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Impact of Climate Risks and Global Uncertainties on Technology and Environmental Protection Stocks: A Study on China

Özge DEMİRKALE[1], Naime İrem DURAN[2]

Abstract

This study aims to examine the relationship between CUM, CPU, CU, and UCT with the FTSE China Technology Index (FTXIN410) and SZSE Environmental Protection Index (SZEPI) using ARDL and NARDL methods. To test the robustness of the model, three additional parametric methods are employed: FMOLS, DOLS, and CCR. The technology and environmental protection sectors in China are crucial for the country's sustainable economic future. Understanding the impact of global and local uncertainties on these sectors is critical for predicting sectoral trends and future market dynamics. Climate uncertainties and global uncertainties can impact investors' returns and market behaviors. In critical sectors such as technology and environmental protection, uncertainties need to be closely monitored for their implications on investment decisions and market stability. The results of the study indicate a long-term relationship between China's climate uncertainties and global uncertainties with technology and environmental protection indices.

Keywords: *Climate Risks, Global Uncertainties, Financial Markets, ARDL, NARDL, FMOLS, DOLS*

Introduction

The concept of uncertainty plays a significant role in affecting the returns of financial instruments. Especially in today's world, with the increase in global uncertainties, it is necessary to make investment decisions considering these uncertainties. When reviewing the literature, it is observed that many uncertainty indicators affecting financial markets and financial instruments are considered. Among these indicators, geopolitical, economic, and political uncertainties stand out. With the increasing prominence of the climate crisis, researchers are conducting various studies on how climate risk indicators may impact financial instruments and financial markets. However, studies in the literature examining the effects of uncertainties such as Twitter-Based China Economic Policy Uncertainty (CUM), Climate Policy Uncertainty (CPU), Climate Uncertainty Index (CU), and US-China Tension Index (UCT) on China's technology and environmental protection stocks are limited. The technology and environmental protection sectors are critical for China's ability to achieve sustainable economic growth in the future. Additionally, for investors and portfolio managers investing in stocks of companies within these sectors, investigating the effects of these uncertainties is important for making informed investment decisions.

CUM is an index developed by Lee et al. (2023) to measure economic policy uncertainty in China. CPU and CU are indices developed by Lee and Cho (2023) to measure climate-related uncertainties. CPU is an index that measures the uncertainty regarding climate-related regulations and policies by the government and its impact on the markets. CU, on the other hand, provides an indicator to understand the effects of changes in climate conditions (such as weather events, environmental factors, etc.) on financial markets, by focusing on climatic changes. UCT, developed by Rogers, Sun, and Sun (2024), is an important index for assessing the impact of geopolitical uncertainties between the US and China on economic and financial conditions.

This study aims to examine the relationship between CUM, CPU, CU, and UCT with the FTSE China Technology Index (FTXIN410) and SZSE Environmental Protection Index (SZEPI) using ARDL and NARDL methods. To test the robustness of the model, three additional parametric methods are employed: FMOLS, DOLS, and CCR. The technology and environmental protection sectors in China are crucial for the country's sustainable economic future. Understanding the impact of global and local uncertainties on these sectors is critical for predicting sectoral trends and future market dynamics. Climate uncertainties and global uncertainties can impact investors' returns and market behaviors. In critical sectors such as technology and environmental protection, uncertainties need to be closely monitored for their implications on investment decisions and market stability. The second section of the study presents the research

[1] Ph.D., Asst. Prof., Istanbul Aydin University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Istanbul, TURKEY. Email: ozgedemirkale@aydin.edu.tr ORCID: 0000-0002-4227-393.
[2] Ph.D., Asst. Prof., Beykent University, Faculty of Economics and Administrative Sciences, Capital Markets Department, TURKEY. Email: iremkosan@beykent.edu.tr ORCID: 0000-0002-8953-2171.

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conducted in the literature. Following this, the third section introduces the econometric model and dataset, and the findings and results obtained from the research are discussed.

