



Climate policy uncertainty and its impact on sovereign borrowing costs

Nannan Guo¹ · Shanghui Jia² · Yingke Liu²

Received: 12 August 2024 / Accepted: 19 April 2025
© The Author(s), under exclusive licence to Springer Nature B.V. 2025

Abstract

Government actions based on widespread and rapid climate change expose the sovereign bond market to climate policy uncertainty. This paper explores the impact of climate policy uncertainty (CPU) on Sovereign Borrowing Costs (SBC), using the global CPU index and a high-dimensional fixed-effects model (HDFE). It employs various methodologies, including an autoregressive (AR) panel data model and Heckman's two-step method, to solve potential endogeneity problems. The findings reveal that CPU exerts a significantly positive influence on SBC, with a more pronounced effect in economies with lower economic development, higher climate vulnerability, or lower climate resilience. Additionally, macro-economic indicators—including inflation, GDP growth, and the domestic savings-to-GDP ratio—enhance the CPU–SBC linkage, while stock market volatility acts as a dampening factor. The study further shows that CPU affects SBC through channels such as political stability and international liquidity. These results highlight the importance of incorporating CPU into investment strategies, policymaking, and sustainable development frameworks.

Keywords Climate policy uncertainty · Sovereign borrowing costs · Climate resilience · Climate vulnerability · Sovereign bond yield

JEL Classification C23 · G15 · Q54 · Q58

✉ Yingke Liu
liuyingke@email.cufe.edu.cn

Nannan Guo
guonn@email.cufe.edu.cn

Shanghui Jia
shjia@lsec.cc.ac.cn

¹ School of Mathematics and Statistics, Ankang University, Ankang, Shaanxi 725000, China

² School of Statistics and Mathematics, Central University of Finance and Economics, Beijing 102206, China

1 Introduction

Climate change has emerged as a profound global challenge, drawing increasing attention from governments due to its extensive implications for both economic stability and financial markets (Boulange et al., 2021; Dibley et al., 2021; Koh et al., 2021; Liang, 2022; Zhang et al., 2022). According to the Financial Stability Board (FSB) of the G20, climate-related risks are generally categorized into two key types: physical risks, arising from extreme weather events and natural disasters, and transition risks, which are the hidden risks faced by economies in shifting to low-carbon development paths. (Bolton & Kacperczyk, 2023). In recent years, the escalating climate crisis and its profound consequences have prompted many economies to adopt more ambitious climate policies (Ding et al., 2022; IPCC, 2021). For instance, more than 100 economies—accounting for close to 50% of global GDP—have joined global multilateral agreements such as the Paris Agreement (Bolton & Kacperczyk, 2023). Nonetheless, there are large uncertainties in the process of realization and outcomes of climate policy, i.e., climate policy uncertainty (CPU) (Gavriilidis, 2021; Ren et al., 2023). The U.S.'s withdrawal from the Paris Agreement in 2017 and its subsequent re-entry in 2021 exemplify this uncertainty (Gavriilidis, 2021). CPU is therefore recognized as a significant climate transition risk (Xu et al., 2023).

Since S&P (2014) recognized that climate-related risk are the key driver influencing sovereign risk, the connection between climate-related and sovereign-related risk has garnered extensive focus. Sovereign risk is the risk that foreign investors or creditors face losses due to the actions of sovereign governments (Agarwala et al., 2021; Mallucci, 2022). Sovereign bonds, which are issued by governments, backed by national credit, and accessible to both domestic and foreign investors, are by far the largest asset class in the world (IIF, 2021). When a country's sovereign risk is high and investors are worried about its debt solvency, the sovereign borrowing costs (SBC) will increase. Both sovereign risk and the sovereign bond markets are significantly affected by climate risk.

Recently, growing academic interest has been directed toward understanding how climate-related risks influence sovereign debt markets. Most research has concentrated on how climate vulnerability, resilience, and physical risks affect sovereign risk (Beirne et al., 2021; Boitan & Marchewka-Bartkowiak, 2022; Kling et al., 2018; Mallucci, 2022). Moreover, climate transition risks linked to political instability have increasingly been recognized as critical influences on sovereign risk (Agarwala et al., 2021; UNEP, 2018). However, measurement challenges hinder the study of the influence of climate transition risks and CPU. Cheng et al. (2023) and Collender et al. (2023) quantified the effect of climate transition-related risk on sovereign bond markets utilizing indirect indicators, which not interpret transition risk as well as CPU. Gavriilidis (2021) developed the U.S. CPU index, and Jia et al. (2024) examined its effect on global sovereign bond volatility. This index, however, focuses primarily on U.S.-related CPU events. Guo et al. (2024) expanded the CPU index to 21 economies and 3 global integrated markets and explored their impacts on sovereign and green bond markets, which provided valuable data for evaluating the influence of CPU. Nevertheless, the linkage between CPU and sovereign bond markets remains underexplored and requires further investigation.

Considering evolving research trajectories and existing gaps in the literature, this paper examines the influence of CPU on sovereign borrowing costs. By utilizing the global CPU indexes developed by Guo et al. (2024) and a high-dimensional fixed effects model (HDFE), we analyze the link between CPU and SBC (sovereign bond yields and spreads across 63 economies, sourced from the DataStream database). Additionally, we apply

several methodologies to address potential endogeneity concerns, including an autoregressive panel data (AR) model and Heckman's two-step method.

The study concludes: First, a 1% increase in CPU leads to a 0.5183 rise in sovereign bond yields and a 0.3343 increase in bond yield spreads, significantly raising SBC. The effect of CPU differs considerably across economic groups, with more pronounced impacts on economies with lower levels of development, higher climate vulnerability, or lower climate resilience. Second, the inflation rate, GDP growth rate, and the ratio of domestic total savings to GDP positively moderate the nexus between CPU and SBC at the 5% significance level. In contrast, stock market volatility (VIX) exhibits a negative moderating effect on it at the 1% level. Third, CPU can impact SBC through political stability and international liquidity.

This work advances the literature through three main contributions. Firstly, it deepens the knowledge of how climate transition risks, as captured by the CPU index, are linked to SBC. The study highlights the positive impact of CPU in SBC, the heterogeneous impacts of CPU, the role of climate readiness, and the channels through which CPU affects SBC, offering precious perspectives to policymakers, investors, and sustainable development. Secondly, it highlights both positive and negative moderating factors and confirms that CPU can affect SBC through political stability and international liquidity, thereby broadening the scope of current research by linking CPU with a wider set of macroeconomic and geopolitical factors. Thirdly, it significantly advances the field by empirically validating and extending the theoretical framework of Battiston and Monasterolo (2019), which established the link between CPU and sovereign bond spreads. The significant impact of CPU on SBC provides empirical validation for the theoretical framework, while the findings on the heterogeneous effects and underlying mechanisms of CPU further enrich and expand this framework.

The article unfolds this way: Sect. 2 presents the theoretical foundation and research hypotheses. Section 3 covers the CPU index construction, empirical modeling, and data statistics. Section 4 examines the CPU's influence on SBC. Section 5 provides policy implications based on the findings. Finally, Sect. 6 summarizes the study.

2 Theoretical analysis and hypothesis development

This section explores the theoretical underpinnings of the relationship between CPU and SBC. It also develops the study's three core hypotheses. Section 2.1 discusses how CPU may influence SBC by increasing risk perception and policy ambiguity. Section 2.2 explains how this relationship may vary across different types of economies and time periods. Section 2.3 identifies key financial and non-financial variables that could act as moderating or mediating factors in the CPU–SBC linkage.

2.1 The potential relationship between CPU and SBC

Incorporating climate risk into financial assessments faces inherent uncertainty (Hallegatte et al., 2012). Predicting when, where, and to what extent climate change will impact remains complex (Weitzman, 2009). As Ackerman (2018) highlights, climate shocks are non-linear, making historical data insufficient for accurately predicting future risks. Moreover, policy decisions shaping the trajectory of climate risks are themselves uncertain. According to Real Options theory, government policy

announcements can influence investor reactions, depending on the credibility of the policy or their general sentiment toward climate issues (Dunz et al., 2021). This uncertainty can lead to disagreements among market participants when assessing climate risks, affecting their evaluation and pricing of sovereign debt.

CPU exacerbates information asymmetry and market instability, further complicating risk assessment. According to Akerlof's (1970) Lemons Market theory, uncertainty about information quality hinders effective risk evaluation, leading to inefficiencies. Similarly, Spence's (1973) Signaling theory suggests that uncertain policy signals, such as those related to climate policies, can generate asymmetric information, complicating risk assessment for investors and markets. These differences in risk evaluation can lead to an overreaction by the market to climate risks, further increasing the risk premium on sovereign debt.

This information asymmetry and market response complexity manifest in SBC. Specifically, CPU, by increasing information asymmetry and inconsistencies in market response, drives up the risk premium on sovereign debt. Real Options theory suggests that, in the context of policy uncertainty, investors seek greater returns to hedge against uncertain policy outcomes. Additionally, Signaling theory implies that uncertain climate policy signals may prompt the market to overreact, further raising SBC.

These theoretical insights lay a solid foundation for understanding how CPU affects SBC. For example, Battiston and Monasterolo's (2019) Climate-financial decision theory framework suggests that countries aligning their economies with climate goals earlier tend to have lower sovereign bond yields, reflecting a negative climate spread. In contrast, economies heavily reliant on fossil fuel revenues show a positive climate spread, indicating higher borrowing costs in response to climate risks. Moreover, Kölbel et al. (2020), using the BERT model, demonstrate that climate transition risks lead to wider CDS spreads, further emphasizing the importance of CPU in sovereign debt pricing.

Based on these theoretical and empirical findings, we propose **Hypothesis 1**: CPU positively influences SBC.

2.2 The potential heterogeneous impact of CPU

The impact of CPU on SBC may depend on the climate concern periods, climate vulnerability and resilience levels, and economic development status. According to Institutional theory, climate transition risks significantly increased CDS spreads following the Paris Agreement (Kölbel et al., 2020; North, 1990), indicating that the impact of CPU on SBC may be influenced by institutional frameworks and policy shifts. From the perspective of Resource Dependence theory, countries with higher climate vulnerability may face greater borrowing costs due to their increased reliance on external resources for climate adaptation and mitigation (Beirne et al., 2021b; Boitan & Marchewka-Bartkowiak, 2022; Pfeffer & Salancik, 1978). Additionally, Transaction Cost Economics theory suggests that countries with limited institutional capacity to manage climate risks or those with low levels of economic development may face higher transaction costs, leading to higher SBC (Cevik & Jalles, 2022; Williamson, 1981).

Therefore, based on these theories, we propose **Hypothesis 2**: The impact of CPU on SBC varies by climate-focused periods, climate vulnerability and resilience.

2.3 Key related variables

2.3.1 Financial variables

CPU can affect the country's financial situation. In line with Resource Dependence theory, economies facing significant climate risks may rely more on external resources for adaptation and mitigation, increasing their exposure to international financial markets (Pfeffer & Salancik, 1978). To meet the Paris Agreement goals and cap global warming, economies need massive investments in greening infrastructure and energy. As projected by the Global Commission on Adaptation (2019), around \$90 trillion should be mobilized by 2030 to support global adaptation efforts. While the private sector invests in this area, government action and incentives are essential. The European Central Bank (2021) report warned that delaying or abruptly implementing climate policies could cause an increase in future carbon costs and the proportion of climate-related debt relative to GDP, adding to the fiscal burden. Boitan & Marchewka-Bartkowiak (2023) highlighted that the strength and timeliness of climate policy affect the climate costs and financial situation of countries, especially those with difficulties in managing CO₂ emissions.

