

Peer-reviewed research

Navigating the Climate Maze: BRICS' Uncertain Path

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Keywords: Climate policy uncertainty, Environment, BRICS, Quantile-on-Quantile approach

JEL Classifications: C36 Instrumental Variables (IV) Estimation, D84 Expectations - Speculations, Q54 Climate - Natural Disasters and Their Management - Global Warming, Q56 Environment and Development - Environment and Trade - Sustainability - Environmental Accounts and Accounting - Environmental Equity - Population Growth

<https://doi.org/10.46557/001c.138284>

Energy RESEARCH LETTERS

Vol. 7, Issue 4, 2026

This study investigates the effect of climate policy uncertainty on CO₂ emissions in BRICS countries from the first quarter of 2000 to the second quarter of 2024. Using Gavrilidis' (2021) climate policy uncertainty (CPU) index and Quantile-on-Quantile Regression (QQR), the findings indicate that CPU has varying effects, both positive and negative, across different quantiles, notably within the 0.1-0.35 and 0.40-0.80 ranges. The results highlight the importance for stakeholders to account for CPU when making decisions related to carbon emissions and environmental sustainability, as it impacts investment, innovation, and market dynamics.

I. Introduction

Environmental literature has long focused on climate change, global warming, and ecological degradation. Nations worldwide have pursued policies to mitigate the adverse impacts of these issues on humans, animals, and the environment. The COP26 summit, hosted by the United Kingdom, is a prime example of these efforts, uniting countries to accelerate policy actions in line with the United Nations Framework on Climate Change and the Paris Agreement. However, implementing these programs and policies has faced significant challenges due to uncertainties, which have hindered the achievement of substantial results (Gavrilidis, 2021). Notable examples of these challenges include the United States' withdrawal from the Paris Accord in 2017, President Bush's 2001 rejection of the Kyoto Protocol, and the EPA's new energy legislation on vehicle greenhouse gas emissions. These events underscore the complexities and uncertainties surrounding climate policy implementation.

Uncertainty, in a broad sense, can impede investment through actual options mechanisms (Bloom, 2009), leading to reduced investment in specific economic sectors (Kang et al., 2014), increased fear (Akadiri et al., 2020; Uzuner et al., 2020), and heightened carbon emissions (Yu et al., 2021). It can also significantly impact Research and Development (Tajaddini & Gholipour, 2020). The current study employs a newly developed climate policy uncertainty (CPU) index proposed by Gavrilidis (2021). This index, based on the scaled frequency of articles from eight major U.S. news-

papers, captures critical climate policy events such as new emissions laws, presidential statements on climate policy, global climate change strikes, and other significant developments. The CPU index used in this study offers better coverage than the index by Engle et al. (2020), as it includes eight key newspapers instead of one and focuses exclusively on news about climate change policy, including discussions of uncertainty and natural disasters. It serves as a crucial tool for quantifying and analyzing climate policy uncertainty, a key factor in understanding its impact on CO₂ emissions.

This study, which uses the newly introduced CPU index, investigates the impact of climate policy uncertainty on CO₂ emissions in BRICS countries (Brazil, Russia, India, China, and South Africa) from 2000Q1 to 2024Q2. The relationship between climate policy uncertainty and CO₂ emissions is analyzed using the quantile-on-quantile regression (QQR) method. The study focuses on BRICS nations because they are among the fastest-growing emerging market economies globally. The findings from this study are particularly relevant for policymakers in the BRICS region and other emerging and developing countries, offering practical insights into sustainable environmental policymaking.

This study makes a significant contribution to literature in keyways. First, it employs the newly introduced CPU index, which uses textual analysis of newspaper articles to extract uncertainty across various fields, including monetary policy, economic policy, geopolitical risk, political risk, and trade policy. This is particularly important for BRICS nations, where such studies are scarce. Second, results show

that CPU has positive and negative effects on economic and environmental outcomes due to its influence on investment, innovation, risk perception, and market dynamics. The study suggests that governments, firms, private individuals, and carbon market traders should consider climate policy uncertainties, which may affect carbon emissions rights, environmental sustainability targets, and the global economy.

II. Methodology

This study evaluates CPU's impact on CO₂ emissions in BRICS nations (2000Q1-2024Q2) using CO₂ data from the British Petroleum (BP) database and CPU data from Gavrilidis (2021), sourced from eight major newspapers. Datasets were transformed using natural logarithms to normalize skewed data.

