Geojournal of Tourism and Geosites
ISSN 2065-0817, E-ISSN 2065-1198

Year XIX, vol. 65, no. 2, 2026, p.877-890
DOI 10.30892/gtg.65223-1728

GLOBAL UNCERTAINTY AND TOURISM STOCK PERFORMANCE: EVIDENCE FROM CHINA–US MARKETS

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Citation: Demirkale, O., Duran, N. I., & Ojaghlou, M. (2026). Global uncertainty and tourism stock performance: Evidence from China–US markets. *Geojournal of Tourism and Geosites*, 65(2), 877–890. https://doi.org/10.30892/gtg.65223-1728

Abstract: Tourism now adds nearly ten trillion dollars to world GDP and sustains about 330 million jobs, yet the sector is acutely exposed to macro-financial downturns, geopolitical rifts and climate-policy shifts. Recent surges in AI-driven news sentiment, US–China frictions and decarbonisation measures have amplified uncertainty facing tourism investors. This study investigates how four uncertainty channels media-based economic policy (TVEPU), US–China tension (UCT), global macro (WUI) and climate policy (CPU) shape tourism equity returns in China and the United States. By combining linear ARDL, asymmetric NARDL and wavelet coherence, we test long-run cointegration, identify whether negative shocks hit harder than positive ones, and pinpoint the time-frequency windows where these effects emerge. Findings aim to guide frequency-sensitive risk management and transparent policy communication in tourism finance. Monthly tourism-equity indices for China and the United States (Jan 2012 – Dec 2023) are matched with four uncertainty proxies TVEPU, UCT, WUI and CPU. Long-run cointegration is tested via bounds-based ARDL; nonlinear shock asymmetries are evaluated with NARDL; and time-frequency co-movements and lead-lag patterns are mapped through continuous wavelet coherence. This three-pillar design jointly uncovers integration, asymmetry and frequency-specific transmission channels. Cointegration exists in both markets, yet risk premiums differ: China's tourism equities react modestly to media-based uncertainty, whereas U.S. returns exhibit a strong positive long-run link with geopolitical tension. Shock asymmetry is clear negative TVEPU surprises depress Chinese stocks more than positive ones, while positive UCT surprises lift U.S. prices. Wavelet coherence reveals that in China, TVEPU drives short-term (2–8 month) inverse co-movements and CPU underpins long cycles (16–64 months); in the United States, UCT dominates the 8–16 month band, and WUI influence fades beyond 32 months. Uncertainty premiums prove source-, country- and frequency-specific. Rapid policy disclosure and climate-finance hedges could dampen media and CPU shocks in China, while U.S. investors should diversify and employ derivatives against recurrent geopolitical cycles. Multi-band sensitivities further imply that tourism firms maintain flexible liquidity buffers and dynamic credit lines. Mapping this heterogeneous architecture advances tourism-finance scholarship and offers actionable guidance for policymakers and portfolio managers.

Keywords: global uncertainty, tourism stocks, ARDL model, NARDL model, wavelet coherence

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INTRODUCTION

Tourism is a major provider of economic development and growth processes globally. Due to the direct and indirect economic impacts that it provides, it is among the significant revenue contributors for most nations. According to the 2024 World Travel and Tourism Council (WTTC) report, the travel and tourism sector added 9.1% of the global Gross Domestic Product (GDP) in 2023. It achieved approximately 9.9 trillion US dollars (WTTC, 2024). The figures above show that tourism is an economy-growing sector, and its share in the world's total economy is continuously growing. The economic impacts of tourism are not only in financial terms but also bring significant outputs when it comes to job creation. In 2023, the tourism sector created 27.4 million new jobs globally, which increased the total number of employees to 330 million (WTTC, 2024). Tourism activities generate direct employment opportunities in various sectors of the service industry and indirect job opportunities in hospitality, restaurant management, transport, entertainment, and cultural services (UNWTO, 2023). This illustrates that tourism results in economic growth, a rise in the labor market, and an increase in the employment rate.

