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IMPACT OF CLIMATE CHANGE ON SOVEREIGN RISK IN ASIA

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Abstract

More than at any time in the history, climate change is having an increasingly unprecedented effect on human lives. Economies are affected severely in terms of sovereign risk due to climate change variations influencing the macroeconomy. Asian countries are highly susceptible to economic downturn due to the consequences of climate change. The purpose of this study is to identify the relationships between sovereign risk and climate change in all Asian countries. Controlling for a range of macroeconomic and financial drivers of sovereign bond spreads, the paper applied a Panel autoregressive distributed lag (ARDL) model to identify the effects of climate change on the sovereign risk. The Panel l ARDL included the pooled mean group (PMG) regression, mean group (MG) estimation, and dynamic fixed effects (DFE) regression for estimating the macroeconomic impacts. The results show that, in the long run, the DFE model, which was selected as the best model for all Asian countries, provides evidence for the existence of a cointegration relationship. These findings have implications for policymakers, both from a fiscal sustainability perspective and with regard to the influence of exposure to climate change.

Keywords: climate change, sovereign risk, Panel ARDL, Asia

JEL Classification: B23, C13, C23, H63, Q54

Contents

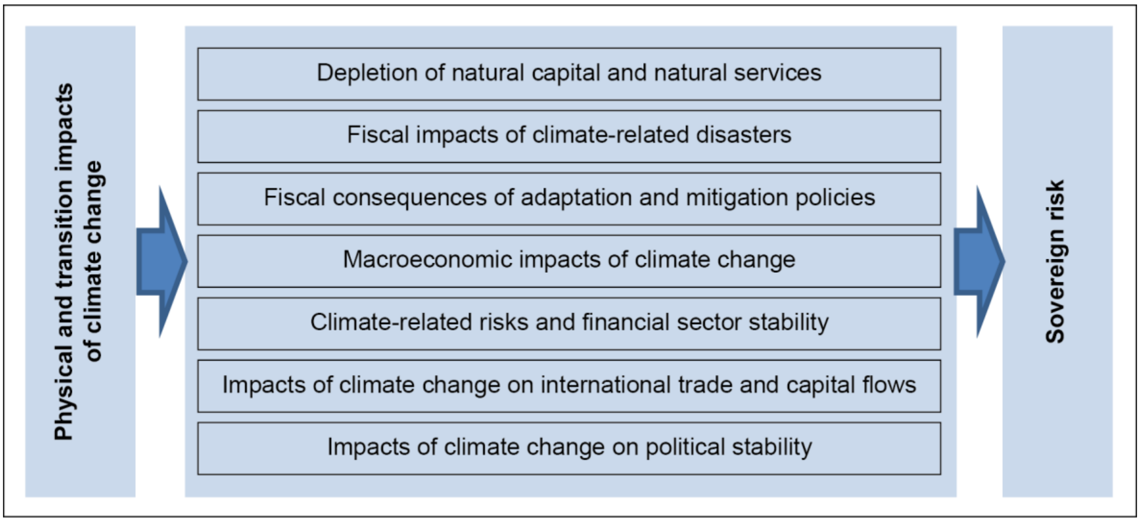
1. INTRODUCTION

At the macroeconomic level, many argue that the impact of climate change and sovereign risk is interlinked. But very few studies have examined the relationship between climate change and sovereign risk in terms of the wider macroeconomic framework. Because of the increase in sovereign risk, in addition to the existing government debt, is becoming critical in the face of the effects of climate change. Until recently, many policymakers have not considered the impact of climate change on sovereign risk, but in the face of unprecedented climatic events, and their severity and frequency, macroeconomic researchers are seeking the regulation of sovereign risks. Thus, policymakers argue that the economy needs to have a systematic approach to the climatic impacts in a macroeconomic framework to reduce the spread of government sovereign bonds.

In developing economies, especially in Asia, economic instability and debt sustainability are significant issues in terms of economic growth. In addition, climate change is creating an extra burden for the Asian economies at the macroeconomic level in their efforts to overcome challenges. In the literature, a number of emerging economies in Asia perform differently than the rest of the countries in the world in debt management and sovereign risk management. However, there is limited literature available to investigate how climate change affect sovereign risk to manage the uncertainties of the economy after the impacts of COVID-19.

This paper also aims to identify the transmission channels proposed in the previous literature, such as the macroeconomic impacts of climate change, and climate-related risks and financial sector stability, as shown in the figure below. The key channel for the identification of macroeconomic impacts of climate change is the connection between the physical and transition impacts of climate change and sovereign risk.

Figure 1: Transition Channels between Climate Change and Sovereign Risk



Source: Volz, et al. 2020. *Climate Change and Sovereign Risk*. London, Tokyo, Singapore, and Berkeley, CA: SOAS University of London, Asian Development Bank Institute, World Wide Fund for Nature Singapore, and Four Twenty-Seven.

Disequilibrium in sovereign bond risk and climate change cause instability in many developing economies. It is essential to evaluate the link between these two factors in terms of increasing climate vulnerability and resilience for macroeconomic policy decisions. This paper intends mainly to apply an econometric model to estimate the impacts of climate change on sovereign risks. With this purpose, the recently developed Panel autoregressive distributed lag (ARDL) model is used to estimate the parameters in Asian markets. First, the paper applies the Pedroni cointegration test to check whether these macroeconomic factors are cointegrated. Then, the Panel ARDL model is employed to estimate the parameters of the model as two groups. The main variable, government sovereign bond spread, is considered an important variable in measuring the risks in order to estimate the coefficients of climate variables while controlling for other determinants. The controlling variables are important to understand the determining factors of the sovereign risks.