This study uses various econometric methods to analyze the relationship between CPU and CO₂ emissions. The Philip-Perron (PP) and Augmented Dickey Fuller (ADF) tests are employed to assess the stationarity of the variables. The Brock, Dechert, and Scheinkman (BDS) test (Broock et al., 1996) confirms the nonlinearity of the variables. To explore the cointegration of independent variables with the load capacity factor, we use Xiao's (2009) quantile cointegration method, which accounts for the distributional fluctuations of the cointegration vector and addresses endogeneity issues by splitting errors into lead-lag components. Additionally, the study investigates the correlation between CPU and CO₂ emissions using Sim & Zhou's (2015) QQR technique, which enhances traditional quantile regression (QR) by focusing on the effects of an exogenous variable's quantiles on the endogenous variable's quantiles. This approach improves upon classic QR (Bassett & Koenker, 1978) and linear regression (Cleveland, 1979) models by providing a more detailed understanding of the relationship across all quantiles. By combining conventional quantile regression (QR) and linear regression (LR), this study offers a more comprehensive analysis of how exogenous variables influence endogenous variables at different quantiles, surpassing the insights of ordinary least square (OLS) or standard QR alone.

Next, we apply QQR estimation method as introduced by Sim and Zhou (2015), utilising the nonparametric quantile regression framework to evaluate the impact of distinct quantiles of X (explanatory variable) on the different quantiles of Y (dependent variable).

$$Y_t = \gamma^\sigma(X_t) + \mu_t^\sigma \quad (1)$$

X_t represents the independent variables in time t , and Y_t represents the load capacity factor in period t . Moreover, σ represents the independent variables' σ^{th} quantile. Additionally, μ_t^σ represents the quantile error term, with the projected σ^{th} quantile being zero. Moreover, the identity of $\alpha^\sigma(\cdot)$ remains unknown due to the lack of knowledge regarding the correlation between CO₂ emissions and climate policy uncertainty. Sim and Zhou (2015) advised using a bandwidth value of $h = 0.05$ in this investigation.

III. Results

The BDS test confirms the nonlinear features of the variables (Table 1), supporting the Jarque-Bera results. Hence, we use nonlinear methods like quantile cointegration (Xiao, 2009) to determine the cointegration relationship between variables. Sim & Zhou (2015) developed QQR to evaluate the impact of an exogenous variable on each quantile of the endogenous variable.

Table 2 shows evidence of cointegration between CO₂ emissions and the uncertainty surrounding climate policy for the BRICS countries.

We next evaluate the impact of CPU on CO₂ emissions following the cointegration of CPU and CO₂. Figure 2 displays the effects of CPU on CO₂ for the BRICS countries. Figure 1a depicts the impact of CPU on CO₂ emissions in Brazil. The CPU-CO₂ combination negatively influences CO₂ in the lower tails (0.1-0.35), illustrating how increased CPU causes a rise in CO₂ in the lower tail.

Additionally, the influence of CPU on CO₂ is negative in the quantiles (0.40-0.80) of both CO₂ and CPU; this suggests that a spike in CPU will reduce CO₂ in Brazil in the middle and higher quantiles (0.40-0.80). Figure 1b depicts the impact of CPU on CO₂ in Russia. For all CPU and CO₂ combination tails (0.1-0.95), the impact of CPU on CO₂ is negligible and positive. This result reveals that the effect of CPU on CO₂ is positive in all tails (0.1-0.95). Figure 1c shows how CPU affects CO₂ in India at every quantile (0.1-0.90). In the lower and middle tails (0.1-0.55) of both CPU and CO₂, there is a positive correlation between CPU and CO₂; this suggests that increased CPU correlates with increased CO₂ in the middle and lower tails (0.1-0.60). Nevertheless, the impact of CPU on CO₂ is negative in the higher tail (0.60-0.85) of CO₂ and all tails (0.1-0.95) of CPU; this illustrates that a spike in CPU in India is responsible for the CO₂ decrease in the higher tail.

Figure 1d shows how CPU affects CO₂ in China for each quantile (0.1-0.95). The relationship between CPU and CO₂ is positive in both variables' middle tails (0.1-0.55), indicating that an increase in CPU may be responsible for China's rising CO₂ levels in the middle and lower tails. Nevertheless, we found that CPU negatively affects CO₂ in the higher tail (0.60-0.75), indicating that CPU is crucial in reducing CO₂ in this region. We found a positive increase in CO₂ between 0.85 and 0.95 quantiles. Figure 1e shows the CPU's impact on CO₂ in each quantile (0.1-0.95) for South Africa. In the quantiles (0.1-0.25), we observed a positive correlation between CPU and CO₂, but toward the end of the lower tail (0.25-0.40), there is evidence of a negative correlation between CPU and CO₂. Additionally, the effect of CPU on CO₂ is positive in the middle tail (0.50-0.65) of both variables, indicating a positive correlation between CPU and CO₂. Furthermore, a negative correlation was observed for both CPU and CO₂ in the extreme quantiles (0.65-0.90), suggesting that an increase in CPU would suppress CO₂ in the higher tail (0.65-90).

