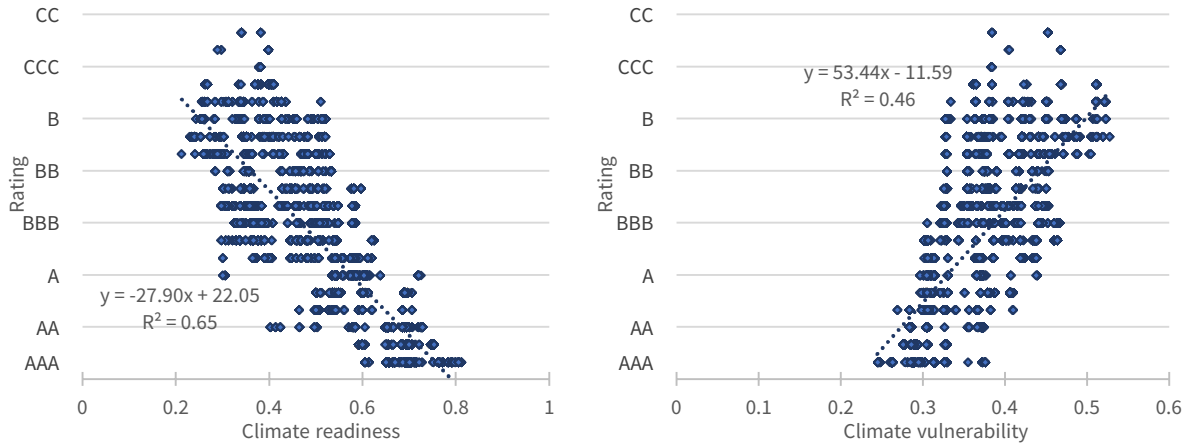
The objective of our regression is to observe and quantify how credit and climate variables potentially drive yields.

First, we will explore the interdependence between these factors, specifically how climate may impact credit ratings. Credit ratings are letter graded, with AAA indicating the lowest risk category, which generally implies the tightest yield or spread. In our study, we map these ratings as ordinal data instead of as pure categorical variables, as higher values do imply higher risk.

Figure 3 shows ratings plotted against both climate readiness and vulnerability. This contains all data points over time, so each sovereign is represented multiple times.

Perhaps unsurprisingly, better credit ratings are associated with higher levels of climate readiness and lower levels of climate vulnerability. Climate readiness has a stronger linear relationship, while vulnerability has a higher coefficient.

Figure 3. Credit rating versus climate data between 2015 and 2021. Source: Notre Dame Global Adaptation Initiative, Bloomberg.



This correlation between the variables is expected. We estimate the multicollinearity problem to increase when we increase the independent variables, especially when we deploy linear regression-based methods.

We still test for multicollinearity and remove variables that correlate with other existing variables. We look for improved fit of the model and the eigenvalues of the correlation matrix to decide whether to drop certain variables, especially when we work with sub-samples of the data.

However, in addition to analysing the direction of the coefficients, we also use SHAP methods, which take this multicollinearity into account and quantify the importance of each variable.[20]

[20] SHAP borrows methods from game theory and measures the performance of the model with all possible combinations of the variables, thus quantifying the importance of each variable. For more details please refer to "A Unified Approach to Interpreting Model Predictions", Advances in Neural Information Processing Systems, Lundberg et al., 2017.

The credit ratings, as discussed earlier, are slower to respond to market changes, and tend to be a lagging indicator. Some rating transitions can cause significant repricing, like a letter notch downgrade from AA to A, but within a letter transition, we might not see any gradual moves from AA to AA- for example. Markets also tend to move ahead of ratings decisions. Typically, the weakness that leads to a downgrade is registered in the market yield ahead of time while the rating downgrade confirms the earlier market move.

The climate metric data behaves differently. The update is timely on an annual basis and on a continuous scale compared to ratings, which are discrete numbers. Depending on the metric, the values range between 0.1 and 0.9. These create some modelling challenges, but we expect with monthly data some of the data to fit better to the regression model because of those few months in a given year which we are likely to miss using quarterly or yearly data. Next we discuss the regression model and the results.

Full regression results

A linear regression model was run with variables grouped into categories (full details in Table 11 in the Appendix), over nine years of data. For climate data, we have used the component variables. This results in coefficients and standard errors for each variable. Next a SHAP analysis was conducted to confirm the importance of each variable in the regressions. Finally, the most significant variables were identified, and the regression was repeated over time to see how the coefficients have changed throughout our dataset.

SHAP results

The results for the full regression are shown in Table 2. A breakdown for each variable is shown in Table 12 in the Appendix.

As can be seen, the model fit is moderately good, with an adjusted R^2 of between 73.4% and 75.9%.[21]

In both regressions, bond structural and technical factors are the most significant driver of yields (the category Others). The significance of this category increases slightly when climate factors are included.

Table 2. Summary SHAP values for regression model. Source: AFII.