Thus, the study examines the factors of sovereign risks in Asia through is empirical evidence. A main consideration of this study is the limited number of existing/available studies in the literature on the link between sovereign risk and climate change at the macroeconomic level in Asia. Understanding the relationship between sovereign risk under climate change vulnerability and resilience in Asia is the main purpose of this study. Thus, this paper adds value to the few empirical studies currently available on climate change impacts on sovereign risk.

The rest of this paper is structured as follows: Section 2 presents the literature review, which includes the theoretical and empirical literature pertaining to sovereign risk and climate change. Section 3 presents data sources and their description. The empirical methodology is explained in Section 4. Section 5 contains the analytical results and discussion. Section 6 provides the conclusion.

2. LITERATURE REVIEW

Even though a large number of papers have been published to estimate the macroeconomic effects of climate change, only a limited number of papers can be found on sovereign risk and the impact of climate change on Asian economies. This paper looks at the most recently available literature.

A seminal paper has been published by Cevik and Jalles (2020) called “This changes everything: climate shocks and sovereign bonds.” The objective of the paper is to examine the impact of climate change variability and resilience on sovereign bond yield in 98 countries from 1995 to 2017. The authors found that climate change has a significant effect on the cost of government borrowing. Notably, countries with more resilience have lower bond yields than the countries with higher vulnerability. Further, they explained that developing countries with weaker adaptive capacity are strongly affected by climate change. In our paper, the impacts of climate change on sovereign risk are measured with the Panel ARDL methodology to provide robust estimates for the controlling variables, focusing especially on the Asian countries.

Beirne Renzhi, and Volz (2020) have also studied climate risks and the cost of sovereign borrowing. In their paper, they applied a panel structural vector autoregressive (VAR) model in advanced and emerging economies and identified that climate risks are important determinants of the cost of sovereign borrowing. The findings revealed that the effect of bond yield is higher in highly vulnerable countries. Our paper contributes to the literature by adding possible variables to the climate risk in emerging Asian countries. We hope that this paper contributes to the limited literature available, filling the gaps by including Asia countries.

Chaudhry et al. (2020) studied the impact of carbon emissions on sovereign risk. In their paper, they applied a fixed effects model for G7 advanced economies from 1996 to 2014. Notably, they applied extreme value theory to measure sovereign risk. They found that climate change, which they considered in terms of carbon emissions, is likely to increase the sovereign risk in those economies. Further, they broke the analysis down into three sectors—namely transportation, electricity, and industry—and implied that the carbon emissions of these three sectors are likely to increase sovereign risks. In our study, we also include the Panel ARDL model with three analyses as explained above: pooled mean group (PMG) regression; mean group (MG) estimation; and dynamic fixed effects (DFE) regression. Thus, by using the Hausman test we confirm that the best possible method in the Panel ARDL is the dynamic fixed effects model, which provides the robust estimation in the analysis.

Boehm (2020) has examined the physical climate change risks and the sovereign creditworthiness of emerging economies. The climate change variable in the study was the temperature anomalies and the study was conducted using monthly temperature data from 54 emerging economies. A regression analysis was performed and found that the temperature anomalies have a significant negative impact on sovereign bond performance. Due to climate change, which results in increased temperatures, the affected countries have significantly increased their sovereign borrowing costs. The model includes temperature anomalies and precipitation in addition to the control variables. Our study differs from this study since it does not include the physical risk but rather deals directly with the macroeconomic impacts.

Stavros (2021) has published a policy paper on the risks to sovereign debt in Europe due to climate change. In this study, climate risk and its impact on sovereign bonds in the European Union, which promotes the transition to low carbon economic activities, has resulted in the repricing of assets. He further argues that the climate innovations can spur the growth of the region as investors assess the risks that can affect sovereign credit ratings. It is essential to test the debt dynamics and climate scenarios using stress tests. Stavros argues that adaptation to climate change situations needs to guide the policymakers. Therefore, exposing the risks to finance due to climate change using risk-sharing tools is required to budget for the climate expenditure and liabilities. This paper addresses the policy scenarios for measuring the impact of climate change and sovereign borrowing.

Mallucci (2020) has studied the relationship between the impact of natural disasters on fiscal vulnerabilities and sovereign default. He modeled the association using a standard sovereign default model which includes disaster risk in Caribbean countries affected by hurricanes. He found that the ability of the governments to issue debt is declining and they have limited market access. Further, the governments borrowing conditions have been mitigated by debt-servicing relief provided by the ability to borrow with "disaster clauses." Moreover, Peel and Markey-Towler (2020) have studied the climate change risk and sovereign bond instruments in Australia. These authors propose that sovereign bonds are considered as a safe investment but not with the effect of climate change, which puts investors at risk. They examined the projections, including the disclosure to investors of the possible climate risks. They argue that the development of climate change litigation and the potential to invest in sovereign bonds are needed to reduce the risk for the investors.

Smyth and Bennett (2016) studied how capital markets help developing countries to manage climate risk. They studied how the economic impact of climate events can be managed by providing improved access to insurance and alternative risk transfer. They discussed how multilateral banks can catalyze creating sovereign risks and facilitate access to the reinsurance capacity of capital markets. Climate risk preparedness and resilience can be improved through development banks investing in the beneficiary countries to maximize the development impacts.