The BRICS countries demonstrate the varied impact of CPU on CO₂ emissions. The study by (Gavrilidis, 2021; Olasehinde-Williams, 2024; Olasehinde-Williams et al.,

Table 1. BDS test

	Z-statistics P-value	Z-statistics P-value	Z-statistics P-value	Z-statistics P-value	Z-statistics P-value	Z-statistics P-value
Dimension	CO ₂ B	CO ₂ R	CO ₂ I	CO ₂ C	CO ₂ S	CPU
M2	35.859*	28.649*	41.010*	30.985*	26.848*	6.2662*
M3	37.856*	29.731*	43.413*	32.985*	27.197*	5.7922*
M4	40.075*	31.192*	46.626*	35.535*	27.819*	6.4438*
M5	43.246*	33.606*	51.515*	39.272*	29.041*	6.2744*
M6	47.555*	37.174*	58.430*	44.407*	30.916*	6.7581*

Note: * denotes statistical significance at 1% level, while CO₂B, CO₂R, CO₂I, CO₂C, and CO₂S, represent CO₂ emissions for BRICS.

Table 2. Quantile cointegration test outcomes

Model	Coefficient	$Sup_{\tau} V_{\pi}(\tau) $	CV1	CV5	CV10
CO ₂ B Vs CPU	β	4731.34	2932.21	1699.07	820.634
	γ	436.629	299.058	111.837	75.9647
CO ₂ R Vs CPU	β	2403.79	1866.32	1172.58	689.764
	γ	337.448	213.025	174.414	62.6824
CO ₂ I Vs CPU	β	3411.37	2766.74	1782.807	1022.46
	γ	412.841	374.945	280.793	111.254
CO ₂ C Vs CPU	β	5311.53	3946.80	2815.26	1113.99
	γ	730.723	615.877	482.646	316.883
CO ₂ S Vs CPU	β	4341.05	3484.79	2826.28	1827.66
	γ	532.389	475.249	324.052	223.694

Note: CO₂B, CO₂R, CO₂I, CO₂C, and CO₂S, represents CO₂ emissions for BRICS.

2023; Olasehinde-Williams & Akadiri, 2024) further supports these diverse consequences of CPU on CO₂ emissions. Therefore, this new measure of CPU piques the interest of scholars and practitioners alike.

A. Testing the legitimacy of the Q.Q. approach

This analysis used QR as a robust check to validate the QQR outcomes. [Figure 2a](#) validates the QQR outcomes for Brazil, as shown by the slope coefficient. Furthermore, the average slope coefficient of QR and QQR are similar in trend. Therefore, we observe the CPU's heterogeneous (positive and negative) effect on CO₂ in all quantiles (0.1-0.95). Moreover, [Figure 2b](#) validates the QQR outcomes, as evidenced by the slope coefficient. In addition, the average slope coefficients of QR and QQR are similar in trend. Therefore, we observe the CPU's heterogeneous (positive and negative) effect on CO₂ in all quantiles (0.1-0.95). [Figure 2c](#) validates the QQR outcomes for India, as shown by the slope coefficient.

Furthermore, the average slope coefficient of QR and QQR are comparable in trajectory. Therefore, we observe the CPU's heterogeneous (positive and negative) effect on CO₂ in all quantiles (0.1-0.95). Furthermore, [Figure 2d](#) endorses the QQR outcomes, as evidenced by the slope coefficient for the case of China. In addition, the average slope coefficient of QR and QQR is analogous in trend. Thus, we observe the CPU's heterogeneous (positive and negative)

effect on CO₂ in all quantiles (0.1-0.95). Lastly, [Figure 2e](#) endorses the QQR outcomes, as evidenced by the slope coefficient for the case of South Africa. In addition, the average slope coefficient of QR and QQR are parallel in pattern. Thus, we observe the CPU's heterogeneous (positive and negative) effect on CO₂ in all quantiles (0.1-0.95).

V. Conclusion

The empirical findings from this research suggest that CPU significantly impacts CO₂ emissions in the BRICS nations, with effects varying across different quantiles (0.1-0.95) and within specific ranges (0.40-0.80). Our analysis reveals that CPU exerts both positive and negative influences on economic and environmental outcomes due to its effects on investment, innovation, risk perception, and market dynamics. While CPU can stimulate beneficial economic and environmental responses, such as fostering innovation and technological progress, it can also result in economic inefficiencies and hinder the transition to a low-carbon economy.