The sector, however, is highly susceptible to global economic downturns, geopolitical uncertainties, and environmental forces. Although crises like the COVID-19 pandemic have led to huge losses for the sector, the recovery journey has picked up pace in recent times. Recent tourism studies also show that crisis conditions and climate-related risks can reshape tourism activity, recovery dynamics, and sectoral resilience (Deb & Nafi, 2020; Pandy & Rogerson, 2021). In particular, digitalization,

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green tourism practices, and government interventions have helped the sector bounce back (Gössling et al., 2021). This close connection between economic development and tourism requires a closer look at the sector's future growth dynamics. Uncertainty indices are key indicators to explain economic and financial market movements and forecast future directions. Macroeconomic uncertainties directly affect investor expectations, company profitability, and industry performance (Baker et al., 2016). Over the last few years, climate policies, global uncertainties, geopolitical risks, and artificial intelligence-based economic uncertainty indices have emerged as deciding indicators influencing financial markets. In this regard, the Climate Policy Uncertainty Index (CPU) reflects the impact of uncertainty in carbon policy and environmental regulation on the economy (Lee & Cho, 2023; Gavriilidis, 2021). The World Uncertainty Index (WUI) addresses the impact of global economic uncertainty on countries (Ahir et al., 2018). Conversely, the US-China Tension Index records the effects of deteriorating trade and political relationships between the two countries on the markets (Rogers et al., 2024), while the AI Cable News-Based EPU Index measures economic policy uncertainty based on artificial intelligence-powered news analysis and evaluates its influence on financial markets (Bergbrant & Bradley, 2022; Hong et al., 2021). These uncertainty measures can directly affect the stock returns of companies in the tourism and entertainment sectors. The tourism sector is most vulnerable to economic uncertainties, with a weak structure against global crises, environmental policies, and geopolitical tensions. In particular, rising operating costs and carbon taxes due to ecological policies can affect the profitability of tourism companies, while increasing global and regional uncertainties can negatively influence consumers' travel decisions. In big economies such as the US and China, investor confidence in the tourism and entertainment sector is prone to levels of uncertainty, and fluctuations in these indices can result in extreme shifts in the stock market performance of tourism companies.

The current research provides three new contributions in the form of the first China–US comparative analysis of the effect of Cable-News Economic Policy Uncertainty (TVEPU), US–China Tension (UCT), World Uncertainty (WUI), and Climate Policy Uncertainty (CPU) on tourism equity markets on both level-asymmetry ((N)ARDL) and time–frequency (wavelet coherence) levels. First, while previous studies typically examine a single country or a single uncertainty measure, we aggregate four indices simultaneously to reveal heterogeneity in US and Chinese tourist systems. Second, by aggregating ARDL linear long-run estimates, asymmetric NARDL shock decompositions, and wavelet phase-arrow patterns, we integrate an evidence base across domains that separates frequency-specific dynamics obscured by average effects. Third, through the analysis of media-induced policy shocks (TVEPU), geopolitical tension cycles (UCT), world macro uncertainty (WUI), and climate-policy risk premiums (CPU) within a single framework, we establish the relative ordering of these channels with respect to impacting tourism stock returns. In parallel, our study answers three main questions:

1. Long-run integration: Are the uncertainty indexes and tourism equity returns in China and the US cointegrated?
2. Shock asymmetry: Do positive and negative uncertainty shocks get asymmetrically passed on to tourism returns?
3. Time–frequency localization: In what time–frequency bands do these effects localize, and what lead–lag (phase) structures occur?

The empirical design of this study rests on three methodological blocks (i) linear ARDL, (ii) asymmetric NARDL, and (iii) wavelet coherence each targeting a distinct research question. Accordingly, we posit the following hypotheses:

$\mathbf{H_1}$**:** The TVEPU, UCT, WUI, and CPU indices exhibit long-run cointegration with tourism equity returns in both China and the United States, as detectable by the Bounds testing framework.

$\mathbf{H_2}$**:** Negative shocks in the uncertainty indices induce greater and more rapid volatility in tourism returns than positive shocks.

$\mathbf{H_3}$**:** The impact of uncertainty shocks is heterogeneous across frequency bands: different indicators dominate in the short (2–8 months), medium (8–16 months), and long (≥16 months) horizons, and wavelet phase arrows predominantly indicate that uncertainty series lead tourism returns.

This article is organized as follows: Section 2 of this study provides a comprehensive literature review, while Section 3 introduces the methods and dataset used. Section 4 presents the empirical findings. Finally, Section 5 summarizes the findings, addresses policy implications, discusses the study's limitations, and offers insights for future research.

LİTERATURE REVİEW

Uncertainty indices affect stock markets by measuring economic, political, and climate uncertainties. These indices shape market volatility and investor decisions, especially in tourism. Research shows that uncertainty affects markets in both the short and long term, and this effect increases during times of crisis. Essential issues in this regard are discussed below.