Collender et al. (2021) studied how no climate change transition risk, measured by CO2 emissions, natural resources rents, and renewable energy consumption, is priced in the sovereign bond market. They used 23 developed and 16 developing countries from 2000–2019. They found that advanced markets that reduce their CO2 emissions lower the risk premium to reduce the earnings from natural resources and increase renewable energy consumption to lower the sovereign borrowing costs. But developing countries with a high dependency on natural resources or limited consumption of renewable energy reduce the sovereign costs. They conclude that advanced countries are managing their climate transition poorly and and therefore have to recover from more macroeconomic effects after severe climate shocks. On the other hand, developing markets meet the climate change targets. They provide evidence that an increase in the significance of transition risk is a determinant of sovereign bond yields.

Zenios (2021) studied the effects of climate change on the transparency of sovereign debt. The author looks at the disclosure of EU sovereigns to climate change, studying international best practices, and describes the transmission flows. He argues that adoption to climate change scenarios by the EU and other authorities can mainstream climate risk in terms of public finance. A network for "climate-proofing" public finance will bring together the EU and member state institutions, and Zenios recommends budgeting for climate expenditures and contingent liabilities, and using risk-sharing instruments, with disclosure of the risks from climate change to public finance.

3. DATA

The secondary data were gathered from the Penn-World Table (PWT 10), the World Development Indicators (WDI) of the World Bank, and the World Economic Outlook (WEO) of the International Monetary Fund from 1980 to 2019 for all Asian countries (included in the appendix. The climate change variables are gathered from the Notre Dame Global Adaptation Initiative (ND-GAIN[1]), which includes climate vulnerability, resilience, economic indicators, social indicators, and governance indicators from 1995 to 2019. Based on the availability of the data, the paper relies on the ND-Gain Index. The time series from 1980 to 2019 is considered because the other time series data for climate change vulnerability are limited. The DN-GAIN includes vulnerability, which refers to "a country's exposure, sensitivity, and capacity to adapt to the impacts of climate change" and comprises indicators of six life-supporting sectors—food, water, health, ecosystem services, human habitat, and infrastructure. Resilience, on the other hand, estimates "a country's capacity to apply economic investments and convert them to adaptation actions" and covers three areas—economic, governance, and social readiness—with nine indicators. The dependent variable, government bond spread, is measured by 10-year foreign currency-denominated government bond spreads using the US benchmark, which are obtained from Bloomberg. Fiscal balance[2] as a percentage of GDP is used as an instrument to measure a government's ability to meet its financing needs and to ensure good management of public finances. The government budget deficits increase the amount of government debt outstanding. The current account balance is concerned as a share of GDP: a country that imports more than it exports funds the difference with foreign capital inflows. The government debt as a share of GDP: high levels of

[1] https://gain.nd.edu/our-work/country-index/.

[2] https://www.focus-economics.com/economic-indicator/fiscal-balance.

government debt reduce investor confidence in debt-service capacity. The credit default swap (CDS) spread: the CDS spread is a market-based measure of a country's level of default risk. Table 1 provides the details of the variables used in the study.

Table 1: Description of the Variables

Variable	Description	Abbreviation
Climate change variables[a]		
Vulnerability	Climate vulnerability index	Vul
Resilience	Climate resilience index	Res
Economic	Economic risk indicator	Econ
Social	Social risk indicator	Soc
Governance	Governance risk indicator	Gov
Macroeconomic and financial variables[b]		
Government Bond Spread	Government bond spread	GBS
GDP per capita	GDP per capita	GDPpc
Sovereign credit default swaps spread	Sovereign credit default swaps spread is a market-based measure of a country's level of default risk	SCDS
GDP growth	GDP growth rate	GDPg
Government debt	Government debt to GDP: the central government debt will increase the risk of sovereign in the countries	Debt
Finance	Credit to private sector: the financial sector plays a significant role in the country's financial balances	Fin
Budget balance	Budget balance to GDP: government budget deficits increase the amount of government debt outstanding	Fis
Inflation	Inflation of the country	Inf
Trade openness	Trade openness	To

[a] Data were obtained from ND-GAIN Climate Change variables.

[b] Data were obtained from various sources, as explained in the data section.

4. EMPIRICAL METHOD

Based on the theoretical framework provided, the following model can be identified:

$$Log\ BondSpread_{i,t} = b_0 + b_1 LogCLIMATE_{i,t} + b_2 LogX_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where, BondSpread is the government bond spread indicator for sovereign risk; CLIMATE is the vector for climate change, including vulnerability, resilience, and economic–social–governance (ESG)-related indices; and X is the exogeneous variables in the model. Accordingly, the Panel ARDL equation can be expressed as:

$$\Delta lnGBS_{it} = \propto_{0i} + \propto_{1i} lnGBS_{i,t-1} + \propto_{2i} lnGDPpc_{i,t-1} + \propto_{3i} lnSCDS_{i,t-1} + \propto_{4i} lnGDPg_{i,t-1} + \propto_{5i} lnDebt_{i,t-1} + \propto_{6i} lnFin_{i,t-1} + \propto_{7i} lnFis_{i,t-1} + \propto_{8i} lnTo_{i,t-1} + \propto_{9i} lnVul_{i,t-1} + \propto_{10i} lnRes_{i,t-1} + \propto_{11i} lnEcon_{i,t-1} + \propto_{12i} lnSoc_{i,t-1} + \propto_{13i} lnGov_{i,t-1} + \sum_{j=1}^{p} \rho_{ij} \Delta lnGBS_{i,t-j} + \sum_{j=0}^{q1} \beta_{1ij} \Delta lnGDPpc_{i,t-j} + \sum_{j=0}^{q2} \beta_{2ij} \Delta lnSCDS_{i,t-j} + \sum_{j=0}^{q3} \beta_{3ij} \Delta lnGDPg_{i,t-j} + \sum_{j=0}^{q4} \beta_{4ij} \Delta lnDebt_{i,t-j} + \sum_{j=0}^{q5} \beta_{5ij} \Delta lnFin_{i,t-j} + \sum_{j=0}^{q6} \beta_{6ij} \Delta lnFis_{i,t-j} + \sum_{j=0}^{q7} \beta_{7ij} \Delta lnTo_{i,t-j} + \sum_{j=0}^{q8} \beta_{8ij} \Delta lnVul_{i,t-j} + \sum_{j=0}^{q9} \beta_{9ij} \Delta lnRes_{i,t-j} + \sum_{j=0}^{q10} \beta_{10ij} \Delta lnEcon_{i,t-j} + \sum_{j=0}^{q11} \beta_{11ij} \Delta lnSoc_{i,t-j} + \sum_{j=0}^{q12} \beta_{12ij} \Delta lnGov_{i,t-j} + \mu_i + \varepsilon_{it} \quad i = 1,2, \dots N; \; t = 1,2,3, \dots . T \tag{2}$$