Consequently, governments, policymakers, businesses, private citizens, and carbon market traders must consider climate policy uncertainties in their decision-making processes. It is imperative for governments and policymakers to develop robust and adaptable policies, while businesses should integrate these uncertainties into their strategic planning and risk management frameworks. Addi-

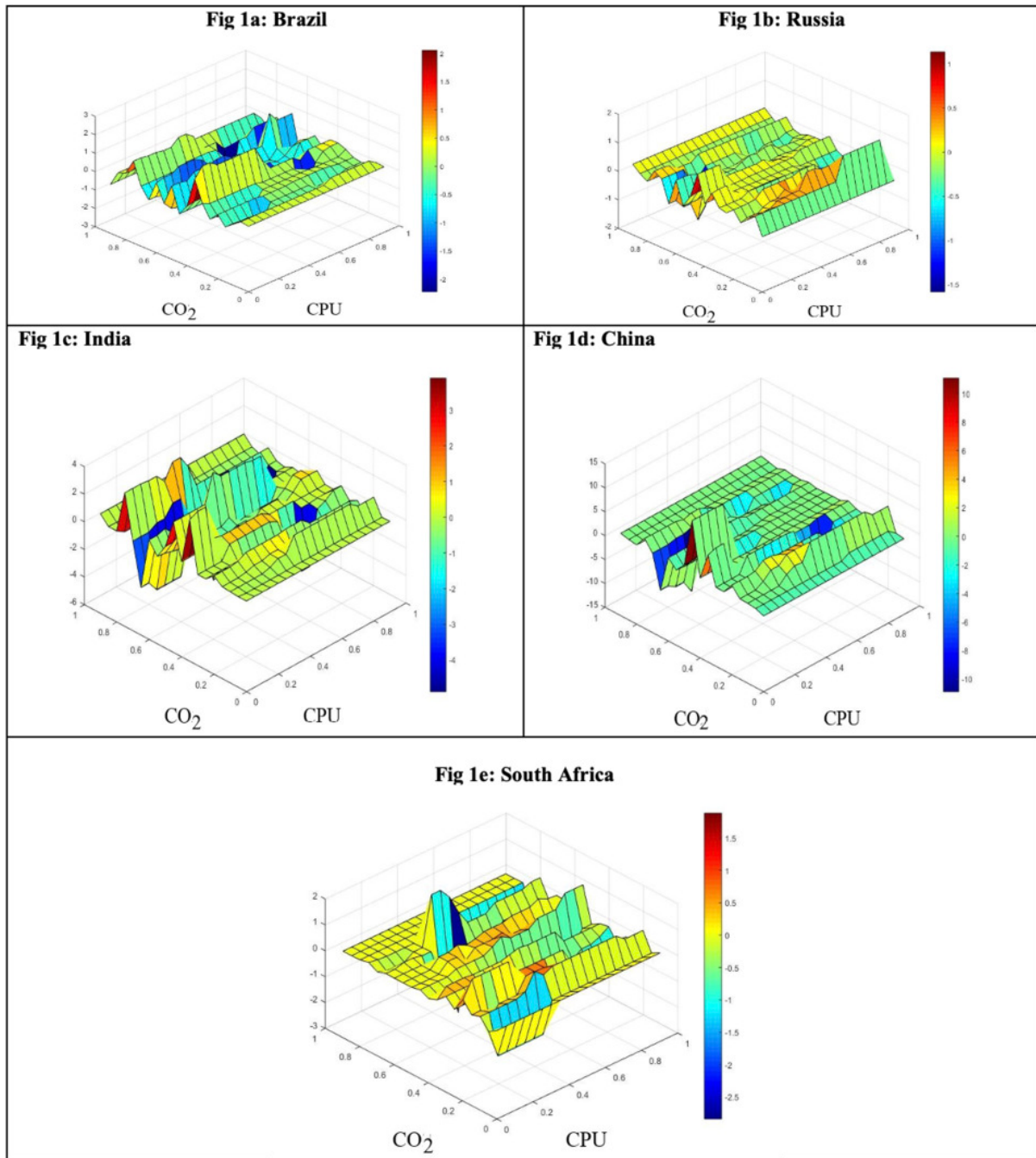


Figure 1. Impact of climate policy uncertainty on CO₂ emissions

tionally, private citizens should remain informed and adopt sustainable practices and carbon market traders should monitor policy developments to make informed decisions and diversify their investments. Addressing climate policy uncertainties can enhance the effectiveness of emission reduction efforts, stabilize carbon markets, and support global environmental sustainability targets and economic stability.