1. The Relationship between Uncertainty Indices and Stock Market Indices

Uncertainty indices are valuable metrics used to measure uncertainty in financial markets. They are widely used to investigate the impact of economic, political, geopolitical, and climate uncertainties on market dynamics. In particular, literature reviews have determined that uncertainty indices are central in describing the volatility levels of financial markets and investors' decisions. Some of the evidence in the literature shows that uncertainty indices generate short-term volatility in stock market indices and dictate the overall direction of markets in the long term (He et al., 2021; He & Zhang, 2022; Khalfaoui et al., 2022; Xu et al., 2022; Ren et al., 2023; Mao et al., 2023; Xu et al., 2023; Ghosh et al., 2023; Mensi et al., 2023; Yu, 2023; Chen & Sharma, 2024; Li et al., 2025; Ma et al., 2025). He et al. (2021) examined the impact of international trade policy uncertainty (TPU) on the US and Chinese stock markets. Based on their results, the US-China trade wars positively influenced the US stock market but negatively influenced the Chinese stock market. Khalfaoui et al. (2022) found that climate policy risk-sensitive investors prefer to invest in clean or green stocks. He & Zhang (2022) and Ren et al. (2023) concluded that an improvement in the US Climate Policy Uncertainty (CPU) leads to increased green stock prices. Xu et al. (2022), using data from March 2, 2020, to March 2, 2021, daily, confirmed that stock returns during the pandemic were influenced by increased access to search engine data by investors, noting that uncertainty influenced stock returns during the pandemic. Mensi et al. (2023) confirmed that uncertainties have asymmetric effects depending on market conditions, with the highest spread occurring during the first wave of COVID-19. Yu (2023) demonstrated that the World Uncertainty Index (WUI) improves sector-specific volatility predictions on the Shanghai Stock Exchange, particularly under periods of elevated volatility and within the materials, industrials, and healthcare industries, and deems the WUI a valuable tool for managing risk. Ghosh et al. (2023) discovered that economic and trade policy uncertainties between China and America create stock market volatility, where US stocks serve as a hedge and a haven from Chinese uncertainty. However, the impact was highly significant only in the DJShenzhen and DJShanghai indices.

Mao et al. (2023) discovered that stock markets are passed on primarily via shocks to the US Climate Policy Uncertainty (CPU). Xu et al. (2023) found that the US CPU and China's CPU have a different effect on stock returns and volatility in both the US and China. Chen & Sharma (2024) examined the causal link between climate policy uncertainty (CPU) and US and Chinese financial markets. The study findings show that CPUs and US and Chinese stock markets have a bidirectional causality under abnormal market conditions. In contrast, CPUs and commodity markets have a multidirectional causality in regular market conditions. Li et al. (2025), in their study of the impact of the US-China Tension Index on fossil fuel price volatility, found that increased tensions between the two countries lead to higher energy price volatility. Ma et al. (2025), in an examination of spillover effects between global climate policy uncertainty (GCPU), biodiversity attention (GBA), and stock markets of G7 and BRICS nations, stated that the impact of GBA on the US market and the effect of GCPU on other markets increased when there were international forums on climate change and biodiversity.

2. The Relationship between Uncertainty Indices and Tourism Stock Market Indices

Studies on the relationship between uncertainty indices and tourism stock market indices are critical in explaining the behavior of the tourism sector during uncertain times. It is commonly established in the literature that the effects of uncertainties on tourism stocks are magnified during periods of crisis, with heightened volatility driven by investor sentiment and market return volatility. Furthermore, empirical studies reveal how financial markets react to different regimes and how the effects change over time (Singal, 2012; Chen, 2015; Demir & Ersan, 2018; Ersan et al., 2019; Wu & Wu, 2019; Jiang et al., 2022; Aharon, 2022; Liu et al., 2024; Bai et al., 2024).

Singal (2012) found that changes in CCI are strongly and contemporaneously connected with the US stock tourism index. Chen (2015) discovered that CCI changes significantly and positively affected the seven listed hotel stocks on the Taiwan Stock Exchange. Demir and Ersan (2018) found that EPU substantially reduced the stock returns of Turkish tourist companies. Ersan et al. (2019) showed that the results of their study were associated with a high negative impact of the EPU on the STOXX Europe 600 Travel and Leisure Price Index. Wu & Wu (2019) mentioned that the European EPU was in bidirectional causality with tourism revenues in Portugal, Ireland, Italy, Greece, and Spain in the long run. Jiang et al. (2022) examined the effects of geopolitical risk (GPR) and China's economic policy uncertainty (EPU) on China's tourism stock returns, and results showed that GPR had persistent negative impacts on tourism stock returns, while EPU had both negative and positive effects at different distribution levels. Aharon (2022) investigated the impact of the Consumer Sentiment Index (CSI), Consumer Confidence Index (CCI), Economic Policy Uncertainty Index (EPU), and Volatility Index (VIX) on the US tourism and leisure (T&L) industry performance. Research findings showed that T&L stock fluctuations are much more sensitive to changes in the CCI and CSI than to changes in the VIX or EPU. Liu et al. (2024) found that global economic policy uncertainty (CEPU) and Chinese economic policy uncertainty (GEPU) both exert significant negative influences on the long-term volatility of China's stock market for tourism. Bai et al. (2024) examined the explanatory information of AI-driven cable news on economic policy uncertainty (TVEPU) and its effect on the stock returns of travel and leisure in the US, EU, and China. They found that TVEPU has more extraordinary predictive ability in bear and bull markets over the long run. It has more extraordinary predictive ability in regular markets over the short run.