The study applied the Panel ARDL model proposed by Pesaran, Shin, and Smith (1999). Under the Panel-ARDL, the mean group (MG), pooled mean group (PMG), and dynamic fixed effects (DFE) model were estimated following Pesaran and Smith (1995) and Pesaran, Shin, and Smith (1999).

Obtained from the ARDL estimator, the MG has not executed any restrictions on the parameters and gives the average of the long-run parameters. Since the estimator is always consistent, pooling data will not have any advantage among panel-forming units. Therefore, dynamic fixed effects (DFE), in which the fixed slope and varied intercept across the countries, is used as an alternative under the assumption of the homogeneity slope, under which DEF estimates are affected by heterogeneity bias (Pesaran and Smith 1995). Hence, to overcome these issues and obtain an efficient estimation, a maximum likelihood-based PMG method was developed by Pesaran, Shin, and Smith (1999). Notably, the PMG was applied to pressure long-term movement among the panels, allowing for constant, error variance, and short-run parameters to be varied. In the Panel ARDL model, the PMG was used to obtain the short-run heterogeneity rather than long-run homogeneity. Pesaran, Shin, and Smith (1999) proposed using the Hausman (1978) test for the homogeneity of long-term parameters (Erdem, Gulbahar, and Bulut 2010).

4.1 Pooled Mean Group (PMG) Model

The PMG is applied when expecting the long-run equilibrium causality among the variables to be similar across panels. In the short run, the model allows for country-specific parameters since it expresses different impacts of susceptibility to financial crisis, external shocks, and stabilization policies. But validity, consistency, and efficiency need to be addressed carefully in the model.

In order to present the long-run relationship, the outcome of interest needs the coefficient on error correction to be negative and not lower than minus two. Then, consistency of the ARDL model is assumed that the residual of error correction model to be serially uncorrelated and the independent variables are considered as exogeneous. By including ARDL (p, q) lags for the dependent and explanatory variables in the error correction term, these conditions can be satisfied. Further, the size of N and T is critical because when both are large enough to allow the use of the dynamic estimator it helps to avoid the bias of the average estimator resolving the heterogeneity. Notably, some literature argues that not fulfilling these conditions produces inconsistency in the PMG. The PMG estimator limits the long-run parameters to being the same, while allowing the short-run coefficient to vary.

The dynamic form of the mean group estimator shows in the self-regression pattern with panel ARDL distributional delays (p, q1, q2, …, qN), so that the equation of Panel ARDL presents in the form of the following equation:

$$y_{i,t} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta'_{ij} X_{i,t-j} + \mu_i + \varepsilon_{i,t} \tag{3}$$

where y denotes the dependent variable; X is the vector of independent variables; μ is the fixed effects; and ε is the disturbing component.

In this study, PMG and MG are used to estimate equation (1) as given in equation (2). Interestingly, the PMG placed in between the MG and fixed effect models; only the long-term coefficients are equal between countries, while short-term coefficients are changing. Thus, the Hausman test is used to choose between the MG and PMG as in the following hypotheses:

H0: the long-term coefficients are homogeneous and can be combined (PMG method efficiency)
H1: the long-term coefficients that are nonhomogeneous and are not combinable/and cannot be combined (efficiency of MG estimator).

The error-correction form of the PMG model is written as follows:

$$\Delta y_{i,t} = \phi_i \left(y_{i,t-1} - \theta'_i X_{it} \right) + \sum_{j=1}^{p-1} \lambda^*_{ij} \Delta y_{i,t-1} + \sum_{j=0}^{q-1} \delta'^*_{ij} \Delta X_{i,t-j} + \mu_i + \epsilon_{i,t} \tag{4}$$

The parameter ϕ_i is the error-correcting speed of the adjustment term. If ϕ_i= 0, then there is no evidence for a long-run relationship. This parameter is expected to be significantly negative under the prior assumption that the variables show a return to a long-run equilibrium. Of particular importance is the vector θ'_i, which contains the long-run relationships between the variables.

4.2 Mean Group (MG) Estimator

After the MG estimator, a separate regression is required for each country and calculating the coefficients as the unweighted means of parameters for individual countries. Therefore, the MG estimator has not imposed any restrictions but allows for all coefficients to be varied and heterogeneous in the long- and short run. Since this study uses sufficiently large time series data, it supports the conditions of consistency and validity (Favara 2003).