	No climate	With climate
Adjusted R^2	73.4%	75.9%
Category of variable		
Credit	23.0%	18.5%
Economic	28.8%	22.1%
Others	48.2%	50.6%
Climate	0.0%	8.8%

Without climate factors, the most significant individual credit or economic variable is Region, followed by Coupon and Rating.

When climate factors are included, they explain 8.8% of bond yields, with a commensurate reduction in credit and economic factors. As the graphs in Figure 3 above show that climate data is correlated with credit ratings, there is some degree of inter-dependency between these variables. Interestingly, including climate factors reduces the significance of economic and credit (which

[21] The literature review shows a value around 60% is considered a good fit.

includes rating) factors. The most significant climate variables are 'Economic (readiness)' and 'Adaptive capacity (vulnerability)'.

These results suggest that climate is a partial driver of credit spreads, although less than credit factors, or credit and economic factors combined, and far less than technical factors.

Regression coefficients

Table 3 gives the regression coefficients for numeric variables. Note that we do not show results for grouped variables (such as Region). Also, we apply a threshold of 5% for the coefficient's P-value.[22]

The coefficients can be interpreted as impacting the yield for a unit change in the underlying variable. For a unit change in rating (a shift from BBB+ to BBB), this would widen yields by 7bps in the no-climate regression model and 2bps in the climate regression model.[27] [27]

The linear changes can sometimes be challenging to interpret depending on the units, but they show the direction of relationships.

Table 3. Coefficients in regression model for numeric variables. Source: AFII.

Variable	Category	No climate	With climate
Adaptive capacity (vulnerability)	Climate		0.08
Exposure (vulnerability)	Climate		0.02
Sensitivity (vulnerability)	Climate		0.05
Economic (readiness)	Climate		-0.19
Governance (readiness)	Climate		-0.03
Social (readiness)	Climate		0.04
GHG emissions by country	Climate		-0.03
GHG emissions by country per capita	Climate		0.01
Coupon	Credit	1.18	1.03
Rating	Credit	0.17	0.04
Gross debt	Economic	-0.07	-0.03
Inflation	Economic	0.23	0.24
Net debt	Economic	0.10	0.04
Amount outstanding (USD bn)	Other	-0.05	High P Value
Time since issuance (years)	Other	-0.04	-0.04
Time to maturity (years)	Other	0.10	0.09

Looking at economic factors, it is interesting to see the direction of relationship for debt variables. Higher net debt is associated with higher yields, but higher gross debt with lower yields. It may be that sovereigns with much more debt outstanding are able to attract more investors, which lowers yields.

Within climate, the relationship with total emissions is negative, i.e., increasing annual emissions by 1 million tonne CO_2 equivalent results in a tightening of bond yields by 0.04%, whereas increasing emissions per capita results in wider bond yields.[23] The SHAP value for absolute emissions is 6x more significant than for emissions per capita, suggesting that the latter is the stronger result, however both are low. **This does suggest that transition risk is not yet being priced**

[22] This aligns with standard literature where p-values below 0.05 or lower are considered statistically significant. This tests the support for the null hypothesis that the coefficient is zero. A value greater than 0.05 confirms the null hypothesis.

[23] Recent analysis from the ECB on corporates suggests that both current emissions and committed emissions trajectories impact lending rates, see "Climate risk, bank lending and monetary policy", ECB, 2024.

by the market, and lowering emissions results in wider funding spreads as lenders perceive this as risky.

With the Notre Dame climate data, the direction of the relationship for 'Social (readiness)' seems surprising; an increase in this factor which represents a higher degree of readiness for climate change results in a widening of bond yields, whereas the two other readiness factors, economic and governance, as associated with lower bond yields. This raises interesting questions for a 'Just Transition', such as whether spending on social readiness increases sovereign funding costs. Increased spending will likely be a phenomenon during the transition, and as some studies show, credit guarantees and contingency-linked mechanisms can mitigate these risks.[9,10]

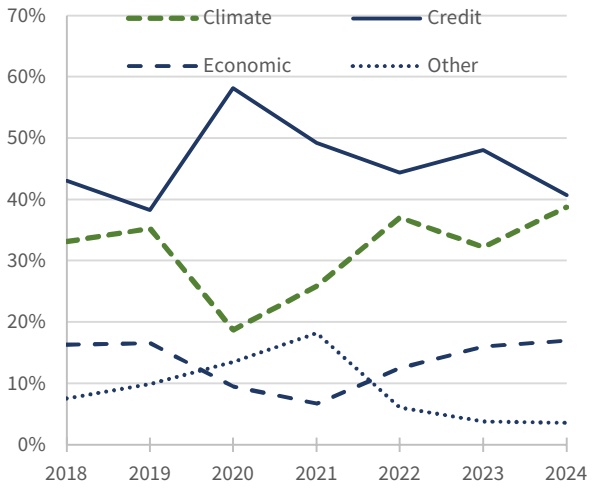
Time series analysis

We also want to understand how the significance of these factors has changed with time. We have identified only the most significant variables and re-run the regression for each year of data; for climate data, we have used the composite scores of 'Vulnerability' and 'Readiness'.