DATA AND MODEL SPECIFICATIONS

This study aims to assess the impact of political and economic uncertainty on tourism equity returns in the world's largest economies, China and the United States. Using monthly data from 2012 through 2023, we link each country's tourism stock index to six uncertainty indicators: the Cable-News Economic Policy Uncertainty (EPU) Index using artificial intelligence, the US–China Tension (UCT) Index, World Uncertainty Indices for the United States and China (WUI-CN, WUI-US), and Climate Policy Uncertainty Indices for the United States and China (CPU-CN, CPU-US). The AI-based EPU records the enthusiasm of policy argument on cable television, and the UCT records trade and diplomatic tensions. Although tourism equities are most directly sensitive to demand-supply dynamics, exchange-rate shocks, and border policy, the literature has comparatively few in-depth studies of this sector; most work relies on single-crisis observations (e.g., COVID-19) or short-horizon regressions. Three complementarity econometric methods are employed in this study. First, ARDL tests long-run cointegration between every uncertainty series and tourist equity returns, offering average long-run elasticities. Second, the NARDL approach breaks down this relationship into positive and negative shocks, thereby detecting behavioral asymmetries. Third, wavelet coherence plots the relationship in the joint time–frequency space, identifying which bands (short, medium, long) dominate and using phase arrows to indicate lead–lag dynamics. All analysis was conducted in R and EViews, with all series reported in logarithmic form. This multi-scale approach assists in explaining how various channels of uncertainty reach the strategically sensitive tourism sector, providing a new analytical template for tourism-finance scholarship. Table 1 reports the variables employed.

Table 1. Definitions Variables

Variable	Codes	Data Source
FTSE China A 600 – Travel & Leisure Index	FTSE China	Investing.com
Dow Jones Travel & Leisure Index	DJUSTT	Investing.com
AI Cable News-based EPU Index	TVEPU	Bergbrant & Bradley, 2022; Hong et al., (2021)
US-China Tension Index	UCT	Rogers et al. (2024)
China World Uncertainty Index	CWUI	Ahir et al., (2018)
US World Uncertainty Index	UWUI	Ahir et al., (2018)
China Climate Policy Uncertainty Index	CPU	Lee & Cho (2023)
US Climate Policy Uncertainty Index	UCPU	Gavriilidis, (2021)

1. ARDL Model

Testing long- and short-run associations between time series is essential for researchers and policymakers. To this effect, the Autoregressive Distributed Lag (ARDL) Model developed by Pesaran et al. (2001) is a robust tool that allows the long-run association to be estimated by applying the bounds testing technique. Unlike other cointegration tests, the ARDL model enables one to have variables of different orders of stationarity I(0) and I(1)) included in the same model. This feature makes the ARDL model particularly attractive to researchers working with macroeconomic and financial time series. The ARDL model is mainly characterized by its ability to provide valid estimation outcomes, particularly for small samples (Pesaran & Shin, 1999). The model can accommodate the examination of long-term dynamics at the same time, thus enabling one to examine both the transient and permanent components of the variable relationship. Also, in contrast to other cointegration methods, the variables do not have to be in the same order of integration as previously. The model permits the incorporation of stationary I(0) and first-order integrated I(1) variables.