4.3 Dynamic Fixed Effects (DFE) Model

The dynamic fixed effects estimator (DFE) is almost equal to the PMG estimator and imposes restrictions on the slope coefficient and error variances to be equal across all countries in the long run. The DFE model further restricts the speed of adjustment coefficient and the short-run coefficient to be equal. However, the model features country-specific intercepts. DFE has a cluster option to estimate intra-group correlation with the standard error (Blackburne and Frank 2007). Nevertheless, Baltagi, Griffin, and Xiong (2000) point out that this model is subject to a simultaneous equation bias due to the endogeneity between the error term and the lagged dependent variable in case of small sample size.

5. RESULTS AND DISCUSSION

The following table shows the summary statistics of the variables used in the analysis.

Table 2: Summary Statistics of the Variables

Variable	Observations	Mean	Std. Dev.	Min	Max
Climate					
Vulnerability	1,125	0.438	0.076	0.301	0.604
Resilience	1,125	0.399	0.111	0.198	0.816
Economic	1,100	0.460	0.143	0.172	0.897
Social	1,125	0.295	0.138	0.079	0.800
Governance	1,100	0.450	0.161	0.114	0.892
Macroeconomic and financial					
Government bond spread	1,224	5.68	7.94	–0.66	14.73
Current account balance	1,309	0.075	21.493	–240.521	311.760
GDP per capita	1,636	10,623.23	15,859.440	194.949	116,233
Sovereign CDS spread	1,242	36.41	44.89	12.63	89.32
GDP growth	1,618	75.786	7.139	–64.047	57.817
Government debt	409	58.782	34.191	1.893	197.284
Credit to private sector	1,212	51.912	45.887	0.962	255.310
Fiscal balance	1,006	–2.644	12.428	–17.680	6.211
Inflation	1,528	5.571	4.321	1.937	12.472
Trade openness	1,506	88.406	61.919	0.021	437.326

The summary of the variables presented above shows the number of observations, mean, standard deviation, and minimum and maximum values.

5.1 All Asian Economies

Table 3 presents the results of the unit root tests of IPS, LLC, and CIPS for the intercept and trend after obtaining the first differences of the variables. All variables are converted into the natural logarithm.

Table 3 presents the test of unit roots. A variety of panel unit root tests were conducted to test the stationarity of the data. Specifically, it included IPS = Im, Pesaran and Shin test; LLC = Levin, Lin, and Chu test; CIPS = Cross-sectional Im, Pesaran, and Shin tests. All these tests are considered first-generation panel unit root tests because they assumed the independence between cross-section units, except CIPS which is a second-generation unit root test. Although this second generation of unit root tests considered the lack of independence of the units when admitting the presence of unobservable common factors, it led to new challenges when interpreting both the unit root test and the cointegration test (Breitung and Pesaran 2008). As can be seen, the statistic value is below the critical value at the 1% or 5% levels of significance. Thus, this second-generation test rejects the null hypothesis of a unit root process for the dependent and independent variables. From Table 3, it can be concluded that all variables under the first difference are significant, so that we can use the Panel ARDL model.

Table 3: Unit Root Test Results (with Individual Intercept and Trend under First Difference)

Variable	IPS Test		LLC Test		CIPS Test	
Natural logarithm	No Trend Statistic	Trend Statistics	No Trend Statistic	Trend Statistics	No Trend Statistic	Trend Statistics
Vulnerability	–4.01**	–6.11***	–6.84***	–5.74***	–4.22***	–4.06***
Resilience	–2.18**	–3.80***	–5.74***	–3.62***	–3.82***	–7.03***
Economic	–2.88**	–3.81***	–4.75***	–14.05***	–4.73***	–4.44***
Social	–2.53**	–4.62***	–4.86***	–3.06***	–5.67***	–6.73***
Governance	–3.34***	–5.92***	–5.75***	–15.54***	–4.48***	–5.27***
Government bond Spread	–3.42***	–4.92***	–8.39***	–10.34***	–3.91***	–5.21***
Current account balance	–1.93**	–3.91***	–6.72***	–4.77***	–4.31***	–4.53***
GDP per capita	–2.36**	–2.64**	–4.90***	–13.02***	–3.45***	–6.83***
Sovereign CDS spread	–1.99**	–2.80**	–5.02***	–5.83***	–4.52***	–4.54***
GDP growth	–2.21**	–3.34***	–5.33***	–4.74***	–3.44***	–4.63***
Government debt	–2.88**	–4.58***	–6.38***	–14.75***	–4.53***	–5.72***
Credit to private sector	–2.28**	–3.99***	–7.84***	–6.88***	–4.49***	–7.01***
Fiscal balance	–2.92**	–5.92***	–6.29***	–3.96***	–4.39***	–6.59***
Inflation	–3.51***	–4.11***	–5.94***	–13.76***	–3.59***	–5.26***
Trade openness	–4.22***	–4.95***	–9.83***	–4.90***	–4.66***	–3.77***

All variables in the above are converted to logarithm form. IPS = Im, Pesaran and Shin test; LLC = Levin, Lin, and Chu test; CIPS = Cross-sectional Im, Pesaran and Shin test. ***, **, and * indicate that the variables are stationary at the 1%, 5%, and 10% level, respectively.

Table 4: Results of Pedroni's (2004) Cointegration Test

	Without Asian Financial Crisis		With Asian Financial Crisis[c]	
Statistic	Statistics	Probabilities	Statistics	Probabilities
Within dimension				
Panel v-Statistics	–0.316	0.180	–0.526	0.799
Panel rho-Statistics	0.624	0.246	0.625	0.854
Panel PP-Statistics	–1.217**	0.072	–1.346**	0.048
Panel ADF-Statistics	1.995**	0.022	1.862	0.052
Between dimension				
Group rho-Statistics	1.390**	0.011	1.604**	0.039
Group PP-Statistics	–1.699***	0.001	1.774***	0.001
Group ADF-Statistics	–2.273***	0.001	–3.125***	0.000

***, **, and * denote significant at the 1%, 5%, and 10% level, respectively. C – A dummy variable was included to determine the impacts of the Asian Financial Crisis in 2008.