Submitted: August 29, 2024 AEDT. Accepted: February 04, 2025 AEDT. Published: April 03, 2026 AEDT.

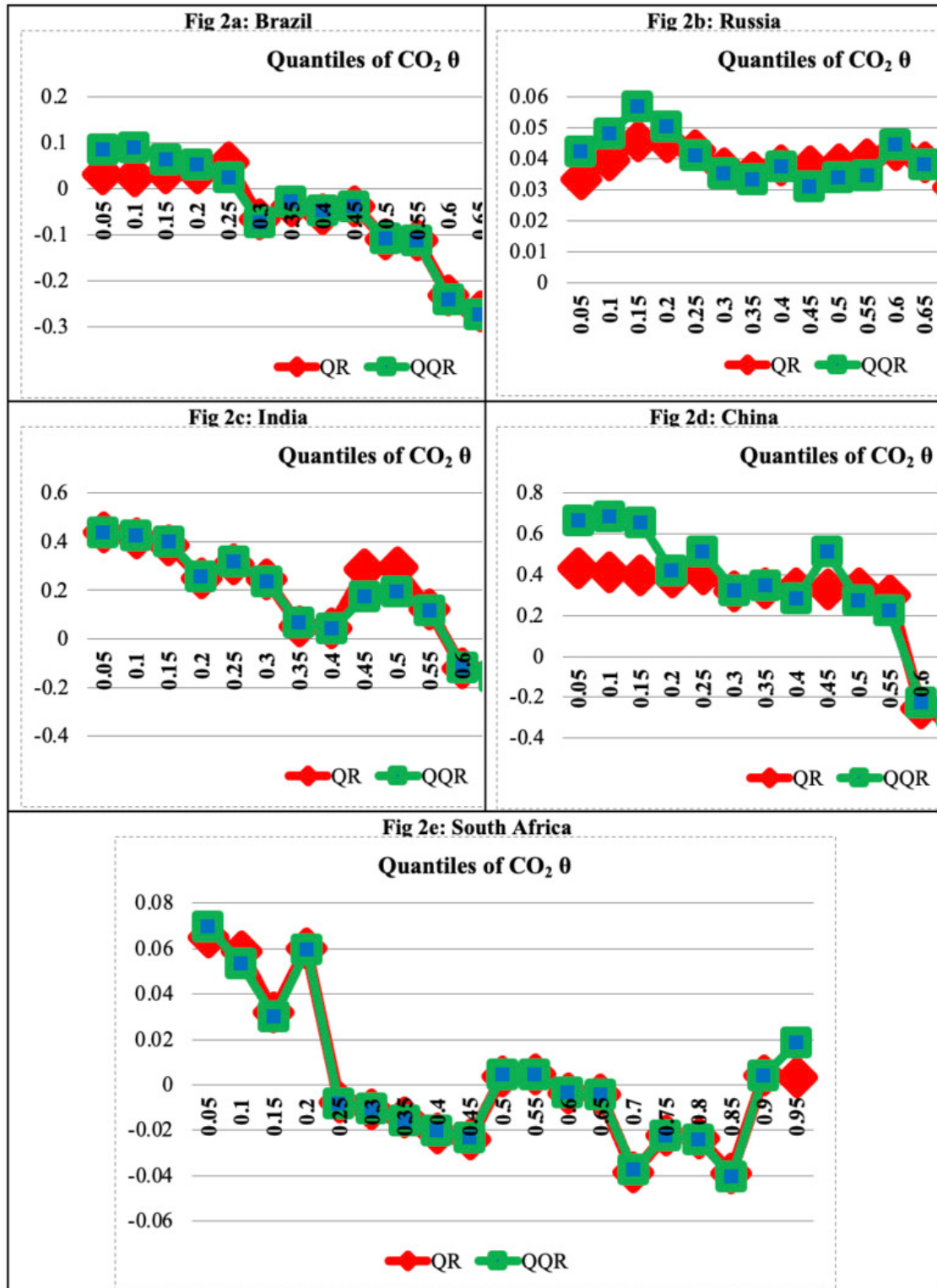


Figure 2. Impact of climate policy uncertainty on CO₂ emissions

Note: The graphs show the standard QR parameter estimates with a red thick line, and the QQR averaged parameters with a green thick line, across various CO₂ and climate policy uncertainty quantiles for BRICS nations.



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