Figure 4 shows the results summed by category (the full table is shown in Table 13 in the Appendix).

Over the period, the importance of climate increased from 33% to 39%, although it was less significant in 2020 and 2021 when credit and other factors were more significant.

Figure 4. SHAP value for variable categories. Source: AFII.



Exploring the individual coefficients in Table 4, we see a change in the relationship between climate vulnerability and yields. In 2018 and 2019, higher vulnerability seems to have driven tighter yields, but since 2020, it has been associated with wider yields. Apart from a negative coefficient for net debt in 2020 (during the market environment associated with the pandemic), all other climate/credit and economic coefficients are in the intuitive direction.

Table 4. Regression coefficients for time series analysis. Source: AFII.

		Regression coefficient						
Variable	Category	2018	2019	2020	2021	2022	2023	2024
Readiness	Climate	-0.26	-0.24	-0.03	-0.10	-0.19	-0.13	-0.14
Vulnerability	Climate	-0.04	-0.06	0.14	0.09	0.07	0.04	0.05
GHG emissions by country	Climate	-0.12	-0.08	-0.02	-0.05	-0.05	-0.04	-0.05
Rating	Credit	0.37	0.26	0.22	0.11	0.11	0.19	0.16
Net debt	Economic	0.18	0.19	-0.05	0.02	0.05	0.04	0.06
Is ASEAN	Economic	-0.12	-0.07	-0.08	-0.08	-0.11	-0.10	-0.10
Time since issuance (years)	Other	-0.03	-0.02	High P Value	High P Value	High P Value	-0.01	High P Value
Time to maturity (years)	Other	0.07	0.09	0.32	0.38	0.12	0.03	0.05

ASEAN region

We have repeated the regression on a sub-set of sovereigns in the ASEAN region, comprising five countries.[24] By considering this population, we have been able to explore the impact of local versus hard currency debt and whether different climate factors influence spreads, given the challenges of climate transition in this region.

This smaller dataset, made up of around 6.6k observations compared to the overall model, with over 105k observations, means that using the same variables creates a less stable regression model with lower convergence. We also observed a few variables that are much more correlated than in the overall data set. We therefore reduced the dataset until 2022 to improve quality issues. We also removed a few variables; 'Coupon', which is quite correlated to 'Rating', as well as 'Amount outstanding' and 'Emissions per capita', which did not compromise the final fit.

SHAP results

Table 5 shows the SHAP results for the ASEAN regression.

Table 5. SHAP regression results for ASEAN model. Source: AFII.

	No climate	With climate
Adjusted R^2	54.6%	71.3%
Category of variable		
Credit	11.2%	25.7%
Economic	26.3%	14.4%
Others	62.5%	34.4%
Climate	0.0%	25.5%

The model fit is lower than for the larger model (54.6%), but improves substantially when climate factors are introduced, to an R^2 of 71.3%.

Other factors, including structural and bond technical variables, remain the most significant category, explaining over 60% of bond yields when not including climate data. By far the most important variable is currency, explaining 36.8% of bond yields (individual details are shown in Table 12).

Interestingly, credit factors are significantly less important than in the full regression, explaining only 11.2% in the no climate model, although this increases to 25.7% when climate factors are introduced.

Introducing climate factors dramatically affects this sub-population, improving the overall model fit and explaining over 25% of yields. This primarily reduces the importance of other factors, but also leads to an increase in significance of credit. Individual factors are shown in Table 12, which show the most significant variable is 'Adaptive capacity', which feeds readiness, with a SHAP figure of 10.0% for this variable.

'Emissions' is nearly the least important variable in this category, with only 1.8% of significance.

Regression coefficients

Table 6 (overleaf) gives the linear coefficients for each model factor, so we can understand the direction of relationships. Three coefficients in the climate section are below our threshold P-value of 5%, however a number of results are in the unintuitive direction.

[24] Philippines (PH), Indonesia (ID), Singapore (SG), Thailand (TH), Malaysia (MY).

'Net debt' and 'Gross debt' both seem unintuitive, as this suggests that an increase in either leads to a lowering in bond yields. This may be driven by larger borrowers being able to access wider pools of capital. Inflation seems intuitive in that higher inflation leads to a higher cost of borrowing.

In terms of climate, the vulnerability data points (both 'Adaptive capacity' and 'Sensitivity', which total 18.8% of yields) suggest that higher vulnerability leads to lower yields, the opposite relationship to that shown in the full model.

Table 6. Coefficients in regression model for credit and climate variables on ASEAN population. Source: AFII.