Table 4 reports the results of Pedroni's (2004) cointegration test. The statistics can be divided into two groups, namely within dimensions and between dimensions. According to the results, two statistics from within dimensions and three statistics from between dimensions are significant at the 1% or 5% level. Altogether, five statistics out of seven are significant, indicating the rejection of the no cointegration null hypothesis in the without financial crisis situation. According to Pedroni (2004) the Panel ADF and Group ADF statistics are considered as more reliable indications. In these results, both statistics rejected the null hypothesis of no-cointegration. Therefore, according to the literature, these results are consistent with country and multi-country specifications of the evidence on cointegration. Second, under the variable with financial crisis, four statistics out of seven are significant, with one from within dimensions and three from between dimensions. Therefore, this suggests the presence of cointegration relationships between these variables even under the financial crisis situation. if the existence of a cointegration relationship is found, the panel data structure is applied to estimate the ARDL model, which serves to help understand the relationship between the sovereign risk and climate variables. In the literature, country-specific evidence of cointegration is extended to regional levels for broader policy implications.

Table 5: PMG, MG, and DFE Estimation Results

Dependent Variable: Log of Government Bond Spread	Pooled Mean Group (PMG)	Mean Group (MG)	Dynamic Fixed Effect (DFE)
Long-run dynamic			
Log of Vulnerability	0.284** (2.93)	0.301** (2.68)	0.307** (2.23)
Log of Resilience	–1.238*** (–3.98)	–0.981** (–2.87)	–1.703*** (–3.78)
Log of Economic	0.427* (1.96)	0.224 (0.25)	0.400 (0.72)
Log of Social	0.328** (2.66)	–0.882** (–2.71)	–0.842** (–3.02)
Log of Governance	0.332** (3.01)	0.106** (3.42)	0.112 (0.84)
Log of Current account balance	–0.159*** (–3.11)	–1.107** (–2.86)	–0.326*** (–3.81)
Log of GDP per capita	0.472 (0.17)	0.305 (0.12)	0.729 (0.30)
Log of Sovereign CDS spread	0.402 (0.11)	0.109 (0.08)	0.973 (0.28)
Log of GDP growth	–1.229** (–2.52)	–1.502** (–2.66)	–1.152*** (–3.43)
Log of Government debt	0.309 (0.19)	0.701 (0.22)	0.629** (2.83)
Log of Credit to private sector	0.196 (0.75)	0.661** (2.19)	0.283** (2.03)
Log of Fiscal balance	0.188** (2.94)	0.290 (2.74)	0.523 (0.01)
Log of Inflation	0.055*** (3.82)	–0.290** (–2.88)	0.462** (2.52)
Log of Trade openness	–1.430** (–2.81)	–1.617*** (–4.91)	–0.484** (–3.27)
Constant	13.073** (–3.02)	–12.281** (–2.56)	120.490 (0.71)
Short-run dynamic			
EC	–0.490*** (–3.01)	–1.290*** (–3.62)	–1.236*** (–5.32)
D. Log of Vulnerability	0.111 (0.36)	0.721* (2.22)	0.233** (2.69)
D. Log of Resilience	–12.620** (–1.71)	26.812** (0.77)	–1.290*** (4.22)
D. Log of Economic	–0.073*** (–3.67)	–0.281** (–2.99)	0.634** (3.02)
D. Log of Social	0.742*** (3.76)	0.240*** (3.52)	0.398** (2.11)
D. Log of Governance	–0.073*** (–3.67)	–0.281** (–2.99)	–0.245** (–2.54)
D. Log of Current account balance	0.475** (2.90)	0.824** (–2.69)	0.237** (2.44)
D. Log of GDP per capita	0.290** (3.94)	0.735 (1.31)	0.449 (0.23)
D. Log of Sovereign CDS spread	0.321 (0.46)	0.212 (0.47)	0.321 (1.04)
D. Log of GDP growth	0.352 (2.01)	0.422 (0.67)	0.237 (0.99)
D. Log of Government debt	0.611** (2.92)	0.214** (2.78)	0.201** (2.33)
D. Log of Credit to private sector	0.437 (0.44)	0.128** (2.45)	0.326** (2.74)
D. Log of Fiscal balance	0.726** (2.38)	0.126 (0.95)	0.126** (2.64)
D. Log of Inflation	0.073*** (–3.67)	–0.281** (–2.99)	–0.345** (–2.54)
D. Log of Trade openness	–0.483** (–3.21)	–0.252 (–0.69)	0.632 (0.90)
Constant	0.742*** (3.76)	0.240*** (3.52)	102.523** (3.56)
No. of observations	189	189	1,018
No. of groups	45	45	45
Hausman Test Statistics	4.16 (0.125)		1.38 (0.742)

All variables are in natural logarithms. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively. Log values of the variables are considered; D. means first difference; Z values are in parentheses.

The Hausman test was performed to select the robust model from PMG, MG, and DFE. In the Hausman test, since the p value is greater than 0.05, PMG is chosen over the MG; and since the p value is greater than 0.05 in the second equation, DFE is chosen over the PMG. Finally, the DFE model is chosen to study the effects. The results of the test accept that DFE is a more efficient estimator than MG and PMG. Thus, the model is re-estimated adding climate variables to the basic model, as below.