Literature Review

The existing literature can be categorized into three primary areas. The first area examines how economic policy uncertainty (EPU) has a significant impact on China's carbon trading market (Wang et al. 2022; Tao Liu et al. 2023; Liu et al. 2023)

The second area focuses on the effects of international climate policy uncertainty, particularly from the United States, on Chinese markets and various sectors (Xin et al., 2022; An et al., 2022; Niu et al., 2023; Zhu et al., 2023; Wang and Li, 2023; Altın et al., 2023; Chen, Zhang, and Weng, 2023; Alqaralleh, 2023; Lv and Li, 2023; Tian, Chen, and Dai, 2024; Iqbal et al., 2024; Zhao and Luo, 2024).

Xin et al. (2022) find that high climate policy uncertainty (CPU) reduces current stock market returns and increases volatility in China, but decreases future volatility. Conversely, for the United States, high CPU decreases stock market returns in the short term but increases them in the long term. An et al. (2022) show that an increase in the Climate Change Index (CCI) raises financial market pressure in the short and medium term, but the effect of a CCI increase on the Chinese financial market in the long term remains uncertain. Niu et al. (2023) found that climate policy uncertainty negatively affects green technology innovation. Zhu et al. (2023) found that climate risks have time-varying effects on stock returns of firms. Wang and Li (2023) studies show that CU and CEU can significantly affect the volatility of the CSI 300 ESG index. Altın et al. (2023) show that the volatility of China Ocean Shipping Company (COSCO) is transmitted to the China ESG index and CPU. Chen, Zhang, and Weng (2023) found that CPU has a significant impact on stock market price volatility. Alqaralleh (2023) examines the extreme return connectedness between five major Chinese stock prices and climate uncertainty from March 2010 to June 2022 using the W-Q-TVP-VAR method. The findings indicate that climate uncertainty primarily reduces investment during stable periods, while altering the lead-lag relationships among these sector groups during times of turmoil. Lv and Li (2023) find that the climate policy uncertainty index can significantly predict the volatility of China's energy, materials, industrials, consumer discretionary, health care, and utility sectors. Tian, Chen, and Dai (2024) identify a strong positive relationship between climate risk perception (CRP) and corporate green innovation (CGI) in high-tech and state-owned enterprises. Iqbal et al. (2024) find that while there is no evidence of asymmetric cointegration between Chinese climate policy uncertainty and the oil and gas stock index, the effect on the clean energy stock index is insignificant. The study also shows that an increase in Chinese climate policy uncertainty significantly decreases carbon emission allowance prices (while increasing the ESG index) in the long run. Zhao and Luo (2024) show that while both CPU and CU have significant predictive power over China's green indices, the effect of the US climate policy uncertainty index is limited.

We aim to address this gap in the literature by examining the effects of the Twitter-Based China Economic Policy Uncertainty Index (CUM), the Climate Policy Uncertainty Index (CPU), the Climate Uncertainty Index (CU), and the US-China Tension Index (UCT) on the FTSE China Technology Index (FTXIN410) and the SZSE Environmental Protection Index. Specifically, we seek to answer the following questions: "Do China's climate policy uncertainty, climate uncertainty, Twitter-Based China Economic Policy Uncertainty, and US-China Tension Uncertainty impact the returns of companies in the technology and environmental protection sectors? Are these effects asymmetric in the long run?"

Data and Methodology

Data Description

In the study, two separate models were established to investigate the effects of climate and global uncertainties on technology and environmental protection indices. China has developed various legal and policy changes for the development of climate and environmental policies since 2008. The 2015 Paris

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Agreement has led to significant changes and improvements in environmental protection sectors, as in all sectors. In this context, the SZSE Environmental Protection Index (SZEPI) data from December 2018 to January 2023 have been selected to directly reflect the impact of climate uncertainty variables. On the other hand, a longer time frame is used for the FTSE China Technology Index (FTXIN410) (December 2015 - January 2023) to provide a broader analysis of changes in the technology sector.

Data for the FTXIN410 and SZSE indices were obtained from investing.com. The Twitter-Based China Economic Policy Uncertainty Index (CUM), Climate Policy Uncertainty Index (CPU), and Climate Uncertainty Index (CU) data were accessed from https://twitterchnepu.github.io/, while the US-China Tension Index (UCT) data were obtained from https://www.policyuncertainty.com/US_China_Tension.html.