Variable	Category	No climate	With climate
Adaptive capacity (vulnerability)	Climate		-0.51
Exposure (vulnerability)	Climate		High P Value
Sensitivity (vulnerability)	Climate		-0.27
Economic (readiness)	Climate		-0.35
Governance (readiness)	Climate		-0.56
Social (readiness)	Climate		High P Value
GHG emissions by country	Climate		High P Value
Rating	Credit	-0.09	-0.47
Gross debt	Economic	-0.46	-0.20
Inflation	Economic	0.27	0.22
Net debt	Economic	-0.23	-0.04
Time since issuance (years)	Other	0.06	0.15
Time to maturity (years)	Other	0.17	0.33

We further observe that the relationship with 'Rating', however, seems to be that a lower rating (higher numeric value) leads to a tighter yield, which is not the expected relationship.

The direction of these coefficients tempers the strength of the result that climate is a driver of bond yields in ASEAN. These results suggest that there is mispricing in the market which may impede the efficient flow of capital into much needed transition investments.

Western Europe region

We also repeated the regression on a sub-set of sovereigns from Western Europe, comprising 14 countries.[25] We hope to understand how dynamics compare in this population, which has a different investor base.

This region is often considered more progressive in terms of climate policy implementation, which may present a different relationship between climate factors and costs-of-capital. Notable litigation results have also been achieved in the region, which could impact sovereign costs. For example, in April 2024, the European Court of Human Rights ruled that the Swiss authorities' inaction on climate change had violated the human rights of the KlimaSeniorinnen, a group of 2,400 older Swiss women.[26]

[25] Austria (AT), Belgium (BE), Denmark (DK), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Netherlands (the) (NL), Norway (NO), Portugal (PT), Spain (ES), Sweden (SE), Switzerland (CH).

[26] "Human rights violated by Swiss inaction on climate, ECHR rules in landmark case", The Guardian, 9 Apr 2024.

SHAP Results

Adjusted R^2 still shows a good fit, with 73.1% for the model excluding climate factors, and 75.8% when climate factors are included (as shown in Table 7).

Table 7. SHAP regression results for Western Europe model. Source: AFII.

	No climate	With climate
Adjusted R^2	73.1%	75.8%
Category of variable		
Credit	9.2%	10.8%
Economic	17.9%	14.2%
Others	72.9%	53.4%
Climate	0.0%	21.7%

Interestingly, the importance of structural and technical variables is much higher - over 70% when climate factors aren't included. Overwhelmingly, the most significant factor is year of data point (38.7%) followed by month of data point (18.4%). This suggests a high market beta, where the underlying market environment is the most significant driver of bond prices at any point in time.

Introducing climate factors leaves credit and economic SHAP values relatively unchanged but weights the importance of climate factors as 21.7%. Emissions data is more material than in earlier models; the two emissions variables explain 6.9% of yields (0.7% in the full model and 1.8% in ASEAN using only absolute emissions as shown in Table 12). This may suggest a stronger link between emissions regimes and cost-of-capital.

Regression coefficients

Regression coefficients for all continuous variables are shown in Table 8.

Table 8. Coefficients in regression model for credit and climate variables on Western Europe population. Source: AFII.

Variable	Category	No climate	With climate
Adaptive capacity (vulnerability)	Climate		0.25
Exposure (vulnerability)	Climate		0.17
Sensitivity (vulnerability)	Climate		0.11
Economic (readiness)	Climate		-0.06
Governance (readiness)	Climate		-0.19
Social (readiness)	Climate		-0.06
GHG emissions by country	Climate		0.15
GHG emissions by country per capita	Climate		-0.08
Coupon	Credit	0.17	0.11
Rating	Credit	0.03	-0.04
Gross debt	Economic	0.25	-0.13
Inflation	Economic	0.24	0.22
Net debt	Economic	-0.03	-0.28
Amount outstanding (USD bn)	Other	-0.06	-0.06
Time since issuance (years)	Other	0.01	0.01
Time to maturity (years)	Other	0.14	0.14

Looking at the coefficients for emissions, we see some relationships going in unintuitive directions, with higher emission per capita driving a tighter yield. However, absolute emissions (which have a higher SHAP value), has a positive relationship, with higher emissions associated with higher yields. This suggests an annual increase in emissions of

1 million tonnes CO_2 drives bond yields wider by 0.14bps.[27]

Introducing climate data also produces some unintuitive relationships; higher gross debt, and poorer rating all lead to tighter bond yields, suggesting multicollinearity between some variables.

Conclusions

In this paper, we have built a comprehensive regression model to investigate the historical relationship between sovereign bond yields and various factors, including climate factors.

- Climate is a partial driver of bond yields, explaining 8.8% of yields in our full model. The significance of climate to two sub-populations, ASEAN and Western Europe, increases meaningfully. All models have better fits when including climate factors.
- When repeating the regression through time, we see the significance of climate factors has increased since 2018, albeit with lower values during the pandemic period.
- In ASEAN, including climate factors significantly improves the model's fit. However, the direction of the relationships seems unintuitive in several cases. This suggests there may be risks to re-pricing as climate risks become more apparent.
- Emissions are the least important climate factor. They are most significant in the two subpopulations, for example, in Western Europe, where an annual increase of 1 million tonnes CO_2 (around the annual emissions of the Seychelles) may drive bond yields wider by 0.14bps. This region has a stronger history of climate policy as well as recent litigation rulings, which may explain this observation.