2.3.2 Non-financial variables

Firstly, CPU may fundamentally and permanently impact the macroeconomy. According to Transaction Cost Economics theory (Williamson, 1981), CPU's unpredictability raises transaction costs and financial risks, especially in countries with weak institutions, undermining long-term stability. For example, Dietz et al. (2016) estimated the risk value associated with climate impacts on worldwide financial assets, noting a potential 1.8% risk under steady emissions, which could escalate to 16.9% in high-risk scenarios. Campagnolo et al. (2016) demonstrated that effective climate policies boost environmental sustainability worldwide, while Batten (2018) cautioned that sudden policy changes, like increased carbon taxes, can disrupt the economy by raising energy prices and slowing global growth. Additionally, Battiston and Monasterolo (2019) pointed out that CPU can harm economic competitiveness and financial stability. Zhang and Du (2020) observed that environmental regulations might temporarily diminish productivity in China, while well-designed policies could promote sustainable growth. Berestycki et al. (2022) noted that CPU can deter investment, especially in sectors with high pollution or capital requirements.

Secondly, CPU can impact SBC through government actions. The effectiveness of government institutions directly influences a country's financial stability according to Institutional theory (North, 1990). For instance, Capelle-Blancard et al. (2019) discovered that nations with strong environmental, social, and governance (ESG) metrics have lower default exposure and narrower sovereign bond spreads. The ineffective management of climate disasters correlates with lower credit ratings and higher risk premiums for sovereign bonds (Boitan & Marchewka-Bartkowiak, 2022). Combined with the Political Economy theory (Acemoglu et al., 2005; North, 1990), political uncertainty may compromise the government's ability to repay debt (Clark, 1997; Cuadra & Sapriza, 2008). Agarwala et al. (2021) also observed that besides physical risks, much risks during the low-carbon transition process comes from political and behavioral factors.

Thirdly, CPU closely aligns with international factors. Numerous studies have corroborated the influence of CPU on U.S. financial market, for example, stock return and

stock volatility (Treepongkaruna et al., 2023; Xu et al., 2023), as well as on the global oil market (He & Zhang, 2022) and the international financial market connectedness (Hoque et al., 2022).

Correspondingly, these financial and non-financial risks are the key influencing factors of SBC. Domestic factors, such as financial conditions, economic development, and institutional stability, significantly influence SBC (Baldacci et al., 2011; Hill Clarvis et al., 2014). Moreover, global factors, including the U.S. financial market (e.g., CBOE volatility index, interest rate structure), international liquidity, and oil prices, also play a crucial role (Banerji et al., 2014; González-Rozada & Yeyati, 2008; Simonyan & Bayraktar, 2023). In emerging economies, sovereign spreads are particularly sensitive to U.S. market shocks (Banerji et al., 2014; Jeanneret, 2015).

Thus, this study posits **Hypothesis 3:** Both domestic factors—including financial conditions, macroeconomic development, and political and institutional stability—and international factors, such as the U.S. financial markets or international liquidity, may serve as either mediating or moderating variables that influence the link between CPU and SBC.

3 Methodology and data

This section summarizes the core empirical design and data sources adopted in this study. Section 3.1 introduces the CPU index as the main explanatory variable. Section 3.2 elaborates on the empirical methods, and Sect. 3.3 covers data sources, variable descriptions, and trends in CPU and SBC across economies.

3.1 Measurement of CPU

This study utilizes the global CPU indexes developed by Guo et al. (2024). They tailored CPU word selection strategies for nine languages and constructed monthly CPU indexes for 21 economies between January 2010 and April 2023, along with three global CPU indexes.

Their text analytics methods, covering aspects such as the selection of economies, newspaper sources, text choices, and calculation methods, are built upon prior research on the economic policy uncertainty (EPU) and CPU indexes. Firstly, the refined keyword search procedure minimizes the risk of overlooking relevant articles and including irrelevant ones. It enhances existing methods by expanding the vocabulary used in CPU index construction. This approach requires that policy and uncertainty terms co-occur within the same paragraph, ensuring thematic relevance and improving measurement precision. It also introduces the “near500” rule, ensuring that climate and policy-related terms are within 500 words of each other, enhancing the reliability of the screening process. The CPU selection strategy is customized for nine languages corresponding to the 21 economies, with nearly 100 articles reviewed in each round to refine the term selection, ensuring an error rate under 10% for all languages. Thirdly, three global CPU indexes were constructed, employing approaches aligned with those used for the global EPU index: *GCPU_per* (weighted by per capita GDP), *GCPU_GDP* (weighted by GDP adjusted for purchasing power parity), and *GCPU_PCA* (based on principal component analysis of the 21 CPU indexes).

3.2 Methodology

To empirically test the research hypotheses proposed in Sect. 2, this research utilizes a high-dimensional fixed effects model, drawing on Ren et al. (2022):

$$Y_{it} = \alpha + \beta \ln GCPU_t + \gamma Controls_{i,t} + \mu_i + \lambda_t + \theta_m + \varepsilon_{it}, \quad (1)$$

where i and t signify the economy and month, respectively. The dependent variable Y_{it} refers to sovereign borrowing costs, measured alternatively by government bond yields or yield spreads. The key explanatory variable $\ln GCPU_t$ represents the natural log of the global CPU index. The vector $Controls_{i,t}$ includes a set of control variables capturing domestic macroeconomic fundamentals, global financial conditions, and climate risk indicators. The fixed effects μ_i , λ_t and θ_m capture unobserved across country, time and other relevant dimensions, respectively. ε_{it} is aggregated at the economic level to ensure robust inference.

To address endogeneity concerns, this study employs three diagnostic approaches.

Firstly, following Fang et al. (2017), Huo and Li (2023), and Li et al. (2023), to mitigate potential issues of reverse causality, this study introduces a one-month lag either to the explanatory and control variables or to the dependent variable.

Secondly, to simultaneously control for the influence of $\ln GCPU_t$ and Y_{it-1} , an autoregressive (AR) panel data model is constructed, as shown in Eq. (2).

$$Y_{it} = \alpha + \delta Y_{it-1} + \beta \ln GCPU_t + \gamma Controls_{i,t} + \mu_i + \lambda_t + \theta_m + \varepsilon_{it}. \quad (2)$$

To mitigate potential deviations in results caused by using OLS, this study adopts the System-GMM method to evaluate the parameters (Blundell & Bond, 1998). This method improves the accuracy by using more instrumental variables (Roodman, 2009). Additionally, the research rigorously examines the validity of the model through the Arellano-Bond and Hansen tests to check for autocorrelation and over-identification problems.

Thirdly, referring to Huo et al. (2023), this study employs Heckman's two-step method to tackle the endogeneity from sample selection bias (Heckman, 1979). First, it uses the Probit model to evaluate the likelihood of the CPU being above its mean, thereby assigning a binary value to the CPU (1 if yes, 0 if no) based on whether it's above its mean. The model considers domestic factors, global factors, and climate risks as predictors. Next, the Inverse Mills Ratio (IMR) is calculated and incorporated into the regression as a covariate to correct for sample selection bias, as shown in Eq. (3). If the significance and direction of α_1 stay unchanged, it indicates that the influence of CPU is stable after controlling the sample selection deviation.

$$Y_{it} = \alpha_0 + \alpha_1 \ln GCPU_t + \beta IMR_{it} + \gamma Controls_{i,t} + \mu_i + \lambda_t + \theta_m + \varepsilon_{it}. \quad (3)$$

To illustrate the full empirical strategy, including the baseline regression, heterogeneity tests, moderating and mediating mechanisms, and various diagnostic checks, we provide an integrated methodological framework as shown in Fig. 1.

3.3 Data

Drawing on the research by Beirne et al. (2021) and Kling et al. (2018), this study utilizes 10-year government bond yields and their spreads over German risk-free

Baseline Model	High-dimensional fixed effects (HDFE) model: $Y_{it} = \alpha + \beta \ln GCPU_t + \gamma Controls_{it} + \mu_i + \lambda_t + \theta_m + \varepsilon_{it}$
Heterogeneity	HDFE model including dummy $\times$ key variable terms: $Y_{it} = \alpha + \beta_1 \ln GCPU + \beta_2 \ln GCPU \times D_i + \gamma_1 Controls_{it} + \gamma_2 Controls_{it} \times D_i + \mu_i + \lambda_t + \theta_m + \mu_i \times D_i + \lambda_t \times D_i + \theta_m \times D_i + \varepsilon_{it}$ $D_i : D_EMDEs; D_time; D_Readiness; D_vuln$
Moderating Effect	HDFE model including $\ln GCPU \times$ moderator terms: $Y_{it} = \alpha + \beta_1 \ln GCPU_t + \beta_2 \ln GCPU \times M_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \theta_m + \varepsilon_{it}$ $M_{it} : Inflation; GDP_growth; Savings-to-GDP; VIX$
Mediating Effect	Baron and Kenny (1986)'s test: $Z_{it} = \alpha + \beta \ln GCPU_t + \gamma Controls_{it} + \mu_i + \lambda_t + \theta_m + \varepsilon_{it}$ $Y_{it} = \alpha + \beta \ln GCPU_t + \delta Z_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \theta_m + \varepsilon_{it}$ $Z_{it} : GPR; US_Yield$
Endogeneity	• Lagging the independent and control variables; • Also lagging the dependent variable; • AR model (System-GMM estimation); • Heckman's two-step method
Robustness	• Replacing the dependent variable; • Replacing the core independent variable; • Subsamples; • Extending fixed effects specifications;

Fig. 1 Overall Methodological Framework, Notes: This figure summarizes the core empirical strategies used in the study, including the baseline HDFE regression model, heterogeneity analysis via interaction terms, moderation and mediation testing, as well as the approaches employed to address endogeneity and robustness

government bonds to proxy SBC. It employs the log-transformed global CPU index weighted by per capita GDP ($\ln GCPU_per$) developed by Guo et al. (2024) as the core explanatory variable. The logarithmic transformation serves to linearize potential non-linear relationships, mitigate impact of outliers, and reduce heteroscedasticity. To test the robustness of the model, several alternative measures of $\ln GCPU_per$ are employed, including the logarithmic forms of $GCPU_PCA$ (Guo et al., 2024), $GCPU_Current$ (Ji et al., 2024), as well as US_CPU (Gavrilidis, 2021). Finally, to reconcile the frequency of daily SBC data with the monthly CPU index, initial monthly values of bond yields or yield spreads were selected, converting daily data into monthly data for analysis.

Table 1 provides detailed information for the variables. The sample spans from January 2010 to December 2021, chosen for its extensive variable availability. The study initially collected government bond yields for 77 economies from the DataStream database and, after matching with relevant control variables, narrowed the sample to 64 economies. These 64 economies were classified into 31 developed economies and 33 emerging markets and developing economies (EMDEs), according to the classification by the International Monetary Fund (2022).