Methodology

To test the existence of long-term relationships between variables, the Engle and Granger (1987) method and the Johansen and Juselius (1990) cointegration test can be used, provided that all series are stationary at the same level. However, these methods become invalid when the series are at different levels of stationarity. In such cases, the bounds testing approach and ARDL (Autoregressive Distributed Lag) approach, developed by Pesaran et al. (2001), are considered the most appropriate methods.

Pesaran (2001) proposed using the bounds testing method to explore the cointegration relationship among variables. If the F-statistic values from the Wald test conducted on the variables' levels are below the critical values listed in the table, the null hypothesis cannot be rejected, suggesting that there is no cointegration among the series. On the other hand, if the computed F-statistic exceeds the critical values, the null hypothesis is rejected in favor of the alternative hypothesis, indicating a long-term relationship between the series. When the bounds test confirms a cointegration relationship, ARDL models are then employed to analyze both long-term and short-term dynamics (Nayan and Smyth, 2005: 103).

The hypotheses for the bounds test should be formulated as follows: (Pesaran et al. 2001: 296):

H0: $\pi_{yy} = 0$, $\pi_{yx.x} = 0$ (There is no cointegration)

H1: $\pi_{yy} \neq 0$, $\pi_{yx.x} \neq 0$ (There is cointegration)

Pesaran et al., (2001), general equation for the unrestricted error correction model the adapted forms of the models used in the study according to ARDL are shown as Equal 2 and Equal 3

$$LFTXIN410_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \qquad 2$$

$$LLSZEPI_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \qquad 3$$

The ARDL model assumes that there is only a linear or symmetric relationship between variables when evaluating the long-term and short-term dynamics of series where cointegration is investigated. The NARDL model, developed by Shin et al. (2011), focuses on the asymmetric relationships between variables in the short and long term. It examines the effects of "negative" and "positive" changes in the explanatory variables on the dependent variable (Shahzad et al., 2017: 215). The asymmetric cointegration model underlying the NARDL cointegration method can be expressed as follows (Shin et al., 2011: 8):

$$y_t = \beta^+ X_t^+ + \beta^- X_t^- + u_t \qquad (4)$$

In place of traditional cointegration tests, FMOLS, DOLS, and CCR methods are increasingly being used to determine long-term relationships between variables. FMOLS, proposed by Phillips and Hansen (1990), DOLS, developed by Stock and Watson (1993), and CCR, introduced by Park (1992), are preferred due to

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their ability to address the endogeneity problem in the estimation phase and the difficulty in interpreting long-term coefficients.

The results of the FMOLS estimation will be obtained using Equations (5) and (6).

$$LFTXIN410_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \quad (5)$$

$$LLSZEPI_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \quad (6)$$

In the FMOLS method, by modifying the error terms to reduce the effects of autocorrelation and endogeneity, more accurate coefficient estimates are provided.

The DOLS estimation will be obtained using Equation (7) and Equation (8):

$$LFTXIN410_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 \sum_{J=-p}^{p} \gamma_{1j}\, \Delta LCPU_{t-j} \sum_{J=-p}^{p} \gamma_{2j}\, \Delta LCU_{t-j} + \sum_{J=-p}^{p} \gamma_{3j}\, \Delta LCUM_{t-j} + \sum_{J=-p}^{p} \gamma_{4j}\, \Delta LUCT_{t-j} + \varepsilon_t \quad (7)$$

$$LLSZEPI_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \sum_{J=-p}^{p} \gamma_{1j}\, \Delta LCPU_{t-j} + \sum_{J=-p}^{p} \gamma_{2j}\, \Delta LCU_{t-j} + \sum_{J=-p}^{p} \gamma_{3j}\, \Delta LCUM_{t-j} + \sum_{J=-p}^{p} \gamma_{3j}\, \Delta LUCT_{t-j} + \varepsilon_t \quad (8)$$

In the DOLS model, estimates are made using the lagged and lead differences of the independent variables. The aim of this model is to provide more reliable estimates by controlling for endogeneity and autocorrelation.