Table 6: Results of the Dynamic Fixed Effect Estimation

Dependent Variable: Log of Government Bond Spread	Dynamic Fixed Effect (DFE) (1)	Dynamic Fixed Effect (DFE) (2)	Dynamic Fixed Effect (DFE) (3)
Long run dynamic			
Log of Vulnerability	–	0.493** (–2.55)	0.307** (2.23)
Log of Resilience	–	–0.444** (–2.72)	–1.703*** (–3.78)
Log of Economic	–	–	0.401 (0.72)
Log of Social	–	–	–0.842** (–3.02)
Log of Governance	–	–	0.112 (0.84)
Log of Current account balance	–0.197*** (–3.41)	–0.812** (–3.01)	–0.326*** (–3.81)
Log of GDP per capita	0.266*** (3.02)	0.720*** (3.99)	0.729 (0.30)
Log of Sovereign CDS spread	0.405** (3.27)	0.250 (0.17)	0.973 (0.28)
Log of GDP growth	–1.304** (2.92)	–1.273** (2.60)	–1.152*** (–3.43)
Log of Government debt	0.727** (3.72)	0.082** (3.31)	0.629** (2.83)
Log of Credit to private sector	0.209 (0.11)	0.602** (2.42)	0.283** (2.03)
Log of Fiscal balance	0.120** (3.60)	0.204** (2.90)	0.523 (0.01)
Log of Inflation	0.099*** (3.55)	0.821** (2.39)	0.462** (2.52)
Log of Trade openness	–0.621** (2.18)	–0.902** (–2.53)	–0.484** (–3.27)
Constant	201.073** (3.67)	124.281** (–2.99)	120.490 (0.71)
Short-run dynamic			
EC	–1.442*** (–2.92)	–1.302*** (–2.93)	–1.236*** (–5.32)
D. Log of Vulnerability	–	0.405** (2.00)	0.233** (2.69)
D. Log of Resilience	–	–2.072** (2.09)	–1.290*** (4.22)
D. Log of Economic	–	–	0.634** (3.02)
D. Log of Social	–	–	0.398** (2.11)
D. Log of Governance	–	–	–0.245** (–2.54)
D. Log of Current account Balance	0.872** (2.45)	0.901** (2.52)	0.237** (2.44)
D. Log of GDP per capita	0.509** (3.16)	0.375** (3.35)	0.449 (0.23)
D. Log of Sovereign CDS spread	0.806 (0.29)	0.196 (0.90)	0.321 (1.04)
D. Log of GDP growth	0.198 (1.01)	0.510 (0.47)	0.237 (0.99)
D. Log of Government debt	0.461** (2.63)	0.211** (2.48)	0.201** (2.33)
D. Log of Credit to private sector	0.321** (3.40)	0.306** (2.55)	0.326** (2.74)
D. Log of Fiscal balance	0.053 (0.37)	0.206 (0.77)	0.126** (2.64)
D. Log of Inflation	–0.863*** (–3.53)	–0.454** (–2.98)	–0.345** (–2.54)
D. Log of Trade openness	0.483 (0.21)	0.278** (2.29)	0.632 (0.90)
Constant	90.32 (3.76)	101.59 (3.52)	102.523** (3.56)
No. of observations	1,038	1,211	1,418
No. of groups	45	45	45

All variables are in natural logarithms. ***, **, and * denote significant at the 1%, 5%, and 10% level, respectively. D. means first difference; t values are in parentheses.

According to Table 6, dynamic fixed effect (1), (2), and (3) equations have been evaluated. DFE (1) shows only the impact of macroeconomic variables; equation (2) shows the inclusion of vulnerability and resilience; DFE (3) shows more climate-related ESG indicators added to the DFE (2).

The results of the DFE (1) show that current account balance, GDP growth, and trade openness are negatively significant, while GDP per capita, sovereign CDS spread, government debt, fiscal balance, and inflation are positively significant in the long run. In the short run, Inflation is negatively significant, while current account Balance, GDP per capita, government debt, and credit to private sector are positively significant at the 5% level. The error correction term is negative, and more than negative two (–1.442) implies that it is evidence of the existence of a long-run relationship between these variables. The DFE (2) model, which is an extension of macro-variables to key climate indicators of vulnerability and resilience, predicts current account balance, GDP growth, trade openness, and resilience are negatively significant whereas GDP per capita, government debt, credit to private sector, fiscal balance, inflation, and vulnerability are positively significant in the long run. In the short run, current account balance, GDP per capita, government debt, credit to private sector, trade openness, and vulnerability are positively significant, although resilience and inflation are negatively significant at the 5% level. This is evidence of the presence of a long-run relationship because of the negative error correction term and because it is more than negative two. The full mode of DFE (3) of the panel ARDL model predicts that the current account balance, GDP growth, trade openness, resilience, and social indicators are negatively significant; however, government debt, credit to private sector, inflation, and vulnerability are positively significant. Even in this equation, there is a long-run relationship between the government bond spread and other independent variables because the negative error correction term is more than negative two.

Consistent with the DFE model, climate change variables have a strong association in terms of vulnerability and resilience, which are at the 5% significant level, at least; the impact of sovereign risk depends on the many other macroeconomic determinants in the long run. In the short-run, DFE, which includes vulnerability, has a positive and resilience has a significant negative relationship with the sovereign risk. Since the presence of the long-run estimation falls within the stabilization range, the DFE estimator is predictable in both the long- and short-run estimation. Moreover, the evidence shows that the estimator is a nonspurious long run and thus variables are cointegrated.