Table 1 Variable Definitions and Data Sources

Variables	Variable Definitions	Source
Panel A: Dependent variables		
<i>Yield</i>	10-year government bond yield	DataStream database
<i>Yield_spreads</i>	Spread between 10-year government bond yield and 10-year German government bond yield	
r_{it} (Alternative variable)	Sovereign bond returns	S&P500 (https://www.spglobal.com/spdji/en/)
Panel B: Core explanatory variables		
<i>GCPU_per</i>	Global CPU Index (weighted by GDP per capita)	Guo et al. (2024)
<i>GCPU_PCA</i> (Alternative variable)	Global CPU Index (first principal component extracted using PCA)	Guo et al. (2024)
<i>GCPU_Current</i> (Alternative variable)	Global CPU Index (weighted by GDP at current prices)	Ji et al. (2024)
<i>US_CPU</i> (Alternative variable)	U.S. CPU index	Gavrilidis (2021)
Panel C: Other key variables		
<i>Net_borrow/GDP</i>	Ratio of net lending/borrowing to GDP	The World Bank
<i>Current_account</i>	Current account balance (in USD)	
<i>GDP_growth</i>	GDP growth rate (%)	
<i>GDP_per</i>	GDP per capita (in USD/10 ⁴)	
<i>Total_save/GDP</i>	Ratio of total savings to GDP	
<i>GDP</i>	GDP (current value, in USD/10 ⁴)	
<i>Inflation</i>	Inflation (GDP Deflator, %)	
<i>VIX</i> (Alternative variable)	Chicago Board Options Exchange Volatility Index (VIX)	Bloomberg
<i>US_FEDE_FUNDS</i>	U.S. Federal funds rate	Federal Reserve

Table 1 (continued)

Variables	Variable Definitions	Source
<i>Vulnerability</i>	Climate Vulnerability Index	DN-GAIN
<i>Readiness</i>	Climate readiness Index	DN-GAIN
<i>US_Yield</i>	10-year U.S. Treasury bond yield	Datastream database
<i>GPR</i>	Geopolitical risk (growth rate, %)	Caldera and Iacoviello (2022)

Table 2 Summary Statistics

Variables	N	Mean	Std. dev	Min	p25	p50	p75	Max	Skewness	Kurtosis
<i>Yield</i>	7970	4.7927	4.8595	-0.9930	1.4750	3.3825	6.8200	38.0000	2.1085	9.7987
<i>Yield_spreads</i>	7826	4.0897	4.8692	-2.0930	0.8050	2.3660	5.6700	38.5860	2.3149	10.7989
<i>lnGCPU_per</i>	7970	4.4540	0.2896	3.8367	4.2248	4.3740	4.6915	5.3418	0.7084	2.7576
<i>lnGCPU_PCA</i>	7925	3.9649	0.7571	1.5909	3.4343	3.9167	4.6700	5.5089	-0.1727	2.5575
<i>lnGCPU_Current</i>	7970	4.5937	0.3875	3.6751	4.3385	4.6025	4.8271	5.5876	0.1347	2.6998
<i>lnCPU_US</i>	7970	4.8304	0.4624	3.6400	4.5341	4.7691	5.1544	6.0193	0.0860	2.6877
<i>VIX</i>	7970	18.3838	6.9767	9.5100	13.7100	16.5200	20.5500	53.5400	1.9357	8.1398
<i>US_FEDE_FUNDS</i>	7970	0.5914	0.7541	0.0400	0.0900	0.1500	1.1500	2.4400	1.3032	3.1937
<i>Net_borrow/GDP</i>	7970	-2.8305	4.0129	-32.1082	-4.7828	-2.5989	-0.6273	14.2404	-0.2807	8.8623
<i>Current_account</i>	7970	0.4847	84.1091	-846.3540	-7.2320	-0.6122	11.4861	329.9690	-3.0928	31.3899
<i>GDP_growth</i>	7970	2.6333	3.6878	-14.5974	1.2667	2.7089	4.6251	24.3705	-0.4957	7.0718
<i>GDP_per</i>	7970	2.7450	2.3035	0.0731	0.7687	1.9925	4.5308	10.3554	0.8251	2.9392
<i>Total_save/GDP</i>	7970	24.0116	7.5896	2.2623	19.1542	23.7001	28.6040	50.5916	0.2871	3.4054
<i>GDP</i>	7970	1062.6270	2618.0720	9.0358	119.1308	323.0317	914.0434	23,315.0800	5.9001	41.5013
<i>Inflation</i>	7970	3.1181	3.6090	-2.8898	1.0488	2.0777	4.2320	28.9506	2.7960	16.0197
<i>Vulnerability</i>	7970	0.3588	0.0688	0.2442	0.3087	0.3451	0.3879	0.5830	0.9432	3.5427
<i>Readiness</i>	7970	0.5486	0.1466	0.2517	0.4388	0.5373	0.6892	0.8232	-0.0480	1.9504
<i>GPR</i>	7970	-0.0179	0.1972	-0.8224	-0.1292	-0.0045	0.0968	0.4634	-0.5746	4.7643
<i>US_Yield</i>	7970	2.1557	0.7065	0.5630	1.6440	2.1590	2.6280	3.8690	-0.1099	2.8275

Table 3 Correlation Matrix

	<i>Yield</i>	<i>Yield _spreads</i>	<i>lnGCPU _per</i>	<i>lnGCPU _PCA</i>	<i>lnGCPU _Current</i>		<i>VIX</i>
<i>Yield</i>	1.0000						
<i>Yield_spreads</i>	0.9762	1.0000					
<i>lnGCPU_per</i>	-0.0914	0.0429	1.0000				
<i>lnGCPU_PCA</i>	-0.0810	0.0432	0.9339	1.0000			
<i>lnGCPU_Current</i>	-0.0889	0.0576	0.7490	0.7104	1.0000		
<i>VIX</i>	-0.0182	-0.0191	0.2541	0.2913	0.1101		1.0000
<i>US_FEDE_FUNDS</i>	-0.0290	0.0545	0.2980	0.3347	0.3092		-0.1545
<i>Net_borrow/GDP</i>	-0.2535	-0.2548	-0.1658	-0.1504	-0.0903		-0.2792
<i>Current_account</i>	-0.0947	-0.0430	0.0177	0.0173	0.0231		-0.0090
<i>GDP_growth</i>	0.0847	0.0572	-0.0826	-0.1104	-0.0436		-0.2857
<i>GDP_per</i>	-0.5535	-0.5586	0.0138	0.0021	-0.0104		0.0170
<i>Total_save/GDP</i>	-0.1176	-0.1028	0.0127	0.0135	0.0230		-0.0214
<i>GDP</i>	-0.1502	-0.1402	0.0000	-0.0029	-0.0057		0.0026
<i>Inflation</i>	0.5726	0.5784	0.1194	0.1038	0.0733		0.0435
<i>Vulnerability</i>	0.6251	0.6359	0.0250	0.0283	0.0376		-0.0225
<i>Readiness</i>	-0.6257	-0.6396	-0.0449	-0.0460	-0.0522		0.0187
<i>GPR</i>	0.0012	-0.0015	0.0484	0.0595	0.0289		-0.0236
<i>US_Yield</i>	0.0868	-0.0629	-0.4729	-0.4006	-0.4203		-0.2747
	<i>US_FEDE _FUNDS</i>	<i>Net_borrow /GDP</i>	<i>Current _account</i>	<i>GDP_ growth</i>	<i>GDP_ per</i>	<i>Total_save /GDP</i>	<i>GDP</i>
<i>US_FEDE_FUNDS</i>	1.0000						
<i>Net_borrow/GDP</i>	0.1867	1.0000					
<i>Current_account</i>	0.0194	0.2556	1.0000				
<i>GDP_growth</i>	0.0166	0.3136	-0.0300	1.0000			
<i>GDP_per</i>	-0.0312	0.3191	0.0273	-0.0951	1.0000		
<i>Total_save/GDP</i>	0.0320	0.4623	0.2952	0.2537	0.2466	1.0000	
<i>GDP</i>	-0.0100	-0.1481	-0.6008	-0.0575	0.2547	-0.0598	1.0000
<i>Inflation</i>	-0.0358	-0.0318	-0.0475	0.2270	-0.3557	0.0356	-0.0763
<i>Vulnerability</i>	0.0502	-0.1796	-0.0172	0.2211	-0.7046	0.0708	-0.1528
<i>Readiness</i>	-0.0595	0.3178	0.0929	-0.1598	0.8425	0.1677	0.2289
<i>GPR</i>	-0.0480	-0.0002	0.0002	0.0475	0.0035	-0.0004	0.0010
<i>US_Yield</i>	0.2119	0.2084	-0.0080	0.2782	0.0128	0.0017	0.0051
	<i>Inflation</i>	<i>Vulnera bility</i>	<i>Readiness</i>	<i>GPR</i>	<i>US_Yield</i>		
<i>Inflation</i>	1.0000						
<i>Vulnerability</i>	0.3580	1.0000					
<i>Readiness</i>	-0.3854	-0.7582	1.0000				
<i>GPR</i>	0.0126	-0.0022	0.0024	1.0000			
<i>US_Yield</i>	-0.0359	-0.0207	0.0337	0.0064	1.0000		

Table 2 summarizes the variables, with the sample comprising 7970 observations. GDP displays the highest standard deviation, at 2618.07, and reaches the highest values for skewness and kurtosis. Except for the climate resilience indicator, all variables exhibit kurtosis exceeding 3, indicating a leptokurtic distribution with heavy tails.

Table 3 shows the correlation matrix. Notably, the core explanatory variable *lnGCPU_per* shows a relatively weak correlation with the control variables, mitigating potential endogeneity concerns within the model. *lnGGDP_per* positively correlates with *Readiness* while negatively with *Vulnerability*. This suggests that economies with higher development levels tend to exhibit better climate readiness and reduced vulnerability. This observation underpins the rationale for classifying economies into developed economies and EMDEs. Due to the strong correlation between *Readiness* and *GDP_per*, this study opts not to include *Readiness* in the list of control variables.

Figure 2 illustrates the trends in climate policy uncertainty (measured by *lnGCPU_per*) and sovereign borrowing costs (proxied by *Yield_spreads*) across 28 representative economies from 2010 to 2022. The first row presents the dynamics of CPU and SBC for 14 developed economies, while the second row depicts the corresponding trends for 14 EMDEs. The remaining 35 economies are presented in Appendix Figure A1 using the same format to facilitate comparison. Several key observations emerge: (1) SBC in developed economies exhibit a narrower range and lower volatility than in EMDEs, where SBC levels are generally higher and more dispersed. (2) The global CPU index shows a pronounced upward trend after December 2015, coinciding with the international escalation of climate policy attention following the Paris Agreement. (3) In many economies, the movements of CPU and SBC seem to align, suggesting a potential positive correlation between the two variables.