Strengthening the relationship between climate risk and sovereign bond yields could have many benefits. It may help to raise affordable capital for sovereigns investing in climate adaptation and transition and it could enable investors to better manage climate risk in sovereign bond portfolios.

[27] We normalised the variables so all variables range from 0 to 1. The GHG Emissions varied from 32 to 837 in real data and the yield range from 0 to 7.57%. To get the impact of 1 Million tonnes the yield increase(y) would be y/(7.57-0) = 0.15*1/(837-32) , where 0.15 is the coefficient , solving for y we get 0.14bps. Similarly for rating which varies from 0 to 18.

Appendix 1: Extended literature review

There have already been many important papers written on the relationship between climate and government funding yields.

Table 9 summarises recent relevant literature in academia. We provide an overview of every study, including a description of the problem, the non-climate data used, which is typically control variables, and the climate data considered in the dataset. The main aim of these studies was to find the impact of climate factors on sovereign spreads. This process also leads us to identify where current research stands and identify gaps in the literature.

Most studies are based on yearly observations. Only Beime et al, 2024, use monthly observations to understand inflation. We use monthly data but unlike all these studies we use the direct bond data instead of normalising it to a specific generic tenor like a 10yr or 5yr bond. This helps to capture bond-specific nuances in different control variables, such as amount outstanding and currency, which could be linked as instrument variables to liquidity and macro interest rate risk volatility. Over a large set of observations, these factors should be effectively captured.

Most studies also agree on the impact of climate transition risk, i.e. it is priced in sovereign risk and it is also asymmetric, with developing nations more impacted by this risk then developed.

Table 9. Literature synthesis with research problem, climate data and nature of the data, along with chosen method. Source: AFII.

Author/Year	Description	Credit data	Climate data	History	Nobs	Freq	Target	Method
(Cheng, and Gupta Rajan, 2023)[28]	Decompose 10yr yield	GDP growth, Debt/GDP, Inflation, fiscal deficit, currency a/c balance, VIX	Sustainable development index, CO2/GDP (Our World in Data), Green Monetary and additional policies tracker)	1995-2018	25 countries	Yearly	10yr yield	2-way fixed effects model
(Klusak et al., 2023)[29]	Credit rating downgrade due to climate change, impact on cost of debt	Sovereign risk indicators (GDP/capita, GDP growth, net debt/GDP, current account balance/GDP)	Climate scenarios	2004-2020	108 countries, 1385 observations	Yearly	credit rating	Random forest
(Boitan and Marchewka-Bartkowiak, 2022)[30]	Focused on EU countries to decompose 10yr yield or spread over UST	Budget balance/GDP, Debt/GDP, Sov credit rating, GDP growth, inflation other macro variables	ND-Gain (vulnerability, readiness), climate liability, German Watch Institute (climate change performance index, climate risk index)	2000-2020	26 countries	Yearly	10yr yield or sprd	Panel estimate generalised least squares

[28] "Do green financial policies offset the climate transition risk penalty imposed on long-term sovereign bond yields?", Research in International Business and Finance, 2023.
[29] "Rising Temperatures, Falling Ratings: The Effect of Climate Change on Sovereign Creditworthiness", *Management Science*, 2023.
[30] "Climate change and the pricing of sovereign debt: Insights from European markets", Research in International Business and Finance, 2022.

(Cevik and Jalles, 2022)[31]	10yr yield, climate impact	Macro (GDP growth and level, inflation, debt/GDP, international reserves)	ND-Gain (vulnerability, resilience)	1995-2017	98 countries, 995 countries	Yearly	10yr yield, spread vs US	Standard fixed effects model, 2stage least squares, system GMM
(Hilscher and Nosbusch, 2010)[32]	EM countries sovereign credit spread determinants	Macro (terms of trade, debt/GDP), mkt (Vix, ted) , credit(rating)		1994-2007	31 countries, 276 obs	Yearly	EM spreads over US (EMBI)	Standard fixed effects model
(Gomez-Gonzalez, Uribe and Valencia, 2024)[33]	Shows spreads react to vulnerability metrics but not so much on physical risks	Macro (GDP growth, inflation, gross debt/GDP), rule of law, natural resource rents as % of GDP	ND-Gain	2000-2019	68 countries,	Yearly	Sovereign yield (1,2,5yr,10yr)	Quantile regression, random forest-based imputation
(Volz, 2020)[34]	Predicting credit ratings of sovereign	Macro (net income per capita, GDP growth, unemployment rate, GDP deflator), Govt indicators (Effectiveness) External (balance % of GDP, net trade), Qualitative indicators (default)	ND-Gain (Vulnerability, Readiness)	1995-2020	1544 obs,114 countries	Yearly	Credit rating	Generalised ordered logit model (GOLM)
(Sun et al., 2023)[35]	Climate vulnerability impact on sovereign ratings after controlling for macro	Macro (GDP, inflation, unemployment, balance, trade)	ND-Gain	1995-2020	117 countries, 1544 observations	Yearly	Credit rating	Ordered logit model, random forest