5.1.1 Short-run Estimates

As for the short-term error correction coefficient, the constant is statistically significant in the DFE model, which means that there is a fixed effect of these variables on the climate variables. The DFE model has a positive relationship with current account balance (0.237), government debt (0.201), credit to private sector (0.326), fiscal balance (0.126), inflation (0.345), vulnerability (0.233), economic (0.634), and social (0.398), and a negative relationship with resilience (–1.290) and governance (–0.245). According to the DFE models, sovereign risk is influenced by the vulnerability, resilience, economic, social, and governance indicators, which indicate 0.233, –1.290, 0.634, 0.398, and –0.245, respectively. The resilience and governance are negatively significant. Increasing 1% of resilience and governance indicators decrease the sovereign risk by 1.29% and 0.245%, respectively. Notably, one of the main concerns is increasing resilience to improve the sovereign risk that expected to be reduced. Resilience exerts a negative short-run impact on sovereign risk in the model. This indicates that the error correction forces the short-run coefficient to proceed to its long-run path.

5.1.2 Long-run Estimates

The DFE (3) model predicts that the current account balance (–0.326), GDP growth (–1.152), trade openness (–0.484), resilience (–1.703), and social (–0.842) indicators are negatively significant, while government debt (0.629), credit to private sector (0.283), inflation (0.462), and vulnerability (0.307) are positively significant at the 5% level. These variables influence the sovereign risk of these countries in the long run. Regarding the long-run coefficient of DFE (3), a 1% increase of explanatory variables, such as current account balance, decreases the sovereign risk by 0.326%, GDP growth by 1.152%, trade openness by 0.484%, resilience by 1.703%, and social indicator by 0.842%. Moreover, a 1% increase in government debt increases the sovereign risk by 0.629%, credit to private sector by 0.283%, inflation by 0.462%, and vulnerability by 0.307%. Therefore, the model predicts the climate change variation has influenced the sovereign risk in terms of resilience, social indicator, and vulnerability significantly.

Regarding the results of Asian economies, the economic interpretation is that the increase of the climate risk has created more vulnerable economies and indebted countries in Asia. The situation is worse in the case of the post-COVID-19 pandemic conditions of the Asian economies. Furthermore, the economic conditions during COVID-19 twisted the economic priorities and led to the creation of economic conditions more susceptible to the climate variations and economic crisis. Therefore, the impact of the climate risk on the sovereign bond spread in Asia is the top priority for the macroeconomic stability of the countries.

6. CONCLUSION

This study examined the impact of climate change on sovereign bond spread in Asia. The study employed the empirical method of the Panel ARDL model, which includes PMG, MG, and DFE estimators. The results revealed that all first differenced variables are stationary resulting from various panel unit root tests. The general results of Pedroni’s (2004) cointegration test predict that evidence on cointegration is consistent with country-specific effects. With regard to cointegration relationship, the panel data structure was used to estimate the panel ARDL model. In all models, the error correction term was negative and significant at 1%, indicating that a long-run relationship exists between the variables of concern. The Hausman test was performed to select the most robust model out of PMG, MG, and DEF; the best model for the analysis was the DFE model for the Asian countries.

In Asia in the short run, according to the DFE which has a positive relationship, current account balance, government debt, credit to private sector, fiscal balance, inflation, vulnerability, economic, and social, are negatively influenced by resilience and governance have significant influence on climate change. Further, sovereign risk is influenced by climate variables such as vulnerability, resilience, economic, social, and governance indicators. Under the long run scenario, the model predicts that the current account balance, GDP growth, trade openness, resilience, and social indicators are negatively significant, but government debt, credit to private sector, inflation, and vulnerability are positively significant.

The COVID-19 pandemic exacerbated the risk to fiscal sustainability created by climate change. Evidence can be found to show that, in the Asian countries that faced the pandemic, the economic environment has worsened along with climate change. Therefore, the post-pandemic lesson is/should be that it is even more vital to strengthen fiscal sustainability in the current economic environment due to the risks of climate change.

The presence of a long-run relationship between the sovereign risk and climate change with its determinants found in this study implies the effectiveness of policymakers targeting one of the variables in influencing the long-run behavior of other variables. Accordingly, even in short run and long run, climate change variables strongly affect the sustainability of the sovereign bond spread for Asian economies. Thus, the adjustment of the macroeconomic indicators is necessary to achieve a sustainable economy while under the climate influence. Last, those determining factors of the climate risks for sovereign bond spread can be integrated into the macroeconomic framework in the Asian economies to help to achieve longer-term resilience and sustainability. Future research can examine more closely the subgroups of Asian economies that are particularly exposed to climate change, where the fiscal sustainability implications will be even more severe.

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APPENDIX

Asian Countries		
Afghanistan	Israel	Pakistan
Armenia	Japan	Philippines
Azerbaijan	Jordan	Qatar
Bahrain	Kazakhstan	Saudi Arabia
Bangladesh	Korea, Rep. of	Singapore
Bhutan	Kuwait	Sri Lanka
Brunei Darussalam	Kyrgyz Republic	Tajikistan
Cambodia	Lao People’s Democratic Republic	Thailand
People’s Republic of China	Lebanon	Timor-Leste
Cyprus	Malaysia	Türkiye
Georgia	Maldives	Turkmenistan
India	Mongolia	United Arab Emirates
Indonesia	Myanmar	Uzbekistan
Iran, Islamic Republic of	Nepal	Viet Nam
Iraq	Oman	Yemen, Republic of