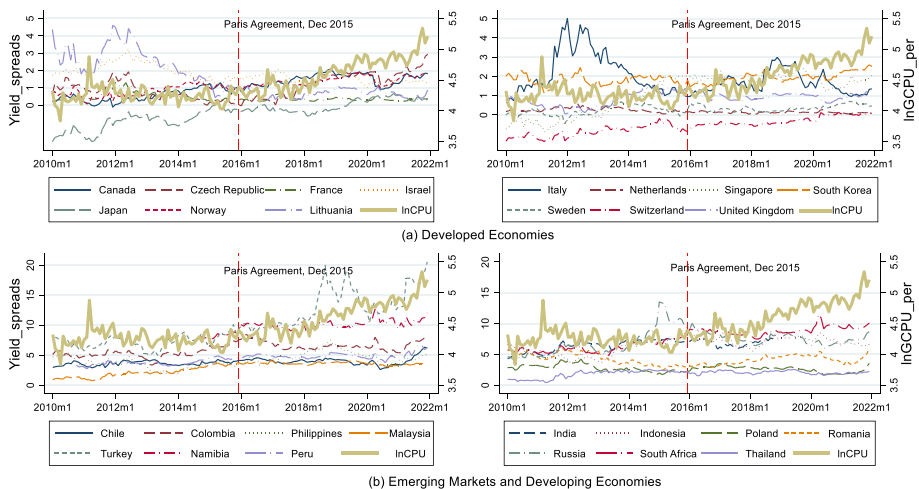


Fig. 2 Trends of CPU and SBC across Selected Economies, Notes: This figure shows the trends in CPU and SBC for 28 economies from 2010 to 2022, with (a) developed economies in the first row and (b) EMDEs in the second. CPU is measured by *lnGCPU_per*, and SBC is proxied by *Yield_spreads* between 10-year government bonds and German risk-free bonds. The vertical dashed line indicates the adoption of the Paris Agreement in December 2015

4 Results and discussion

Building on Sect. 2, this section focuses on how CPU affects SBC, including bond yields and spreads, from January 2010 to December 2021. Section 4.1 employs *lnGCPU_per* as the proxy for CPU, investigating its impact on SBC. Section 4.2 further examines the heterogeneous influence of CPU, moderating factors and influencing channels of CPU. Section 4.3 conducts endogeneity tests, while Sect. 4.4 evaluates the robustness of the findings. Section 4.5 discusses these results in relation to prior research.

4.1 Baseline results

Table 4 shows the findings from the baseline regression. The key explanatory variable, *lnGCPU_per*, exhibits positive coefficients across all models. Specifically, in columns (4) and (8), the coefficients for *lnGCPU_per* are 0.5183 and 0.3343, both significant at the 1% level. The positive coefficients suggest that a 1% rise in CPU corresponds to an increase of 0.5183 in *Yield* and 0.3343 in *Yield_spreads*. This further supports the positive linkage between CPU and SBC, thereby confirming the validity of Hypothesis 1.

This positive relationship implies that higher CPU, which reflects greater uncertainty in climate policy, leads to an increased perception of risk in sovereign debt markets. One possible explanation is that, as CPU rises, investors may seek higher returns to offset the risks associated with potential policy changes or delays in action. Additionally, this effect may reflect broader market sentiment, where uncertainty surrounding climate-related policies diminishes the attractiveness of sovereign bonds, consequently increasing borrowing costs for governments.

4.2 Mechanism analysis

4.2.1 Heterogeneity analysis

This study further explores the heterogeneous impacts of CPU by incorporating interaction terms between categorical dummy variables with both core explanatory variables and control variables.

Table 5 summarizes the corresponding results, segmenting economies by development status, time frames relative to January 1, 2016, and levels of climate readiness and vulnerability. $D_EMDEs = 0$ denotes developed economies, whereas EMDEs are captured by $D_EMDEs = 1$, with outcomes reported in columns (1) and (2). The time-based division uses $D_time = 0$ for periods before January 1, 2016, and $D_time = 1$ for afterward, with findings in columns (3) and (4). Climate readiness differentiation relies on median readiness scores from 2010 to 2021 across 64 economies; $D_read = 0$ signifies economies with below-median readiness (lower readiness), and $D_read = 1$ indicates those with above-median readiness (higher readiness), with respective results in columns (5) and (6). Climate vulnerability is similarly categorized using median vulnerability scores, with $D_vuln = 0$ for economies below the median (lower vulnerability) and findings in columns (7) and (8). Appendix Table A1 presents the classification of economies according to the values of D_read and D_vuln .

The results from columns (1)–(2) reveal that the coefficient estimates for $lnGCPU_per * D_EMDEs$ are significantly positive at the 1% level, suggesting that CPU exerts a more pronounced impact on SBC in EMDEs than in developed economies.

Table 4 Baseline Regression Results

Variables	(1) Yield	(2) Yield	(3) Yield	(4) Yield	(5) Yield _spreads	(6) Yield _spreads	(7) Yield _spreads	(8) Yield _spreads
<i>lnGCPU_per</i>	0.1211 (0.0993)		0.1382 (0.0953)	0.5183*** (0.0963)	0.3500*** (0.1030)		0.3630*** (0.0988)	0.3343*** (0.1023)
<i>VIX</i>		-0.0013 (0.0024)	-0.0013 (0.0024)	-0.0005 (0.0024)		0.0118*** (0.0024)	0.0119*** (0.0024)	0.0129*** (0.0024)
<i>US_FEDE_FUNDS</i>		0.1502** (0.0649)	0.1551** (0.0647)	0.1322* (0.0666)		0.0094 (0.0653)	0.0221 (0.0652)	0.0350 (0.0674)
<i>Net_borrow/GDP</i>		-0.1733*** (0.0545)	-0.1733*** (0.0545)	-0.1733*** (0.0545)		-0.1744*** (0.0545)	-0.1744*** (0.0546)	-0.1744*** (0.0546)
<i>Current_account</i>		0.0003 (0.0035)	0.0003 (0.0035)	0.0003 (0.0035)		0.0010 (0.0034)	0.0010 (0.0034)	0.0010 (0.0034)
<i>GDP_growth</i>		-0.2127*** (0.0694)	-0.2127*** (0.0694)	-0.2125*** (0.0694)		-0.2150*** (0.0699)	-0.2150*** (0.0699)	-0.2150*** (0.0699)
<i>GDP_per</i>		-0.2147 (0.2667)	-0.2147 (0.2667)	-0.2143 (0.2669)		-0.2191 (0.2664)	-0.2191 (0.2664)	-0.2192 (0.2666)
<i>Total_save/GDP</i>		0.0902 (0.0750)	0.0902 (0.0750)	0.0904 (0.0750)		0.0921 (0.0750)	0.0920 (0.0750)	0.0920 (0.0751)
<i>GDP</i>		0.0002 (0.0001)	0.0002 (0.0001)	0.0002 (0.0001)		0.0003* (0.0001)	0.0003* (0.0001)	0.0003* (0.0001)
<i>Inflation</i>		0.1191 (0.0878)	0.1191 (0.0878)	0.1190 (0.0878)		0.1190 (0.0876)	0.1190 (0.0876)	0.1191 (0.0876)
<i>Vulnerability</i>		-17.8379 (42.9631)	-17.8455 (42.9700)	-17.5782 (42.9720)		-17.0890 (42.7435)	-17.1089 (42.7527)	-17.1701 (42.7940)

Table 4 (continued)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Yield	Yield	Yield	Yield	Yield _spreads	Yield _spreads	Yield _spreads	Yield _spreads
Obs	7970	7970	7970	7970	7826	7826	7826	7826
Number of countries	64	64	64	64	63	63	63	63
R-squared	0.8749	0.8945	0.8945	0.8949	0.8739	0.8940	0.8941	0.8941
r2_within	0.0001	0.1566	0.1567	0.1576	0.0006	0.1596	0.1602	0.1603
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Mon FE	N	N	N	Y	N	N	N	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Heterogeneity Analysis

Variables	(1) Yield	(2) Yield _spreads	(3) Yield	(4) Yield _spreads	(5) Yield	(6) Yield _spreads	(7) Yield	(8) Yield _spreads
<i>lnGCPU_per</i>	0.1269** (0.0548)	-0.0935* (0.0557)	0.4265*** (0.1052)	-0.0471 (0.1074)	1.0544*** (0.2418)	0.9445*** (0.2513)	0.1543** (0.0738)	-0.0703 (0.0765)
<i>lnGCPU_per</i> *	0.8405*** (0.1689)	0.9076*** (0.1775)						
<i>D_EMDEs</i>								
<i>lnGCPU_per</i> *			0.3269** (0.1413)	0.9748*** (0.1442)				
<i>D_time</i>								
<i>lnGCPU_per</i> *					-0.7251*** (0.2573)	-0.8257*** (0.2677)		
<i>D_read</i>								
<i>lnGCPU_per</i> *							0.6299*** (0.1599)	0.6907*** (0.1678)
<i>D_vuln</i>							Y	Y
Controls	Y	Y	Y	Y	Y			
Controls* <i>D_EMDEs</i>	Y	Y						
Controls* <i>D_time</i>								
Controls* <i>D_read</i>			Y	Y	Y	Y		
Controls* <i>D_vuln</i>								
Obs	7970	7826	7970	7826	7970	7826	Y	Y
Number of countries	64	63	64	63	64	63	7970	7826
R-squared	0.9079	0.9073	0.9325	0.9319	0.9127	0.9121	64	63
r2_within	0.1990	0.2006	0.1230	0.1226	0.2221	0.2248	0.9068	0.9062
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Mon FE	Y	Y	Y	Y	Y	Y	Y	Y
Country* <i>D_</i> * FE	Y	Y	Y	Y	Y	Y	Y	Y
Year* <i>D_</i> * FE	Y	Y	Y	Y	Y	Y	Y	Y
Mon* <i>D_</i> * FE	Y	Y	Y	Y	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Specifically, a 1% increase in CPU in EMDEs leads to a larger rise in SBC than in developed economies, suggesting that these economies are more sensitive to CPU. Similarly, the positive and significant coefficients for $\ln GCPU_per * D_time$ and $\ln GCPU_per * D_vuln$ at the 5% significance level further demonstrate that CPU exerts a stronger influence on SBC post-2016 or in economies with greater climate vulnerability. This highlights the increasing importance of CPU as climate policies gain greater attention or climate risks intensify. In contrast, the negative and statistically significant coefficient for $\ln GCPU_per * D_read$ indicates that economies with higher levels of climate readiness experience a substantially lower impact of CPU on SBC. This suggests that well-prepared economies, with stronger mitigation and adaptation strategies, are better able to manage the risks posed by CPU, resulting in lower borrowing costs despite rising CPU. These findings support Hypothesis 2.

4.2.2 Moderating effect analysis

Following the moderator variable test framework outlined by Baron and Kenny (1986), this subsection adds interaction terms between the moderator variables and the core explanatory variable, $\ln GCPU_per$, to the baseline model. The significance of these interaction terms is tested to assess the moderating effects. As outlined in Sect. 2, the selected moderator variables include the inflation rate (*Inflation*) and GDP growth rate (*GDP_growth*) as proxies for the domestic macroeconomic situation, total savings as a percentage of GDP (*Total_save/GDP*) to reflect the fiscal situation, and stock market volatility (*VIX*), which represents financial market stability and investor sentiment.