The CCR estimation will be obtained using Equation (9) and Equation (10):

$$LFTXIN410_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \quad (9)$$

$$LLSZEPI_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \quad (10)$$

The CCR method transforms the data in cointegration analyses by using only the stationary components and separates the error terms from the explanatory variables, providing more efficient and reliable estimates.

Econometric Findings

In order to determine the stationarity levels of the series, the ADF unit root test developed by Dickey and Fuller (1979) and the Phillips-Perron tests developed by Phillips and Perron (1988) were used.

According to these results, the variables LCPU, LCU, LCUM, and LUCT are found to be stationary at their original levels according to both the ADF and PP tests, while the variables LFTXIN410 and LSZEPI are found to be stationary at I(1) levels. Upon examining the test results, it is determined that none of the series are stationary at I(2) (Table 1).

Table 1: Unit Root Test[1]

I(0)			I(1)	
ADF[2]	**Intercept**	**Intercept and trend**	**Intercept**	**Intercept and trend**
Variables	**Prob.**	**Prob.**	**Prob.**	**Prob.**
LFTXIN410	0.33	0.47	0.00	0.00
LSZEPI	0.69	0.42	0.00	0.00

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LCPU	0.05	0.00	0.00	0.00
LCU	0.05	0.00	0.00	0.00
LCUM	0.25	0.00	0.00	0.00
LUCT	0.00	0.00	0.00	0.00
I(0)			**I(1)**	
PP[3]	**Intercept**	**Intercept and trend**	**Intercept**	**Intercept and trend**
Variables	**Prob.**	**Prob.**	**Prob.**	**Prob.**
LFTXIN410	0.32	0.43	0,00	0,00
LSZEPI	0.68	0.56	0.00	0.00
LCPU	0.00	0.00	0,00	0,00
LCU	0.00	0.00	0,00	0,00
LCUM	0.03	0.00	0,00	0,00
LUCT	0.00	0.00	0.00	0.00

[1]The natural logarithms of all series have been taken.

[2]Based on Schwartz Info Criterion

[3]Based on Bartlett Kernel

Table 2 presents the results of the cointegration test for linear and nonlinear ARDL models as specified in Equation 1. To investigate the presence of a cointegration relationship in ARDL models, Pesaran's (2001) bounds test was employed. In the study, when testing the significance of coefficients collectively for the bounds test, it was found that the F-statistic values exceed both the lower and upper bound values in the ARDL and NARDL models. As a result, the null hypothesis (H0), which proposed that there is no cointegration relationship among the variables in the model, was rejected. Consequently, the alternative hypothesis (H1) was supported, indicating that a long-term relationship exists.

Table 2. Bounds Test for Linear and Nonlinear ARDL Models

Dependent Variable: LFTXIN410	**F-statistic**	**Significance Level** %10 **I(0)**	**I(1)**	%5 **I(0)**	**I(1)**	**Conclusion**
ARDL Model	4.67	2.2	3.09	2.56	3.49	Long-term relationship exists
NARDL Model	4.10	1.85	2.85	2.11	3.15	Long-term relationship exists

Since a cointegration relationship was identified in the model, the next step was to estimate the long-term parameters reflecting the relationships for the ARDL (1, 0, 3, 4, 3) model based on the AIC information criterion. Diagnostic test results of the model indicate that it does not suffer from autocorrelation or changing variance issues. The long-term coefficients derived from the ARDL model are dynamically stable and do not exhibit any structural breaks. According to the results from the ARDL model, the long-term forecast results for the variables LCU, LCUM, and LUCT are statistically significant. It was found that there

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is a positive long-term relationship between the FTXIN410 index and the LCU and LUCT variables, while a negative long-term relationship exists with the LCUM variable (Table 3).