However, the model does not accommodate the second-order integrated I(2) variables. This ability corrects the condition under which the variables have different stationarity levels, a common condition encountered in economic research, thus making the ARDL model more applicable. The ARDL model is also used with the ARDL Bounds Testing Approach to verify long-run relationships. Pesaran (2001) proposed the bounds test for the cointegration relationship among variables. Suppose the F-statistic values of the Wald test for the variables at their level are less than the critical values in the table. In that case, the null hypothesis will not be rejected, and it will be inferred that no cointegration exists among the series. Suppose the calculated F-statistic is larger than the critical values in the table. In that case, the null hypothesis is rejected, and the alternative hypothesis is accepted such that there is a long-run relationship between the series. If the variables are shown to be cointegrated using the bounds test, the ARDL models are estimated to establish both short-run and long-run relationships (Narayan & Smyth, 2005: 103). The model supports the estimation of the long-run equation within the Error Correction Model (ECM) framework. Careful choice of lag length is crucial. By default, the optimal lag length will be selected using the Akaike Information Criterion (AIC) and Schwarz Criterion (SIC).

The general equation for the unrestricted error correction model is presented as follows (Pesaran et al., 2001:296):

$$\Delta y_t = c_{0+}c_1 t + \pi_{yy} y_{t-1} + \pi_{yxx} X_{t-1} \sum_{i=1}^{p-1} \psi_i \Delta z_{t-i} + \omega \Delta x_t + \theta w_t + u_t \quad (1)$$

In the model, π_{yy} and $\pi_{yx.x}$ represents the long-term coefficients, c_0 denotes the parameter vector, t is the trend, w_t is the control variable, and is the error term. The hypotheses for the ARDL bounds test should be formulated as follows: (Pesaran et al. 2001: 296):

H_0: $\pi_{yy} = 0$, $\pi_{yx.x} = 0$ (There is no cointegration)

H_1: $\pi_{yy} \neq 0$, $\pi_{yx.x} \neq 0$ (There is cointegration)

The adapted forms of the models used in the study according to ARDL are shown as Equal 2 and Equal 3.

$$\text{LFTSE China}_t = \alpha_0 + \beta_1 \text{LTVEPU}_1 + \beta_2 \text{LUCT}_2 + \beta_3 \text{LCWUI}_3 + \beta_4 \text{LCPU}_4 + \varepsilon_t \quad (2)$$

$$\text{LDJUSTT}_t = \alpha_0 + \beta_1 \text{LTVEPU}_1 + \beta_2 \text{LUCT}_2 + \beta_3 \text{LUWUI}_3 + \beta_4 \text{LUCPU}_4 + \varepsilon_t \quad (3)$$

2. NARDL Model

With most conventional cointegration methods assuming symmetry in relationships between variables, many economic variables are prone to be affected asymmetrically. In such applications, the Nonlinear Autoregressive Distributed Lag (NARDL) model developed by Shin et al. (2014) is an effective econometric tool used to ascertain whether positive and negative shocks in independent variables have an asymmetric impact on the dependent variable. The NARDL model is an extension of the linear structure assumption made by the ARDL model. It attempts to measure the differential effects of rises and falls in independent variables on the dependent variable. The model accommodates stationarity of variables I(0) or order-one integration I(1) variables simultaneously, eliminating the need for all variables to be on the same level of integration required in standard cointegration. Besides establishing long-run relationships, the model also leaves space for testing short-run dynamics within the Error Correction Model (ECM) framework. For the model to be accurate, there should be a cointegration over the long-run relationship between the positive and negative components of the independent variables and the dependent variable. The cointegration relationship is done using the bound test method suggested by Pesaran et al., 2001; Shahzad et al., 2017: 215). The following is the asymmetric cointegration model that provides the basis of the NARDL cointegration method (Shin et al., 2014: 8):

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

The factors indicating the increases and decreases in the equation in terms of positive and negative variations are the sum totals of the increases and decreases of the variables, and can be calculated as follows (Shin et al., 2014: 285):

$$X_t^+ = \sum_{j=1}^{t} \Delta x_j^+ = \sum_{j=1}^{t} \max(\Delta x_j, 0) \quad (5)$$

$$X_t^- = \sum_{j=1}^{t} \Delta x_j^- = \sum_{j=1}^{t} \min(\Delta x_j, 0) \quad (6)$$

The ARDL model used to identify the long-term relationship expressed in the equation, along with the unrestricted error correction model of the NARDL approach, can be expressed as follows:

$$y_t = \sum_{j=1}^{p} \theta_j y_{t-j} + \sum_{p}^{q} (\theta^{+,} X_{t-j}^{+} + \theta_j^- X_{t-j}^-) + \epsilon_t \quad (7)$$

The NARDL model's approximate dynamic impulse response functions provide the effect of a shock (decrease or increase) in the independent variable on the dependent variable over time. These graphs provide insight into the dynamic adjustment process of the model, with short- and long-run asymmetric responses plotted visually. The graph employs the X-axis for the time horizon, representing how the effect changes over time. The Y-axis represents the magnitude of response of the dependent variable to increases (favorable variations) and reductions (negative variations) in the independent variable. Different curves portray the impact of positive and negative shocks in the independent variable on the dependent variable with asymmetric adjustments.