Table 6 presents the empirical results, which indicate that *Inflation*, *GDPgrowth*, and *Total_save/GDP* significantly and positively influence the link between CPU and SBC, while *VIX* has a significantly negative effect. High inflation, suggesting an overheating economy, may cause investors to be concerned about uncertainties, possibly decreasing sovereign bond demand and increasing spreads. Conversely, rapid GDP growth signals strong economic activity but could imply greater uncertainty under CPU conditions, potentially raising the bond market's risk premium. A typical example of these dynamics can be observed during the post-2010 Eurozone debt crisis, when countries like Greece and Spain faced high inflation, while emerging markets such as Brazil, India, and Indonesia saw strong GDP growth, resulting in higher sovereign bond yields in these countries (Maltritz, 2012). A high savings rate reflects a future-oriented saving and investment mindset; this might elevate the bond market's risk premium amid CPU. Conversely, the *VIX*'s negative influence indicates that during significant financial market turmoil, investors might seek the relative safety of sovereign bonds, boosting their demand and narrowing the spreads. For instance, in 2020, as COVID-19 spread globally, the *VIX* surged, and U.S. sovereign bond yields declined as investors flocked to safe-haven assets (Inoguchi, 2024).

4.2.3 Mediating effect analysis

Following the test method of mediator variables proposed by Baron and Kenny (1986) and the existing literatures, this subsection discusses the channels through which CPU affects SBC. Previous research identifies global factors, such as international liquidity, and institutional and political factors as key determinants of SBC (Boitan & Marchewka-Bartkowiak, 2022; Clark, 1997; Cuadra & Saprizza, 2008; González-Rozada & Yeyati, 2008; Moody's Investor Service, 2008). To capture these factors, we select the U.S. 10-year Treasury yield

(*US_Yield*) and the Geopolitical Risk (*GPR*) Index as proxies for the mediator variables in this study (Caldara & Iacoviello, 2022; González-Rozada & Yeyati, 2008).

Using Baron and Kenny's mediator variable test method and the high-dimensional fixed effects model, we assess the impact of CPU on the mediator variables (*GPR* and *US_Yield*), the effect of these mediator variables on SBC, and their joint influence on SBC. The empirical results, presented in Table 7, show that CPU significantly impacts the mediator variables (columns (1) and (2)), which in turn significantly affect SBC (columns (3) and (4)). Notably, when both *lnGCPU_per* and the mediator variables are included (column (5)), the coefficients for the mediators remain significant, while the coefficient for *lnGCPU_per* decreases notably compared to the baseline regression in Table 4. This suggests that international liquidity and institutional and political factors serve as key channels through which CPU affects SBC. Therefore, the findings uphold Hypothesis 3.

4.3 Endogeneity test

Table 8 employs three strategies to tackle potential issues of endogeneity. To avoid potential reverse causality, columns (1)–(2) lag the independent and control variables, while columns (3)–(4) use the lagged dependent variable. The findings are robust.

Columns (5)–(6) showcase the results of System-GMM estimation within the AR model, including tests of first- and second-order autocorrelation processes in the error term ε_{it} . It also presents p-values for the Hansen instrument validity test, indicated in parentheses. The empirical findings from columns (5)–(6) indicate no second-order autocorrelation in the random error term ε_{it} , and the instruments used are valid. Moreover, *lnGCPU_per* shows a significantly positive effect, with significance at the 5% level, demonstrating robust results.

Columns (7)–(9) present the outcomes of applying Heckman's two-step method. Following the approach outlined in Sect. 3.2, the first step involves setting *lnGCPU_per* as a binary 0–1 variable and using it as the dependent variable in a Probit regression to compute the IMR. The second step incorporates the IMR as a control variable. Column (7) shows that most control variables significantly affect CPU, while columns (8)–(9) display the second-stage results. At this stage, the coefficient for IMR is not significant, but *lnGCPU_per* remains significantly positive, suggesting that endogeneity due to selection bias is unlikely.

4.4 Robustness analysis

In the subsequent analysis, we assess robustness through five tests: alternative variables, lagged terms, subsample analysis, augmented fixed effects, and outlier-resistant estimation.

First, we test robustness by replacing the dependent variables in Table 9. We employ three alternative measures: end-of-month sovereign bond yields and yield spreads (columns (1)–(2)), monthly average yields and spreads (columns (3)–(4)), and 10-year sovereign bond returns for 39 economies (columns (5)–(6)),¹ contrasting with the original

¹ This study opts for the S&P 500 sovereign bond price index denominated in U.S. dollars for the i -th day of month t (P_{it}), converting data from local currencies to U.S. dollars using the daily exchange rates of the Bank for International Settlements. Source: <https://www.spglobal.com/spdji/en/>. Subsequently, the daily return rit is derived based on P_{it} , calculated as $rit = 100(\ln P_{i,t} - \ln P_{i,t-1})$. After matching all variables, the sample finally retained 39 economies.

Table 6 Moderating Effect Analysis

Variables	(1) <i>Yield</i>	(2) <i>Yield</i> <i>_spreads</i>	(3) <i>Yield</i>	(4) <i>Yield</i> <i>_spreads</i>
Panel A: Moderating Effect 1				
<i>lnGCPU_per</i>	−0.9502** (0.4139)	−1.1308*** (0.4139)	−0.7458** (0.3692)	−0.9215** (0.3710)
<i>lnGCPU_per</i> * <i>Inflation</i>	0.4121*** (0.1089)	0.4072*** (0.1087)		
<i>lnGCPU_per</i> * <i>GDP_growth</i>			0.3538*** (0.1106)	0.3495*** (0.1108)
Controls	Y	Y	Y	Y
Obs	7970	7826	7970	7826
Number of countries	64	63	64	63
R-squared	0.9033	0.9024	0.8985	0.8977
r2_within	0.2252	0.2622	0.1869	0.1886
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Mon FE	Y	Y	Y	Y
Panel B: Moderating Effect 2				
<i>lnGCPU_per</i>	−3.4987** (1.6992)	−3.7190** (1.7029)	0.8109*** (0.1303)	0.6333*** (0.1339)
<i>lnGCPU_per</i> * <i>Total_save/GDP</i>	0.1675** (0.0716)	0.1696** (0.0722)		
<i>lnGCPU_per</i> * <i>VIX</i>			−0.0167*** (0.0040)	−0.0171*** (0.0040)
Controls	Y	Y	Y	Y
Obs	7970	7826	7970	7826
Number of countries	64	63	64	63
R-squared	0.9002	0.8996	0.8949	0.8941
r2_within	0.1999	0.2035	0.1587	0.1605
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Mon FE	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

specification using beginning-of-month yields or spreads. The results remain robust across all specifications, confirming our main findings.

Second, we examine robustness by replacing our core independent variable *lnGCPU_per* with three alternative measures: *lnGCPU_PCA* (Guo et al., 2024), *lnGCPU_Current* (Ji et al., 2024), and the lagged logarithm of the U.S. CPU index (*L.lnUS_CPU*) (Gavriilidis, 2021). Following Ren et al. (2022), we include *L.lnUS_CPU* to account for potential lagged effects of U.S. CPU on global sovereign bond markets. The results remain robust across all specifications, confirming our main findings. In all alternative settings, the

Table 7 Mediating Effect Analysis

Variables	(1) <i>GPR</i>	(2) <i>US_Yield</i>	(3) <i>Yield</i>	(4) <i>Yield</i>	(5) <i>Yield</i>
<i>lnGCPU_per</i>	0.2241*** (0.0026)	0.2790*** (0.0092)			0.3727*** (0.0897)
<i>GPR</i>			0.0519** (0.0227)		0.0423* (0.0233)
<i>US_Yield</i>				0.4999*** (0.1021)	0.4878*** (0.1011)
Controls	Y	Y	Y	Y	Y
Obs	7,970	7970	7,970	7,970	7,970
Number of countries	64	64	64	64	64
R-squared	0.1169	0.8413	0.8948	0.8956	0.8957
r2_within	0.0168	0.1954	0.1568	0.1635	0.1640
Country FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Mon FE	Y	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

coefficients for the independent variables remain robustly positive and significant at the 1% threshold, affirming the conclusions' robustness (Table 10).

Table 11 presents robustness tests conducted on subsamples to address two key concerns. First, to control for possible disturbances stemming from the COVID-19 outbreak, columns (1)-(2) restrict the sample to the pre-pandemic period by excluding all observations from 2020 onward. Second, to specifically examine the post-Paris Agreement regime and mitigate potential structural breaks associated with its adoption in 2015, columns (3)-(4) further exclude data from 2015 and earlier. This dual approach ensures our results are robust to both pandemic-related anomalies and climate policy regime changes.

Fourth, Table 12 presents robustness tests incorporating extended fixed effects specifications. While our baseline regression includes country, year, and month fixed effects, we now further incorporate economic development level, climate readiness, and vulnerability fixed effects. Columns (1)-(2) estimate the model for sovereign bond yields without and with control variables respectively, while columns (3)-(4) repeat this specification for yield spreads. The consistent results across specifications confirm that our findings are robust to more demanding fixed effects requirements.

Fifth, Table 13 addresses potential outlier concerns by implementing a 0.5% winsorization of *lnGCPU_per* at both tails of the distribution. Columns (1)-(2) present results for sovereign bond yields without and with control variables respectively, while columns (3)-(4) show the corresponding specifications for yield spreads. The robustness of our core findings persists across all specifications, demonstrating their insensitivity to extreme values in the climate policy uncertainty measure.

Table 8 Endogeneity Test

Variables	(1)	(2)	(3)	(4)	
	Independent and control variables lagged by 1 period		Dependent variable lagged by 1 period		
	<i>Yield</i>	<i>Yield</i> <i>_spreads</i>	<i>Yield</i>	<i>Yield</i> <i>_spreads</i>	
<i>L.lnCPU_per</i>	0.7005*** (0.0852)	0.2894*** (0.0897)			
L.Controls	Y	Y			
<i>lnCPU_per</i>			0.4507*** (0.0992)	0.1809* (0.1055)	
Controls			Y	Y	
Obs	7358	7226	7911	7768	
Number of countries	64	63	64	63	
R-squared	0.8990	0.8975	0.8947	0.8940	
r2_within	0.1802	0.1826	0.1576	0.1595	
Country FE	Y	Y	Y	Y	
Year FE	Y	Y	Y	Y	
Mon FE	Y	Y	Y	Y	