Table 3. ARDL Long-Term Test Results

Dependent Variable: FTXIN410			
Variable	Coefficient	t-Statistic	Prob.
LCPU	0.03	0.71	0.47
LCU	0.18	2.26	0.02
LCUM	-0.26	-4.08	0.00
LUCT	1.07	3.40	0.00
C	-3.61	-0.98	0.32
ECT_{t-1}	-0.20	-5.47	0.00
Diagnostic Test Statistics			
R^2			0.89
Adjusted-R^2			0.87
Breusch-Godfrey LM Test (B-G LM) Prob.			0.28
Heteroskedasticity Test: B-G LM Prob.			0.64
Ramsey Reset (RR) Test			0.88
CUSUM Test			Stationary
CUSUM-SQ Test			Stationary

To test the symmetric effects of the CPU, CU, CUM, and UCT variables on FTXIN410, the NARDL test was applied. The results of the NARDL model are summarized in Table 5. According to Table 5, the error correction term coefficient falls within the accepted range $(-1 < ECT < 0)$ and is statistically significant, similar to the ARDL model. The diagnostic test results of the model indicate that it does not suffer from autocorrelation or changing variance issues. The long-term coefficients obtained from the NARDL models are dynamically stable, and no structural breaks are observed. The results obtained from the NARDL model show similarities to those of the ARDL model. Specifically, the coefficients for LCU^{poz} and LCU^{neg} are positive, indicating that the effects of positive shocks are more dominant. On the other hand, the coefficients for $LCPU^{poz}$ and $LCPU^{neg}$ are negative, suggesting that the effects of negative shocks are more pronounced. Moreover, positive shocks in the LUCT variable significantly affect FTXIN410 statistically. (Table 4).

Tablo 4. NARDL Long-Term Test Results

Dependent Variable: FTXIN410			
Variable	Coefficient	t-Statistic	Prob.
$LCPU^{poz}$	-0.36	-3.40	0.00
$LCPU^{neg}$	-0.22	-2.89	0.00
LCU^{poz}	0.43	3.18	0.00
LCU^{neg}	0.19	1.71	0.09
$LCUM^{poz}$	-0.24	-3.61	0.00
$LCUM^{neg}$	-0.03	-0.43	0.66
$LUCT^{poz}$	0.46	1.53	0.10
$LUCT^{neg}$	-0.26	-1.00	0.31
C	5.24	6.70	0.00
ECT_{t-1}	-0.26	-6.86	0.00

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Diagnostic Test Statistics	
R^2	0.93
Adjusted-R^2	0.91
B-G LM Test Prob.	0.10
Heteroskedasticity Test: B-G Prob.	0.11
RR Test	0.048
CUSUM Test	Stationary
CUSUM-SQ Test	Stationary

Table 5 presents the results of the cointegration test for linear and nonlinear ARDL models as specified in Equation 2. In the study, when testing the significance of coefficients collectively for the bounds test, it was found that the F-statistic values exceed both the lower and upper bound values in the ARDL and NARDL models. Therefore, the alternative hypothesis (H1) which accepts the presence of a cointegration relationship among the variables in the model was accepted.

Table 5. Bounds Test for Linear and Nonlinear ARDL Models

Dependent Variable: LSZEPI	**F-statistic**	**Significance Level**				**Conclusion**
		%10		%5		
		I(0)	**I(1)**	**I(0)**	**I(1)**	
ARDL Model	4.13	2.2	3.09	2.56	3.49	Long-term relationship exists
NARDL Model	4.64	1.85	2.85	2.11	3.15	Long-term relationship exists

Since a cointegration relationship was identified in the model, the next step was to estimate the long-term parameters reflecting the relationships for the ARDL (2, 0, 3, 4, 3) model based on the AIC information criterion. The diagnostic test results of the model indicate that it does not suffer from autocorrelation or changing variance issues. The long-term coefficients from the ARDL model are consistently stable and do not display any structural changes. According to the results from the ARDL model, the long-term forecast results for the LCPU, LCU ,LCUM variables are statistically significant. A strong positive long-term relationship was found between the SZEPI index and the LCU variable, while a negative long-term relationship was identified with the LCPU and LCUM variables. (Table 6).

Table 6. ARDL Long-Term Test Results

Dependent Variable: SZEPI			
Variable	Coefficient	t-Statistic	Prob.
LCPU	-0.59	-1.59	0.10
LCU	0.98	2.88	0.00
LCUM	-0.64	-2.33	0.02
LUCT	-0.34	-0.44	0.66
C	1.40	1.33	0.19
ECT_{t-1}	-0.12	-5.34	0.00
Diagnostic Test Statistics			
R^2			0.97
Adjusted-R^2			0.97

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B-G LM Test Prob.	0.056
Heteroskedasticity Test: B-G Prob.	0.12
RRTest	0.75
CUSUM Testi	Stationary
CUSUM-SQ Testi	Stationary

The long-term coefficients obtained from the NARDL models are dynamically stable, and no structural breaks are observed (Figure 1).