[31] "This changes everything: Climate shocks and sovereign bonds", Energy Economics, 2022.
[32] "Determinants of Sovereign Risk: Macroeconomic Fundamentals and the Pricing of Sovereign Debt", Review of Finance, 2010.
[33] "Asymmetric Sovereign Risk: Implications for Climate Change Preparation", Inter-American Development Bank, 2024.
[34] "Climate Change and Sovereign Risk", SOAS, 2020.
[35] "Sovereign ratings change under climate risks", Research in International Business and Finance, 2023.

(Beirne et al., 2024)[36]	Understanding the impact of climate shocks on inflation	Macro (industrial production, unemp rate)	Disaster data (Storms, Floods, Wildfires, Extr. temp., Droughts, Landslide)	Jan 1996 - Mar 2021	19 countries	Monthly	Inflation	Panel structural VAR
(Collender et al., 2022)[37]	Evidence of climate risk pricing in sovereign bond yields and spreads	Macro (GDP /capita, GDP growth, inflation, trade openness, current account balances)	Global carbon project(emissions, natural resource rents, energy consumption)	1999-2021	39 countries	Yearly	10yr yield or sprd	One-way fixed effects model

Appendix 2: Regression model details

We use a quantitative regression to understand the drivers of bond yields.

We use the 'least-squares dummy-variable' (LSDV) panel regression model to explain the spreads as given in the following equation (1). Where y_{ijt} is the yield of the ith issuer's jth bond at time t. S_{ijt} are the bond-specific variables that vary over time, B_{ij} are time-invariant such as coupon, currency, the amount issued and callability. I_i, I_{it} are issuer-specific variables that are time-invariant and time-varying, respectively. The T_t are categorical dummy variables representing the year and month of the sampling period of the companies. The coefficients $[\beta_1, \beta_2, \beta_3, \beta_4, \beta_5]$ are the appropriate dimensional coefficient vectors that are to be determined using the generalised linear regression. The ϵ_{ijt} is the residual term and α is a fixed intercept term.

$$y_{ijt} = \alpha + \beta_1 S_{ijt} + \beta_2 B_{ij} + \beta_3 I_i + \beta_4 T_t + \beta_5 I_{it} + \epsilon_{ijt} \quad (1)$$

The coefficients' p-values tell us how significant a given variable is to bond yields, and thus we can assess whether sustainability performance drives a sovereign's cost of capital.

We scale all the variables in the regression to minimum and maximum values to centre them, as each variable has a different scale. The yields vary from 0 to 1000 (bps), while the climate data, such as GHG emissions, ranges from 0 to 12,800. We scale all the variables to be between 0 and 1.

The detailed results of the regression are shown in Table 10. The model has 0.759 R-squared, which shows a good fit for the yields. More market-specific variables and other data sources could improve the fit by increasing the R squared value, but this study focuses on quantifying the climate risk element.

The regression has 105,980 month-country observations, and the 1.843 Durbin Watson statistic shows a positive correlation in the data. This means the yields are dependent on the previous month's yields, which is to be expected when the country has similar risk characteristics.

[36] "Weather-related disasters and inflation in the euro area", *Journal of Banking & Finance*, 2024.
[37] "Climate Transition Risk in Sovereign Bond Markets", *Global Finance Journal*, 2022.

The coupon and the yield have similar characteristics. The coefficient is 1.0872, which shows that the yields are around the bond's coupon values. The coupon is generally the bond yield at the time of issuance, and this shows that when credit factors are similar, we should expect the bond to trade at similar coupon yield levels.

Table 10. Summary statistics of full regression model. Source: AFII.

GLS regression results			
Dep. variable:	Spd	R-squared:	0.759
Model:	GLS	Adj. R-squared:	0.759
Method:	Least Squares	F-statistic:	7408
No. Observations:	105,926	Prob (F-statistic):	0
Df Residuals:	105,880	Log-Likelihood:	112,860
Df Model:	45	AIC:	-225,600
Covariance Type:	Non-robust	BIC:	-225,200
Omnibus:	27863.964	Durbin-Watson:	2.01
Prob (Omnibus):	0	Jarque-Bera (JB):	541171
Skew:	0.782	Prob (JB):	0
Kurtosis:	13.962	Cond. No.	70.8

Appendix 3: Methodology review

In designing our model, we were focused on simplicity, such that the interpretation could be easier to understand. In this section, we briefly present the results of other methodologies that we tried.