Variables	(5)	(6)	(7)	(8)	(9)
	AR Model		Heckman's two-stage		
	<i>Yield</i>	<i>Yield_spreads</i>	<i>lnGCPU_per</i>	<i>Yield</i>	<i>Yield_spreads</i>
<i>L.Yield</i>	0.9570*** (0.0151)				
<i>L.Yield_spreads</i>		0.9288*** (0.0143)			
<i>lnGCPU_per</i>	0.1222*** (0.0371)	0.0978** (0.0399)		0.0980** (0.0402)	0.1689*** (0.0410)
<i>IMR</i>				0.4565 (1.3214)	0.4716 (1.3346)
<i>VIX</i>	−0.0027*** (0.0009)	0.0024** (0.0012)	0.1334*** (0.0052)	0.0035 (0.0129)	0.0171 (0.0129)
<i>US_FEDE_FUNDS</i>	0.0053 (0.0243)	0.0662*** (0.0253)	2.2379*** (0.0547)	0.1570 (0.1081)	0.0644 (0.1097)
<i>Net_borrow/GDP</i>	0.0085 (0.0057)	0.0066 (0.0075)	−0.2073*** (0.0112)	−0.1801*** (0.0654)	−0.1814*** (0.0657)
<i>Current_account</i>	−0.0006 (0.0006)	−0.0005 (0.0014)	0.0012** (0.0005)	0.0004 (0.0035)	0.0011 (0.0034)
<i>GDP_growth</i>	−0.0018 (0.0033)	0.0034 (0.0060)	−0.0110 (0.0087)	−0.2129*** (0.0698)	−0.2154*** (0.0703)
<i>GDP_per</i>	−0.0342 (0.0476)	−0.1902*** (0.0714)	0.1805*** (0.0215)	−0.2067 (0.2565)	−0.2113 (0.2561)
<i>Total_save/GDP</i>	0.0045 (0.0128)	0.0173 (0.0177)	0.0337*** (0.0052)	0.0913 (0.0765)	0.0929 (0.0765)
<i>GDP</i>	−0.0000 (0.0000)	−0.0000 (0.0001)	−0.0000*** (0.0000)	0.0002 (0.0001)	0.0003* (0.0001)

Table 8 (continued)

<i>Inflation</i>	0.0030 (0.0074)	0.0104 (0.0092)	0.1066*** (0.0087)	0.1233 (0.0944)	0.1235 (0.0943)
<i>Vulnerability</i>	0.3149 (1.7199)	-5.0398* (2.9318)	-0.0460 (0.6645)	-17.5887 (42.9258)	-17.1621 (42.7475)
Constant	-0.4040 (0.5970)	1.6610 (1.1732)	-6.4665*** (0.2942)		
Obs	7906	7763	7970	7970	7826
Number of countries	64	63	64	64	63
AR (1)	-2.8564 (0.0043)	-2.8787 (0.0040)			
AR (2)	-0.5923 (0.5537)	-0.6444 (0.5193)			
Hansen test	58.9879 (0.2066)	57.3301 (0.2219)			
Pseudo R2			0.3335		
R-squared				0.8948	0.8942
r2_within				0.1570	0.1605
Country FE			Y	Y	Y
Year FE			Y	Y	Y
Mon FE			Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. In columns (5)–(6), the AR model utilizes the Arellano-Bond test to assess serial correlation in the random error terms, with the null hypothesis asserting the absence of autocorrelation. The Hansen test is an over-recognition test, with the null hypothesis stating that the instruments are uncorrelated with the error term

4.5 Discussion

Our empirical findings provide significant insights into the economic implications of CPU on SBC. The analysis reveals that an increase in CPU is linked to a notable rise in SBC, particularly when climate policies gain greater attention, or in economies with lower economic development, higher climate vulnerability, or lower climate resilience. Domestic factors, such as financial conditions, macroeconomic development, and political and institutional stability, as well as international factors, such as U.S. financial markets or global liquidity, may influence the relationship between CPU and SBC. These findings suggest that investors perceive CPU as a risk, which results in a higher risk premium on sovereign bonds. The greater uncertainty surrounding climate policy increases perceived financial risk, thus raising the borrowing costs for sovereign economies. Our results emphasize the critical role of policy credibility and long-term planning in fostering financial stability, reinforcing the argument that climate preparedness is a key determinant in shaping sovereign debt markets.

These findings align with existing literature. For instance, Battiston and Monasterolo (2019) developed a framework to evaluate the risks linked to climate-financial uncertainty. Emphasizing the impact of policy timing and credibility on economic performance, their

Table 9 Robustness Tests Using Alternative Dependent Variables

Variables	(1)	(2)	(3)	(4)	(5)
	<i>Yield</i>	<i>Yield_spreads</i>	<i>Yield</i>	<i>Yield_spreads</i>	S&P sovereign bond returns
	end-of-month value		monthly average		
<i>lnGCPU_per</i>	0.5183*** (0.0963)	0.3343*** (0.1023)	0.4672*** (0.1088)	0.3226*** (0.1142)	0.5323*** (0.0906)
Controls	Y	Y	Y	Y	Y
Obs	7970	7826	7970	7826	4497
Number of countries	64	63	64	63	39
R-squared	0.8949	0.8941	0.8968	0.8961	0.1041
r2_within	0.1576	0.1603	0.1610	0.1651	0.0321
Country FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

model provides a useful foundation for our study. While their research focused on the theoretical consequences of a disorderly transition, our empirical approach provides concrete evidence of the effects of CPU on sovereign bond yields and spreads, thus contributing to the practical understanding of how CPU impacts sovereign debt markets. Our findings corroborate those of Jia et al. (2024), who explored the link between CPU and sovereign bond

Table 10 Robustness Tests Using Alternative Independent Variables and Lagging Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Yield</i>	<i>Yield_spreads</i>	<i>Yield</i>	<i>Yield_spreads</i>	<i>Yield</i>	<i>Yield_spreads</i>
<i>lnGCPU_PCA</i>	0.0842*** (0.0292)	0.1073*** (0.0307)				
<i>lnGCPU_Current</i>			0.2513*** (0.0599)	0.3084*** (0.0607)		
<i>L.lnCPU_US</i>					-0.0296 (0.0186)	0.1005*** (0.0190)
Controls	Y	Y	Y	Y	Y	Y
Obs	7925	7782	7970	7826	7926	7783
Number of countries	64	63	64	63	64	63
R-squared	0.8952	0.8944	0.8949	0.8943	0.8953	0.8945
r2_within	0.1593	0.1627	0.1578	0.1615	0.1585	0.1619
Country FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11 Robustness Tests Using Subsamples

Variables	(1)	(2)	(3)	(4)
	<i>Yield</i>	<i>Yield_spreads</i>	<i>Yield</i>	<i>Yield_spreads</i>
	Exclude data after 2019		Exclude data before 2016 and after 2019	
<i>lnGCPU_per</i>	0.3749*** (0.1264)	0.2704** (0.1331)	0.6006** (0.2343)	0.9749*** (0.2379)
Controls	Y	Y	Y	Y
Obs	6554	6434	2827	2875
Number of countries	64	63	63	62
R-squared	0.9081	0.9081	0.9648	0.9641
r2_within	0.2163	0.2178	0.0620	0.0515
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 12 Robustness Tests Using High-dimensional Fixed Effects

Variables	(1)	(2)	(3)	(4)
	<i>Yield</i>	<i>Yield</i>	<i>Yield_spreads</i>	<i>Yield_spreads</i>
<i>lnGCPU_per</i>	0.5144*** (0.1000)	0.5183*** (0.0963)	0.3199*** (0.1069)	0.3343*** (0.1023)
Controls	N	Y	N	Y
Obs	7970	7970	7826	7826
Number of countries	64	64	63	63
R-squared	0.8753	0.8949	0.8740	0.8941
r2_within	0.0009	0.1576	0.0003	0.1603
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
<i>D_EMDEs</i> FE	Y	Y	Y	Y
<i>D_vuln</i> FE	Y	Y	Y	Y
<i>D_read</i> FE	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

volatility (SBV). While they found that CPU volatility increases SBV, we extend their work by highlighting the intensified impact of CPU on SBC, which also has a more lasting effect in economies with higher climate vulnerability. Furthermore, we extend the research conducted by Guo et al. (2024), who developed the CPU index for 21 economies and 3 global integrated markets and examined their impact on sovereign and green bond returns. We

find that key climate policy events, such as the Paris Agreement, significantly influence the relationship between CPU and sovereign bond returns.

Overall, this study advances the existing climate finance literature by presenting a wider and deeper perspective on the economic and financial ramifications of CPU. It also sheds light on how sovereign debt markets respond to climate risks. These insights have important implications for both financial risk management and the development of climate-conscious investment portfolios.

5 Policy implications

Drawing upon the empirical evidence presented in this study, we propose several specific and actionable policy recommendations for investors, policymakers, and stakeholders involved in sovereign borrowing and climate finance:

Policy Area 1: Integrating CPU into sovereign risk assessment The analysis demonstrates that increases in CPU significantly elevate SBC. This result underscores the importance of developing frameworks for assessing sovereign risk to incorporate CPU indexes as a core component of climate-related financial risk evaluation. Credit rating agencies and financial institutions are encouraged to develop CPU-adjusted sovereign risk models to better reflect the potential implications of policy volatility. Such tools would allow investors to more accurately price sovereign credit risk and incentivize governments to strengthen the credibility, transparency, and consistency of their climate policy agendas.

Policy Area 2: Strengthening climate readiness and economic development The impact of CPU on SBC appears stronger in EMDEs, particularly in economies with higher climate vulnerability or lower climate readiness, and has intensified since January 1, 2016. Investors should consider reallocating capital toward economies with stronger climate readiness and more robust macroeconomic fundamentals. For policymakers, reducing climate vulnerability, improving institutional readiness, and aligning national climate strategies with

Table 13 Robustness Tests Excluding Outliers

Variables	(1) <i>Yield</i>	(2) <i>Yield</i>	(3) <i>Yield_spreads</i>	(4) <i>Yield_spreads</i>
<i>lnGCPU_per</i>	0.4803*** (0.1120)	0.4838*** (0.1078)	0.3005** (0.1199)	0.2953** (0.1147)
Controls	N	Y	N	Y
Obs	7867	7867	7725	7725
Number of countries	64	64	63	63
R-squared	0.8756	0.8953	0.8741	0.8945
r2_within	0.0007	0.1591	0.0003	0.1619
Country FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y

Values in parentheses next to parameter estimates represent their standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

international agreement are essential for mitigating CPU's financial effects. The growth of CPU and its influence after January 2016 highlights that financial markets are increasingly responsive to climate policy developments, reinforcing the need for coherent and transparent policy communication.

Policy Area 3: Enhancing macroeconomic stability and financial market resilience Macroeconomic factors—such as inflation, GDP growth, and domestic savings—positively moderate the CPU-SBC relationship, while financial market volatility (e.g., VIX) exerts a dampening effect. To improve resilience against CPU-induced increases in borrowing costs, governments should maintain stable macroeconomic environments by controlling inflation, promoting sustainable economic growth, and stimulating domestic demand. Simultaneously, reducing financial market volatility—through stronger regulatory oversight and effective investor guidance—can enhance a country's attractiveness in sovereign debt markets. Investors may find more favorable risk-return profiles in economies with stable fundamentals and low financial market turbulence.

Policy Area 4: Promoting political stability and international financial coordination CPU also affects SBC through institutional and global channels, such as political stability and international liquidity. Investors should incorporate geopolitical risks and global financial conditions into sovereign bond investment decisions. For governments, reinforcing political stability and institutional quality is vital to reducing the indirect effects of CPU and attracting long-term international capital. Strengthening domestic governance and improving global coordination on climate finance frameworks will be critical not only for mitigating CPU-driven financial risks but also for supporting broader sustainable development and climate transition goals.

6 Conclusion

Employing the CPU index developed by Guo et al. (2024) and a multidimensional fixed effects model, this study comprehensively analyzes the influence CPU on SBC. Multiple strategies are implemented to address potential endogeneity concerns, and robustness checks further validate the reliability of the findings.