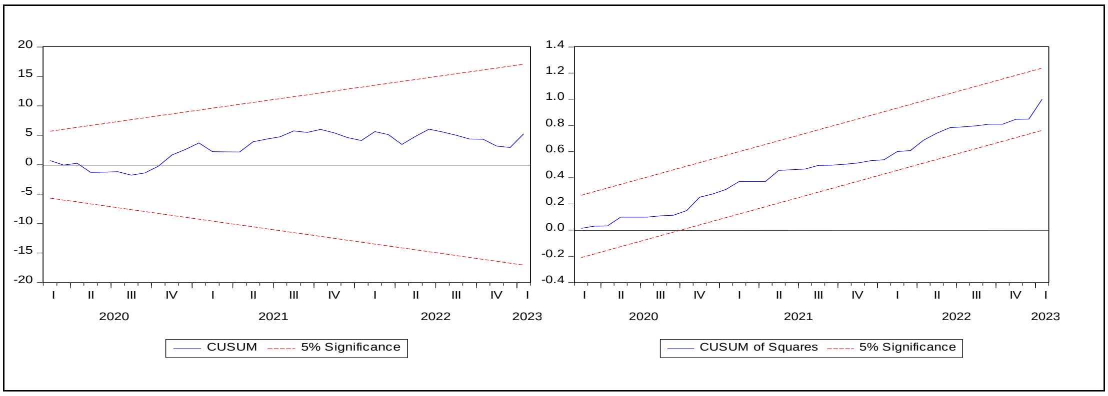

Figure 1 CUSUM and CUSUM-SQ Test for the NARDL Model

To test the symmetric effects of the CPU, CU, CUM, and UCT variables on SZEPI, the NARDL test was applied. The results of the NARDL model are summarized in Table 7. According to Table 7, the error correction term coefficient falls within the accepted range $(-1 < ECT < 0)$ and is statistically significant, similar to the ARDL model. The diagnostic test results of the model indicate that it does not suffer from autocorrelation or changing variance issues. According to Table 7, the coefficients $LCPU^{poz}$ and $LCPU^{neg}$ are negative and significant, indicating that the effects of negative shocks are more dominant .The coefficients $LCU^{poz}$and LCU^{neg} are positive, indicating that the effects of positive shocks are more dominant. However, these coefficients are not statistically significant. Additionally, the coefficients for the negative changes in the LCPU and LUCT variables are statistically significant.

Tablo 7. NARDL Long-Term Test Results

Dependent Variable: SZEPI			
Variable	Coefficient	t-Statistic	Prob.
$LCPU^{poz}$	-1.27	-1.62	0.10
$LCPU^{neg}$	-1.30	-1.71	0.09
LCU^{poz}	0.60	1.43	0.15
LCU^{neg}	0.04	0.13	0.89
$LCUM^{poz}$	-0.31	-1.52	0.10
$LCUM^{neg}$	0.23	0.85	0.39
$LUCT^{poz}$	-1.08	-1.41	0.16
$LUCT^{neg}$	-1.68	-2.41	0.02
C	-0.71	-0.19	0.84
ECT_{t-1}	-0.15	-7.61	0.00
Diagnostic Test Statistics			
R^2			0.99

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Adjusted-R^2	0.98
B-G LM Test Prob.	0.25
Heteroskedasticity Test: B-G Prob.	0.55
RRTest	0.50

The results obtained from the ARDL technique in Table 8 and Table 9 were analyzed using the FMOLS, DOLS, and CCR techniques. These methods, which are increasingly preferred over traditional cointegration tests, can be applied to both stationary and non-stationary series.