3. Wavelet-Coherence Analysis

To capture the time–frequency heterogeneity that lies beyond the "average" effects of level models, we computed the continuous wavelet transform (CWT) using the Morlet mother wavelet ($\omega_0 = 6$) following Grinsted et al. (2004). We then derived the squared wavelet coherence between the two series to quantify their localized co-movement in the joint time–frequency domain.

$$R_{xy}^2(a,b) = \frac{\left|S\left(b^{-1}W_{xy}(a,b)\right)\right|^2}{S\left(b^{-1}W_x(a,b)\right)^2 S\left(b^{-1}W_y(a,b)\right)^2} \quad (8)$$

Here, S denotes a smoothing operator in both time and scale (Torrence and Compo, 1998). The resulting wavelet coherence coefficient, R2(a, b), ranges between 0 and 1, indicating the degree of linear correlation between the signals at each time-frequency point. Values close to 1 suggest a strong correlation, while values near 0 indicate little to no correlation (Grinsted et al., 2004). The phase difference in the function as;

$$\phi_{xy} = \arctan\left(\frac{\mathrm{Im}\left[S\left(b^{-1}W_{xy}(a,b)\right)\right]}{\mathrm{RE}\left[S\left(b^{-1}W_{xy}(a,b)\right)\right]}\right), \text{with } \phi_{xy} \in [-\pi, \pi] \quad (9)$$

Equations (8) and (9) show that the real (Re) and imaginary (Im) parts of the smoothed cross-wavelet spectrum capture distinct features of the underlying signals. From these components one obtains the phase angle (ϕ_xy), which conveys how the two series move together and whether one consistently leads or follows the other. In the resulting wavelet-coherence plots, arrows directed rightward (→) denote an in-phase, positive comovement, whereas arrows directed leftward (←) indicate an out-of-phase, negative association. Arrow orientation also signals lead–lag structure: a right-and-upward arrow (↗) means that x(t) tends to lead y(t), while a left-and-downward arrow (↙) implies that y(t) generally leads x(t).

ECONOMETRIC FINDINGS

1. CHINA

Table 2, summarises the unit-root test outcomes, confirming that each variable is stationary in levels. None of the variables is integrated of order two I(2), thereby validating the use of the ARDL/NARDL framework. Wavelet coherence, which projects each series into the time–frequency domain independently of its integration order, remains fully applicable under these conditions. High-power regions observed at low frequencies (≥16 months) for the stationary series are accordingly interpreted as common low-frequency oscillations, without implying a formal cointegration relationship.

Table 2. Unit Root Test[1] ([1]L shows natural logarithms of all series have been taken; [2]Based on Schwartz Info Criterion; [3]Based on Bartlett Kernel)

	ADF[2]		PP[3]	
	Constant	**Constant and trend**	**Constant**	**Constant and trend**
LFTSEChina	-13.17	-13.129	-13.17	-13.128
LTVEPU	-5.98	-6.07	-12.68	-12.75
LUCT	-16.40	-16.35	-25.98	-26.58
LCWUI	-5.88	-6.12	-12.94	-13.06
LCPU	-5.16	-5.84	-5.31	-6.82

Table 3. Results of Bounds Testing Based on the NARDL Model for China

LFTSE China	Value	Signif.	I(0)	I(1)
F-statistic	8.028	%10	2.2	3.09
		%5	2.56	3.49

For Equation 2, the ARDL (4, 4, 4, 4, 4) specification yields an F-statistic of 8.028, exceeding the upper critical bounds at both the 5 % and 10 % levels. Hence, the null of no cointegration is rejected and H_1 is accepted, confirming that the variables are cointegrated. Accordingly, Table 3 evidences a pronounced long-run linkage among the model's variables.

The ARDL bounds-testing procedure is applied to gauge the long-run linkage between the FTSE China Index and four uncertainty measures: the AI Cable News–based Economic Policy Uncertainty Index (TVEPU), the US–China Tension Index (UCT), China's World Uncertainty Index (CWUI), and China's Climate Policy Uncertainty Index (CPU). The long-run estimate for LTVEPU is 0.00, positive and highly significant ($p < 0.01$), pointing to a mild upward influence on the stock index. Within the associated error-correction model, the ECM term is negative and significant, confirming a stable long-run equilibrium and the system's ability to return to that equilibrium after short-run shocks. The bounds test yields an F-statistic of 8.02, which exceeds the I(0) and I(1) critical values for both asymptotic and finite-sample distributions, thereby providing robust evidence of cointegration among the variables (Table 4).