This research draws three main findings. First, CPU significantly and positively affects SBC, with distinct variations across economic classifications. Specifically, whether comparing periods after January 1, 2016, to those before, contrasting EMDEs with developed ones, analyzing economies with higher climate vulnerability, or considering those with lower climate readiness, SBC has significantly increased. Second, the inflation rate, GDP growth, and domestic savings relative to GDP significantly and positively moderate the nexus between CPU and SBC. Conversely, stock market volatility exerts significant adverse moderating effects. Third, CPU can influence SBC through political stability and international liquidity.

These findings have important practical implications. For investors, greater attention should be paid to CPU when managing sovereign bond portfolios. Although higher CPU may indicate higher yields—particularly in EMDEs and economies with greater climate vulnerability or lower readiness—it also entails elevated risks. Investors are therefore advised to diversify toward countries with stronger climate resilience, stable macroeconomic fundamentals (such as low inflation and sustained growth), and lower financial market volatility.

In addition, geopolitical risks and international liquidity conditions should be carefully considered in sovereign bond allocation decisions. Policymakers are urged to prioritize credible and well-timed climate measures, as well as improvements in climate readiness capacity. Incorporating CPU into sovereign risk management frameworks, improving political stability, and strengthening international coordination are key strategies to lower borrowing costs and reinforce investor confidence. More broadly, this research highlights the critical role of sound economic governance, macro-financial stability, and global cooperation in promoting climate finance and achieving long-term sustainable development goals.

This research has several limitations and areas for future exploration. First, while the sample is diverse, it may not fully capture the heterogeneity of CPU impacts in smaller or less economically developed countries, which often face heightened exposure to climate-related risks. Expanding the analysis to include more countries, especially those from regions with higher exposure to climate transition risks, could deepen our understanding. Second, CPU is a complex concept, and future studies could explore alternative measures, incorporating more granular data on climate policy actions and their indirect consequences on sovereign risk. Qualitative factors, such as political discourse and shifts in public opinion, could also be considered. Furthermore, examining the role of government interventions, climate-related fiscal policies, and international agreements could provide valuable insights into how these factors mitigate CPU's effect on SBC.

Appendix

Table A1 Classification of Economies by Climate Readiness and Vulnerability

	0	1
<i>D_read</i>	Bangladesh Brazil Colombia Egypt Ghana India Indonesia Jordan Kenya Mexico Morocco Namibia Peru Philippines South_ Africa Sri_Lanka Tanzania Uganda Zambia	Australia Austria Belgium Bulgaria Canada Chile Croatia Cyprus Czech Denmark Finland France Georgia Germany Greece Hungary Iceland Ireland Israel Italy Japan Kazakhstan Lithuania Malaysia Malta Mauritius Neth- erlands New_Zealand Norway Poland Portugal Romania Russia Serbia Singapore Slovakia Slove- nia South_Korea Spain Sweden Switzerland Thailand Turkey U.K. U.S
<i>D_vuln</i>	Australia Austria Belgium Canada Czech Fin- land France Germany Greece Iceland Ireland Israel Italy Kazakhstan New_Zealand Norway Poland Portugal Russia Slovenia Spain Swe- den Switzerland U.K. U.S	Bangladesh Brazil Bulgaria Chile Colombia Croatia Cyprus Denmark Egypt Georgia Ghana Hungary India Indonesia Japan Jordan Kenya Lithuania Malay- sia Malta Mauritius Mexico Morocco Namibia Netherlands Peru Philippines Romania Serbia Singapore Slovakia South_Africa South_Korea Sri_Lanka Tanzania Thailand Turkey Uganda Zambia

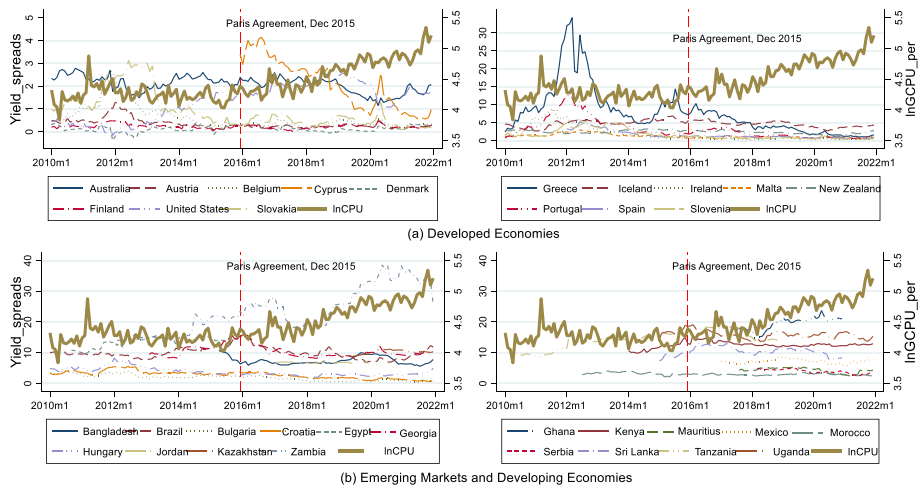


Fig. A1 Trends of CPU and SBC across Additional Economies, **Notes:** This figure complements Fig. 2 by presenting trends in CPU and SBC for the remaining 35 sample economies, including (a) 16 developed economies and (b) 19 EMDEs. The measurement and visualization approach are consistent with Fig. 2. The red vertical dashed line indicates the adoption of the Paris Agreement in December 2015

This table classifies the 64 economies based on climate readiness (*Vulnerability*) and climate vulnerability (*Readiness*) according to their median from 2010 to 2021. Economies with $D_{read} = 0$ have lower climate readiness, while those with $D_{read} = 1$ exhibit higher readiness. Similarly, $D_{vuln} = 0$ represents economies with lower climate vulnerability, whereas $D_{vuln} = 1$ includes those with higher vulnerability. This classification complements the heterogeneity analysis in Table 5.

Funding This work was supported by the General Projects of Special Philosophy and Social Science Research in Shaanxi Province (CN) (2025YB0001), the National Social Science Fund of China (24BTJ043, 20BTJ042), the Fundamental Research Funds for the Central Universities (CN).

Data availability The datasets are available upon request.

References

- Acemoglu, D., Johnson, S., & Robinson, J. (2005). The Rise of Europe: Atlantic Trade, Institutional Change, and Economic Growth. *American Economic Review*, 95(3), 546–579. <https://doi.org/10.1257/0002828054201305>
- Ackerman, F. (2018). *Worst-case economics: Extreme events in climate and finance*. Anthem Press. <https://anthempress.com/worst-case-economics-pb>. Accessed 3 May 2025.
- Agarwala, M., Burke, M., Klusak, P., Mohaddes, K., Volz, U., & Zenghelis, D. (2021). Climate change and fiscal sustainability: Risks and opportunities. *National Institute Economic Review*, 258, 28–46. <https://doi.org/10.1017/nie.2021.37>
- Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, 84(3), 488–500. <https://doi.org/10.2307/1879431>

- Baldacci, E., Gupta, S., & Mati, A. (2011). Political and Fiscal Risk Determinants of Sovereign Spreads in Emerging Markets: SOVEREIGN SPREADS IN EMERGING MARKETS. *Review of Development Economics*, 15(2), 251–263. <https://doi.org/10.1111/j.1467-9361.2011.00606.x>
- Banerji, S., Ventouri, A., & Wang, Z. (2014). The sovereign spread in Asian emerging economies: The significance of external versus internal factors. *Economic Modelling*, 36, 566–576. <https://doi.org/10.1016/j.econmod.2013.09.040>
- Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
- Batten, S. (2018). *Climate change and the macro-economy: A critical review*. SSRN Scholarly Paper. <https://doi.org/10.2139/ssrn.3104554>
- Battiston, S., & Monasterolo, I. (2019). A Climate Risk Assessment of Sovereign Bonds' Portfolio. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3464206>
- Beirne, J., Renzhi, N., & Volz, U. (2021). Feeling the heat: Climate risks and the cost of sovereign borrowing. *International Review of Economics & Finance*, 76, 920–936. <https://doi.org/10.1016/j.iref.2021.06.019>
- Berestycki, C., Carattini, S., Dechezleprêtre, A., & Kruse, T. (2022). Measuring and assessing the effects of climate policy uncertainty (No. 1724). *OECD Economics Department Working Papers*, No. 1724. OECD Publishing. <https://doi.org/10.1787/34483d83-en>
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143. [https://doi.org/10.1016/S0304-4076\(98\)00009-8](https://doi.org/10.1016/S0304-4076(98)00009-8)
- Boitan, I. A., & Marchewka-Bartkowiak, K. (2022). Climate change and the pricing of sovereign debt: Insights from European markets. *Research in International Business and Finance*, 62, Article 101685. <https://doi.org/10.1016/j.ribaf.2022.101685>
- Boitan, I. A., & Marchewka-Bartkowiak, K. (2023). Sovereign debt management in the face of climate liabilities: Perspective of European Union member states. *Economic Research-Ekonomska Istraživanja*, 36(1), 1120–1145. <https://doi.org/10.1080/1331677X.2022.2081864>
- Bolton, P., & Kacperczyk, M. (2023). Global Pricing of Carbon-Transition Risk. *The Journal of Finance*, 78(6), 3677–3754. <https://doi.org/10.1111/jofi.13272>
- Boulangé, J., Hanasaki, N., Yamazaki, D., & Pokhrel, Y. (2021). Role of dams in reducing global flood exposure under climate change. *Nature Communications*, 12(1), 1–7. <https://doi.org/10.1038/s41467-020-20704-0>
- Caldara, D., & Iacoviello, M. (2022). Measuring Geopolitical Risk. *American Economic Review*, 112(4), 1194–1225. <https://doi.org/10.1257/aer.20191823>
- Campagnolo, L., Carraro, C., Davide, M., Eboli, F., Lanzi, E., & Parrado, R. (2016). Can climate policy enhance sustainability? *Climatic Change*, 137(3–4), 639–653. <https://doi.org/10.1007/s10584-016-1701-6>
- Capelle-Blancard, G., Crifo, P., Diaye, M.-A., Oueghli, R., & Scholtens, B. (2019). Sovereign bond yield spreads and sustainability: An empirical analysis of OECD countries. *Journal of Banking & Finance*, 98, 156–169. <https://doi.org/10.1016/j.jbankfin.2018.11.011>
- Cevik, S., & Jalles, J. T. (2022). This changes everything: Climate shocks and sovereign bonds. *Energy Economics*, 107, Article 105856. <https://doi.org/10.1016/j.eneco.2022.105856>
- Cheng, R., Gupta, B., & Rajan, R. S. (2023). Do green financial policies offset the climate transition risk penalty imposed on long-term sovereign bond yields? *Research in International Business and Finance*, 65, Article 101976. <https://doi.org/10.1016/j.ribaf.2023.101976>
- Clark, E. (1997). Valuing political risk. *Journal of International Money and Finance*, 16(3), 477–490. [https://doi.org/10.1016/S0261-5606\(97\)00008-9](https://doi.org/10.1016/S0261-5606(97)00008-9)
- Collender, S., Gan, B., Nikitopoulos, C. S., Richards, K.-A., & Ryan, L. (2023). Climate transition risk in sovereign bond markets. *Global Finance Journal*, 57, Article 100868. <https://doi.org/10.1016/j.gfj.2023.100868>
- Cuadra, G., & Sapriza, H. (2008). Sovereign default, interest rates and political uncertainty in emerging markets. *Journal of International Economics*, 76(1), 78–88. <https://doi.org/10.1016/j.jinteco.2008.05.001>
- Dibley, A., Wetzter, T., & Hepburn, C. (2021). National COVID debts: Climate change imperils countries' ability to repay. *Nature*, 592(7853), 184–187. <https://doi.org/10.1038/d41586-021-00871-w>
- Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). 'Climate value at risk' of global financial assets. *Nature Climate Change*, 6(7), 676–679. <https://doi.org/10.1038/nclimate2972>
- Ding, H., Ji, Q., Ma, R., & Zhai, P. (2022). High-carbon screening out: A DCC-MIDAS-climate policy risk method. *Finance Research Letters*, 47, Article 102818. <https://doi.org/10.1016/j.frl.2022.102818>