We attempted quantile regression, time series-based auto regressions, heteroscedasticity and autocorrelation (HAC) adjusted regression, and principal component analysis (PCA). One of the main motives of these various methodologies, as can been in Table 9, is to quantify the impact of climate risk. Multicollinearity and assumptions on distribution of data certainly complicate a direct interpretation. We include the correlation matrix of all the variables in the large regression model in Figure 5 which shows 'spd' (yield of the sovereign) and the target variable as well. The dummy variables are generally uncorrelated, while there is high degree of interaction with ND-Gain data.

To overcome these problems, we introduced SHAP, which is a separate interpretability tool borrowed from game theory. This tests all permutations of the features on a subset of the dataset and can thus isolate the joint and single feature impact on the model. LSDV regression is similar in style to one-way fixed effects models and standard fixed effects models. The literature is not conclusive about fixed effects or random effects for these panel data regressions. Therefore, we elected to use a simpler model, but with a comprehensive interpretability framework.

We tested for the robustness of the errors with the F-test, Durbin-Watson and Jarque-Bera test, which confirms the stability of the model performance. Table 10 shows the results of these tests. The F-test examines whether the explained variance is greater than unexplained variance overall by testing whether all coefficients together can be 0. The p-value shows no support for the null

hypothesis which shows the coefficients have some explanatory power. The Durbin-Watson tests for autocorrelation in time series data of the residuals. A value less than 2 suggests positive correlation (+ve returns follow +ve returns) and greater than 2 is negative correlation and value near to 2 has no autocorrelation which is the case in all our models performance. The Jarque-Bera test shows the errors are not randomly distributed. The high kurtosis value means most errors are grouped around the mean than normal distribution would suggest, or expressed differently, the distribution of errors exhibit 'fat tails'. This is a feature of any yield data with large clusters of similar values that occasionally have large variation.

We present briefly the results of the different regression methods.

Quantile regression

This method brings about some clear adjustment based on the yield of the sovereign. Dividing into quantiles makes the interpretability hard as each spread or yield level generates a different set of coefficients.

Auto lagged variable regression

The lagged yield variables are also quite highly correlated with macro data and other independent variables.; including them creates more spurious results. The current approach with no lagged variables makes the model learn the coefficients by treating each observation independently. The objective of the model is to keep the overall error low. This helps in understanding the importance of each factor rather than a powerful predictor of yields. In a different scenario, where predictions are important, lagged variables would be more suitable along with changes in the other independent variables to capture only the novel move since last value. Here we are interested in decomposing each spread into specific factors, so we chose the model without lagged variables.

HAC adjusted covariance matrix regression

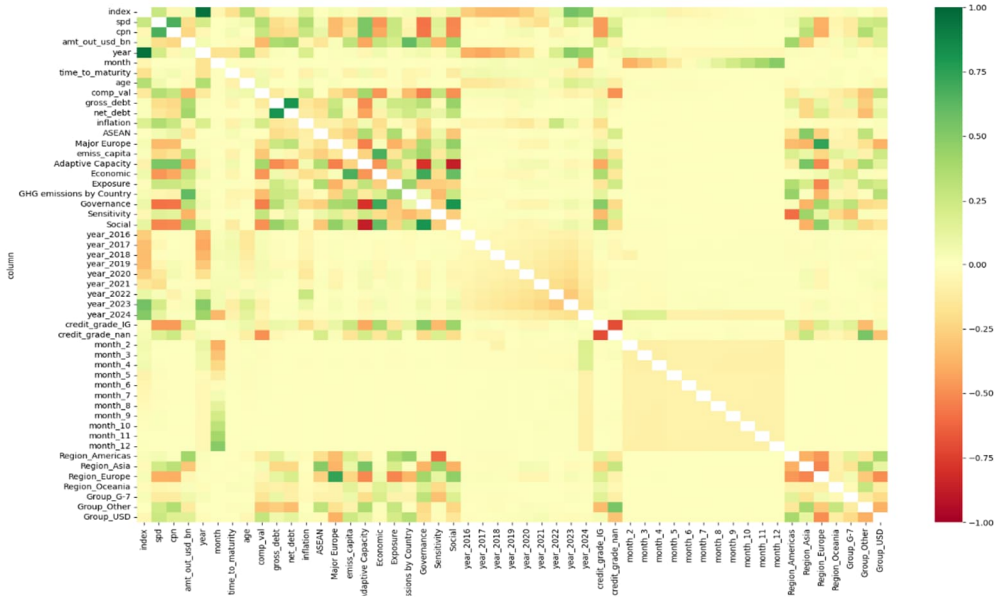
We also tested the LSDV regression with Newy-west adjustment to the covariance matrix. The adj. R^2 remains unchanged and most of the statistical tests such as F-test, JB test still show same results compared to the regression model. The standard errors of the coefficients changed slightly but the magnitude of each coefficient or the p-value were not changed which shows stability in the results.