Table 8. FMOLS, DOLS,CCR Results

Dependent Variable:FTXIN410	FMOLS	D0LS	CCR
LCPU	0.081**	-0.344	0.091**
LCU	0.075*	0.769**	0.072*
LUCT	0.292*	3.004***	0.302*
LCUM	-0.119***	-0.442***	-0.132***
C	5.356***	-26.932***	5.256***

Note: ***, ** and * indicate significance at 1%, 5%, and 10%, respectively

In the FMOLS model, a 1% increase in LCPU results in a 0.081% rise in the FTXIN410 average. Similarly, a 1% increase in LCU leads to a 0.075% increase in the FTXIN410 average, while a 1% increase in LUCT causes a 0.292% increase in the FTXIN410 average. Conversely, a 1% increase in LCUM results in a 0.119% decrease in the FTXIN410 average. These values are statistically significant and corroborate the results obtained from the ARDL analysis, as detailed in Table 5.

In the DOLS model, a 1% increment in LCU, LUCT uplift an average of 0.769%, 3.004 % in FTXIN410. LCPU is insignificant which supports the ARDL model as shown in Table 5 .On the other hand, a 1% increment in LCUM %0.442 decline of the FTXIN410 average.

In the CCR model, a 1% increment in LCPU ,LCU and LUCT uplift an average 0.091% ,0.072% and %0.302 of FTXIN410. On the contrary, a 1% increment of LCUM on average, 0.132%, decline in FTXIN410.

Table 9. FMOLS, DOLS,CCR Results

Dependent Variable: SZPEI	FMOLS	D0LS	CCR
LCPU	0.107	0.945**	0.169
LCU	0.367***	-0.304	0.301**
LCUM	-0.234**	-0.247***	-0.230**
LUCT	-0.01	0.774	-0.04
C	7.455	-2.774	7.777

Note: ***, ** and * indicate significance at 1%, 5%, and 10%, respectively

In the FMOLS model, a 1% increase in LCU results in a 0.367% rise in the average SZPEI. On the contrary, a 1% increment in LUCM %0.234 decline of the SZPEI average . The variables LCPU and LUCT were determined to be statistically insignificant. Upon evaluation, the estimated results of the FMOLS model are found to be consistent with those obtained using the ARDL model.

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In the DOLS model, a 1% increment in LCPU uplift an average of 0.945% in SPEI.. On the contrary, a 1% increment in LCUM %0.247 decline of the SZPEI.. The variables LCU and LUCT were found to be statistically insignificant in the DOLS model .

In the CCR model, a 1% increment in ,LCU uplift an average %0.301 of the SZPEI average .On the contrary, a 1% increment of LCUM on average, %0.230 decline in SZPEI. The variables LCPU and LUCT were determined to be statistically insignificant. Upon evaluation, the estimated results of the CCR model are found to be consistent with those obtained using the ARDLmodel.

Conclusion and Recommendations

This study aims to examine the relationship between CUM, CPU, CU, and UCT with the FTSE China Technology Index (FTXIN410) and SZSE Environmental Protection Index (SZEPI) using ARDL and NARDL methods. To test the robustness of the model, three additional parametric methods are employed: FMOLS, DOLS, and CCR. The results of the study indicate a long-term relationship between China's climate uncertainties and global uncertainties with technology and environmental protection indices. The study found that the CPU and CUM variables significantly affect the technology and environmental protection indices.

For investors and portfolio managers, these results are highly valuable as they suggest that financial investment decisions should consider not only price movements but also these uncertainties. Especially in today's environment, where uncertainties are increasing due to technological advancements, making informed investment decisions is essential. Identifying the impact of climate uncertainty on financial markets is crucial for enhancing the predictability of climate policies. The results obtained from this study suggest that understanding climate and global uncertainties can assist policymakers in making more informed decisions, thereby facilitating more robust economic growth.

While the study has important contributions, it is not possible to continue the research without some limitations. However, these limitations are considered to offer opportunities for future researcher. For example, this study was conducted solely with a focus on China and specific sectors. Conducting the study with different countries particularly by identifying a common sector for cross-country comparisons, is believed to contribute to the literature.

Disclosure Statement

No potential conflict of interest was reported by the author(s)

Declarations

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Authors' contributions

Dr. Özge Demirkale contributed to the study conception, design, literature review and analysis.

Dr. Naime İrem Duran contributed to the study conception, results interpretation and analysis.

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