- Dunz, N., Naqvi, A., & Monasterolo, I. (2021). Climate sentiments, transition risk, and financial stability in a stock-flow consistent model. *Journal of Financial Stability*, 54, Article 100872. <https://doi.org/10.1016/j.jfs.2021.100872>
- European Central Bank. (2021). Climate-related risks to financial stability. *ECB/ESRB Project Team on climate risk monitoring* (pp. 1–40). https://www.ecb.europa.eu/pub/financial-stability/fsr/special/html/ecb.fsrart202105_02~d05518fc6b.en.html. Accessed 3 May 2025.
- Fang, L. H., Lerner, J., & Wu, C. (2017). Intellectual Property Rights Protection, Ownership, and Innovation: Evidence from China. *The Review of Financial Studies*, 30(7), 2446–2477. <https://doi.org/10.1093/rfs/hhx023>
- Gavrilidis, K. (2021, May 16). *Measuring Climate Policy Uncertainty*. SSRN Scholarly Paper. <https://doi.org/10.2139/ssrn.3847388>
- Global Commission on Adaptation. (2019). Adapt now: A global call for leadership on climate resilience. *Global Center on Adaptation and World Resources Institute*. <https://gca.org/reports/adapt-now-a-global-call-for-leadership-on-climate-resilience/>. Accessed 3 May 2025.
- González-Rozada, M., & Yeyati, E. L. (2008). Global Factors and Emerging Market Spreads. *The Economic Journal*, 118(533), 1917–1936. <https://doi.org/10.1111/j.1468-0297.2008.02196.x>
- Guo, N., Jia, S., & Liu, Y. (2024). Climate policy uncertainty and its impact on the volatility, correlation, and hedging of sovereign and green bonds. *Journal of Environmental Management*, 370, Article 122953. <https://doi.org/10.1016/j.jenvman.2024.122953>
- Hallegatte, S., Shah, A., Lempert, R., Brown, C., & Gill, S. (2012). Investment Decision Making under Deep Uncertainty - Application to Climate Change. *The World Bank*. <https://doi.org/10.1596/1813-9450-6193>
- He, M., & Zhang, Y. (2022). Climate policy uncertainty and the stock return predictability of the oil industry. *Journal of International Financial Markets, Institutions and Money*, 81, Article 101675. <https://doi.org/10.1016/j.intfin.2022.101675>
- Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1), 153. <https://doi.org/10.2307/1912352>
- Hill Clarvis, M., Halle, M., Mulder, I., & Yarime, M. (2014). Towards a new framework to account for environmental risk in sovereign credit risk analysis. *Journal of Sustainable Finance & Investment*, 4(2), 147–160. <https://doi.org/10.1080/20430795.2013.837810>
- Hoque, M. E., Soo-Wah, L., Bilgili, F., & Ali, M. H. (2022). Connectedness and spillover effects of US climate policy uncertainty on energy stock, alternative energy stock, and carbon future. *Environmental Science and Pollution Research*, 30(7), 18956–18972. <https://doi.org/10.1007/s11356-022-23464-0>
- Huo, M., Li, C., & Liu, R. (2023). Climate policy uncertainty and corporate green innovation performance: From the perspectives of organizational inertia and management internal characteristics. *Managerial and Decision Economics mde*, 3981. <https://doi.org/10.1002/mde.3981>
- Huo, M., & Li, C. (2023). Impact of managerial power on enterprise innovation performance: The mediating roles of financing constraints and strategic orientation. *Chinese Management Studies*, 17(3), 637–659. <https://doi.org/10.1108/CMS-06-2021-0249>
- IIF. (2021). Global debt monitor: COVID drives debt surge—stabilization ahead? *Institute of International Finance (IIF) Publication* (pp. 1–5). https://www.iif.com/Portals/0/Files/content/Global%20Debt%20Monitor_Feb2021_vf.pdf. Accessed 3 May 2025.
- Inoguchi, M. (2024). The impact of global shocks on sovereign risk: Role of domestic factors. *Economic Systems*, 101277. <https://doi.org/10.1016/j.ecosys.2024.101277>
- International Monetary Fund. (2022). World economic outlook: War sets back the global recovery. *International Monetary Fund* (pp. 1–178). <https://www.imf.org/en/Publications/WEO/Issues/2022/10/11/world-economic-outlook-october-2022>. Accessed 3 May 2025.
- IPCC. (2021). Climate change 2021: The physical science basis. *Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. <https://www.ipcc.ch/report/ar6/wg1/>. Accessed 3 May 2025.
- Jeanneret, A. (2015). The Dynamics of Sovereign Credit Risk. *Journal of Financial and Quantitative Analysis*, 50(5), 963–985. <https://doi.org/10.1017/S002210901500040X>
- Ji, Q., Ma, D., Zhai, P., Fan, Y., & Zhang, D. (2024). Global climate policy uncertainty and financial markets. *Journal of International Financial Markets, Institutions and Money*, 95, Article 102047. <https://doi.org/10.1016/j.intfin.2024.102047>
- Jia, S., Guo, N., & Jin, J. (2024). Climate policy uncertainty risk and sovereign bond volatility. *Journal of Cleaner Production*, 434, Article 140145. <https://doi.org/10.1016/j.jclepro.2023.140145>
- Kling, G., Lo, Y., Murinde, V., & Volz, U. (2018). Climate Vulnerability and the Cost of Debt. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3198093>

- Koh, L. P., Zeng, Y., Sarira, T. V., & Siman, K. (2021). Carbon prospecting in tropical forests for climate change mitigation. *Nature Communications*, 12(1), 1–9. <https://doi.org/10.1038/s41467-021-21560-2>
- Kölbel, J., Leipold, M., Rillaerts, J., & Wang, Q. (2020). Does the CDS Market Reflect Regulatory Climate Risk Disclosures? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3616324>
- Li, C., Huo, M., Li, C., Li, G., & Liu, R. (2023). Economic policy uncertainty and enterprise strategic change: Evidence from China. *Strategic Change*, 32(4–5), 125–137. <https://doi.org/10.1002/jsc.2549>
- Liang, X.-Z. (2022). Extreme rainfall slows the global economy. *Nature*, 601(7892), 193–194. <https://doi.org/10.1038/d41586-021-03783-x>
- Mallucci, E. (2022). Natural disasters, climate change, and sovereign risk. *Journal of International Economics*, 139, Article 103672. <https://doi.org/10.1016/j.jinteco.2022.103672>
- Maltritz, D. (2012). Determinants of sovereign yield spreads in the Eurozone: A Bayesian approach. *Journal of International Money and Finance*, 31(3), 657–672. <https://doi.org/10.1016/j.jimonfin.2011.10.010>
- Moody's Investor Service. (2008). Rating methodology: Sovereign bond ratings. *Moody's Investors Service*. [https://data.cbonds.info/comments/2008/33966/Sovereign_Bond_Ratings_\(English\).pdf](https://data.cbonds.info/comments/2008/33966/Sovereign_Bond_Ratings_(English).pdf). Accessed 3 May 2025.
- North, D. C. (1990). Institutions, institutional change and economic performance. *Cambridge University Press*. <https://doi.org/10.1017/CBO9780511808678>
- Pfeffer, J., & Salancik, G. R. (1978). The external control of organizations: A resource dependence perspective. *SSRN Scholarly Paper: Social Science Research Network*. <https://papers.ssrn.com/abstract=1496213>. Accessed 22 Jan 2025.
- Ren, X., Zhang, X., Yan, C., & Gozgor, G. (2022). Climate policy uncertainty and firm-level total factor productivity: Evidence from China. *Energy Economics*, 113, Article 106209. <https://doi.org/10.1016/j.eneco.2022.106209>
- Ren, X., Li, W., Duan, K., & Zhang, X. (2023). Does climate policy uncertainty really affect corporate financialization? *Environment, Development and Sustainability*. <https://doi.org/10.1007/s10668-023-02905-x>
- Roodman, D. (2009). How to do Xtabond2: An Introduction to Difference and System GMM in Stata. *The Stata Journal*, 9(1), 86–136. <https://doi.org/10.1177/1536867X0900900106>
- Simonyan, S., & Bayraktar, S. (2023). Asymmetric dynamics in sovereign credit default swaps pricing: Evidence from emerging countries. *International Journal of Emerging Markets*, 18(12), 5607–5629. <https://doi.org/10.1108/IJOEM-03-2021-0469>
- S&P. (2014). Climate change is a global mega-trend for sovereign risk. *RatingsDirect. Standard & Poor's Ratings Services*.
- Spence, M. (1973). Job Market Signaling*. *The Quarterly Journal of Economics*, 87(3), 355–374. <https://doi.org/10.2307/1882010>
- Treepongkaruna, S., Chan, K. F., & Malik, I. (2023). Climate policy uncertainty and the cross-section of stock returns. *Finance Research Letters*, 55, Article 103837. <https://doi.org/10.1016/j.frl.2023.103837>
- UNEP. (2018). Navigating a new climate: Assessing credit risk and opportunity in a changing climate. *Outputs of a Working Group of 16 Banks Piloting the TCFD Recommendations Part 2: Physical Risks and Opportunities*. <https://wedocs.unep.org/xmlui/handle/20.500.11822/33117>. Accessed 1 Mar 2025.
- Weitzman, M. L. (2009). On Modeling and Interpreting the Economics of Catastrophic Climate Change. *Review of Economics and Statistics*, 91(1), 1–19. <https://doi.org/10.1162/rest.91.1.1>
- Williamson, O. E. (1981). The Economics of Organization: The Transaction Cost Approach. *American Journal of Sociology*, 87(3), 548–577. <https://doi.org/10.1086/227496>
- Xu, X., Huang, S., & Haizhong, A. (2023, February 15). The impacts of climate policy uncertainty on stock markets: Comparison between China and the US. *SSRN Scholarly Paper*. <https://doi.org/10.1016/j.irfa.2023.102671>
- Zhang, D., & Du, P. (2020). How China “Going green” impacts corporate performance? *Journal of Cleaner Production*, 258, Article 120604. <https://doi.org/10.1016/j.jclepro.2020.120604>
- Zhang, D., Mohsin, M., & Taghizadeh-Hesary, F. (2022). Does green finance counteract the climate change mitigation: Asymmetric effect of renewable energy investment and R&D. *Energy Economics*, 113, Article 106183. <https://doi.org/10.1016/j.eneco.2022.106183>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.