PCA factor regression

We also tried principal component analysis by varying the number of components and studying the impact on the overall fit of the model. The fit is slightly better, but interpretability becomes hard as it is necessary to isolate each feature into a specific component and then calculate each variable's impact.

We also looked into structural Var models, but to achieve any convergence it would need a large amount of historical data. We would need to exclude countries and focus on a single region to achieve any convergence. As Beirne et al., 2024 study, which focused on European countries with long monthly histories, has shown, these models are not suitable when N or the number of countries is large with less frequent data. We wanted to keep the scope of our study broad and hence did not consider it further.

Figure 5: Correlation matrix of all variables in full regression model. Source: AFII.



Appendix 4: Regression detailed results

Table 11. Variables used in regression model. Source: AFII.

Variable		Used in full regression	Used in historic regression
Adaptive capacity	Climate	1	
Economic	Climate	1	
Exposure	Climate	1	
GHG emissions by country	Climate	1	
GHG emissions by country per capita	Climate	1	
Governance	Climate	1	
ND-Gain	Climate		1
ND Gain-Country Index adj. GDP	Climate		
Readiness	Climate		
Sensitivity	Climate	1	
Social	Climate	1	
Vulnerability	Climate		
Coupon	Credit	1	
Is IG/HY/Unrated	Credit	1	
Rating	Credit	1	
Gross debt	Economic	1	
Inflation	Economic	1	
Net debt	Economic	1	
Region	Economic	1	
Amount outstanding (USD bn)	Other	1	
Currency is G7	Other	1	
Currency is not G7	Other	1	
Currency is USD	Other	1	
Month of data point	Other	1	
Time since issuance (years)	Other	1	
Time to maturity (years)	Other	1	
Year of data point	Other	1	

Table 12. SHAP results for regression models. Source: AFII.

		All		ASEAN		WE	
Variable	Category	No climate	With climate	No climate	With climate	No climate	With climate
Adaptive capacity (vulnerability)	Climate		3.9%		10.0%		5.2%
Exposure (vulnerability)	Climate		0.8%		3.2%		6.3%
Sensitivity (vulnerability)	Climate		1.7%		8.7%		1.1%
Economic (readiness)	Climate		5.8%		7.9%		1.4%
Governance (readiness)	Climate		1.1%		7.8%		5.8%
Social (readiness)	Climate		1.7%		1.7%		2.1%
GHG emissions by country	Climate		0.6%		1.8%		5.0%
GHG emissions by country per capita	Climate		0.1%				1.9%
Coupon	Credit	9.0%	8.0%			5.8%	2.5%
Is IG/HY/Unrated	Credit	6.0%	8.6%	4.4%	6.3%	2.2%	7.3%
Rating	Credit	7.9%	1.9%	6.8%	19.4%	1.2%	1.0%
Gross debt	Economic	2.0%	0.9%	10.3%	2.6%	9.1%	2.9%
Inflation	Economic	1.5%	1.7%	6.9%	3.1%	7.8%	4.7%
Net debt	Economic	2.1%	0.9%	9.1%	0.8%	1.0%	5.2%
Region	Economic	23.1%	12.9%				
Amount outstanding (USD bn)	Other	0.9%	0.1%			1.8%	1.0%
Currency	Other	14.1%	16.3%	36.8%	0.0%	11.2%	8.3%
Month of data point	Other	8.4%	8.7%	3.9%	2.0%	18.4%	10.8%
Time since issuance (years)	Other	0.7%	0.7%	1.9%	2.6%	0.3%	0.2%
Time to maturity (years)	Other	1.5%	1.5%	5.6%	5.3%	2.4%	2.5%
Year of data point	Other	22.5%	22.2%	14.4%	16.7%	38.7%	24.9%

Table 13. SHAP results for time series regression model. Source: AFII.

		SHAP result						
Variable	Category	2018	2019	2020	2021	2022	2023	2024
Readiness	Climate	23.0%	24.4%	3.4%	13.0%	24.7%	20.9%	23.6%
Vulnerability	Climate	2.9%	5.2%	13.0%	8.5%	7.1%	5.6%	7.8%
GHG emissions by country	Climate	7.3%	5.6%	2.4%	4.4%	5.2%	5.7%	7.4%
Rating	Credit	34.1%	28.8%	28.7%	15.4%	18.1%	33.1%	29.9%
Is IG/HY/Unrated	Credit	8.9%	9.5%	29.5%	33.8%	26.3%	14.9%	10.7%
Net debt	Economic	9.2%	11.9%	3.3%	1.7%	4.6%	6.1%	8.1%
Is ASEAN	Economic	7.1%	4.7%	6.3%	5.1%	7.9%	9.9%	8.9%
Time since issuance (years)	Other	1.8%	2.0%	0.8%	0.0%	0.7%	2.0%	0.5%
Time to maturity (years)	Other	5.8%	7.9%	12.7%	18.2%	5.4%	1.8%	3.1%

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