Table 4. ARDL Long-Term Test Results

Variable	Coefficient	t-Statistic	Prob.
LCPU	5.73	0.36	0.71
LCWUI	0.0004	0.19	0.84
LTVEPU	0.000155	3.90	0.00
LUCT	-0.0214	-0.19	0.84
C	1.0184	9.29	0.00
[4]ECT_{t-1}	-1.27	-7.09	0.00
Diagnostic Test Statistics			
Breusch-Godfrey LM Testi Prob.			0.056
Heteroskedasticity Test: Breusch-Pagan-Godfrey Prob.			0.93
CUSUM Test			Stability

$$EC^4 = LFTSEChina - (5.73LCPU - 0.0214LUCT + 0.0004LCWUI + 0.000LTVEPU + 1.01)$$

Employing the NARDL specification (5, 0, 0, 0, 0, 3, 5, 1, 0) for Equation 2, the computed F-statistic of 5.12 surpasses the upper-bound critical values at both the 5 % and 10 % significance thresholds. Accordingly, the null of no cointegration is rejected and H_1 is upheld, confirming that the variables are cointegrated. Table 5 therefore documents a substantive long-run relationship among the model's variables. Using the NARDL approach, the symmetric effects of the AI Cable News-based EPU Index (TVEPU), the US-China Tension Index (UCT), China's World Uncertainty Index (CWUI), and China's Climate Policy Uncertainty Index (CPU) on LFTSE China have also been tested. The results of the NARDL model are presented in Table 6. Accordingly, from Table 6, the coefficient of the error correction term (ECT) falls within the accepted interval, ($-1 < ECT < 0$), and is statistically significant, which also indicates its statistical significance revealed by the ARDL model. According to Table 6, the coefficients of $LTVEPU^{poz}$ and $LTVEPU^{neg}$ are negative, indicating that the impact of negative shocks is more dominant. These coefficients are statistically significant.

Table 5. Bounds Test for NARDL Model

Dependent Variable: LFTSE China	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	5.12	%10	1.85	2.85
		%5	2.11	3.15

Table 6. NARDL Long-Term Test Results

Variable	Coefficient	t-Statistic	Prob.
$LCPU^{poz}$	0.0000	0.83	0.407
$LCPU^{neg}$	0.0000	1.18	0.239
$LCWUI^{poz}$	-0.0004	-0.30	0.759
$LCWUI^{neg}$	-0.0002	-0.14	0.887
$LTVEPU^{poz}$	-0.0590	-2.19	0.030
$LTVEPU^{neg}$	-0.0590	-2.19	0.030
$LUCT^{poz}$	-0.0553	-1.17	0.24
$LUCT^{neg}$	-0.058	-1.23	0.21
C	1.6753	2.97	0.003
[5]ECT_{t-1}	-1.153266	-7.44	0.00
Diagnostic Test Statistics			
Breusch-Godfrey LM Testi Prob.			0.181
Heteroskedasticity Test: Prob.			0.102
CUSUM Test			Stability

[5]EC = LFTSE China - ($0.0000*LCPU^{poz}+ 0.0000 *LCPU^{neg}-0.0004*LCWUI^{poz}-0.0002*LCWUI^{neg}0.0590 * LTVEPU^{poz}-0.0590*LTVEPU^{neg}-0.0553*LUCT^{poz}-0.0580*LUCT^{poz}+ 1.6753$)

Wavelet coherence maps indicate prominent dark-red clusters at the 16–64-month band, which reflect a high-power, in-phase co-movement between the tourism equity index and the CPU series. The clusters are encircled by white contour lines and occur above the 5 % significance level in 1 000 Monte Carlo permutations and therefore soundly reject the null of random association. Besides, the prevalence of right-pointing phase arrows indicates that CPU shocks lead those of the tourism index, and both series move in sync. Notably, both (i) the 2016 Paris Agreement carbon-neutral commitments and (ii) the 2021 Chinese passage of definite net-zero legislation triggered CPU spikes, establishing a persistent state of low-frequency oscillation. This suggests that investors embed the news on carbon-neutral policy immediately, writing regulatory uncertainty into long-horizon risk premia. These findings underlie evidence that uncertainty around climate policy acts not only as an environmental issue but also as a main driver of the financial sector (Broadstock et al., 2021). CPU accordingly emerges as a stable, forward-oriented, and economically relevant risk indicator for Chinese tourism equities that deserves open acknowledgment in strategic planning by industry operators. Because the regions encircled by white contours fall within the cone of influence, they are free from edge effects, while the grey-shaded outer areas are excluded from interpretation. This visual and statistical filtering confirms the robustness of the CPU–tourism coherence. Consequently, the wavelet analysis demonstrates that CPU constitutes a persistent, predictive, and economically significant risk factor for Chinese tourism equities. This risk hinges not only on the content of policy announcements but also on the continuity of regulatory uncertainty, and therefore warrants dedicated attention in strategic planning (Figure 1).

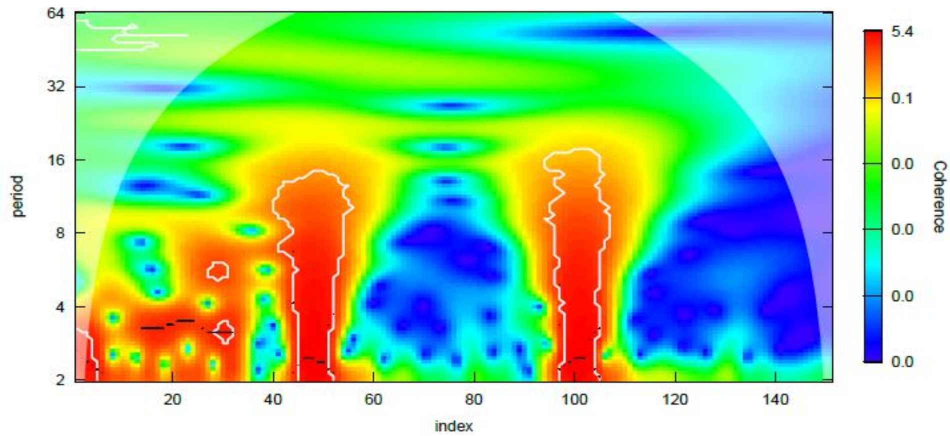


Figure 1. FTSE China and CPU (Note: Authors' wavelet calculations; data from Lee & Cho (2023) for CPU and Investing.com for the FTSE China a 600 – Travel & Leisure Index)

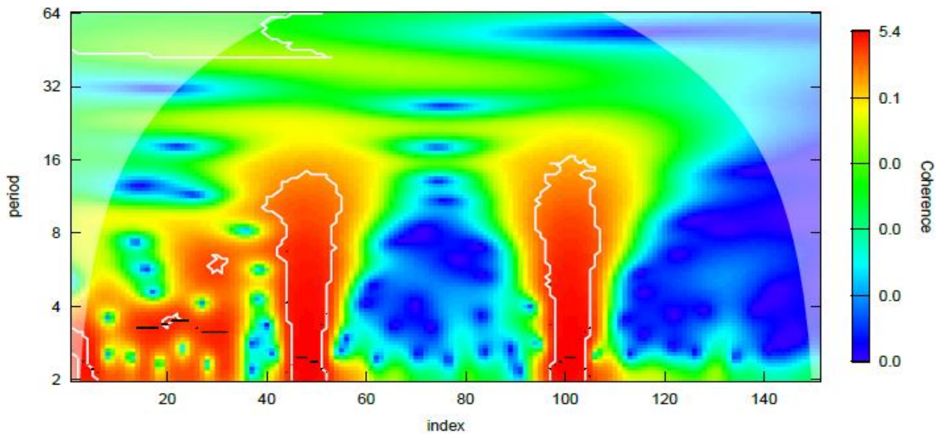


Figure 2. FTSE China and TVEPU (Note: Authors' wavelet calculations; data from Bergbrant & Bradley, 2022; Hong et al., (2021) for TVEPU and Investing.com for the FTSE China a 600 – Travel & Leisure Index)

In Figure 2, the wavelet coherence map shows robust warm-color clusters confined within the short-scale band (2–8 months), graphically emphasizing the relationship between the tourism equity index and TVEPU. White contour lines denote locations that exceed the 5 % significance level in a 1 000-permutation Monte Carlo test, thereby confirming that such clusters are not artifactual. The most powerful clusters coincide with spikes in news cycles—i.e., the mid-2015 Chinese stock market correction and early 2020 COVID-19 epidemic. The predominance of phase arrows directed down-right reveals two significant results: the vertical component (down) points toward TVEPU volatility preceding the tourism index by a –90° phase shift, i.e., policy uncertainty based on media triggers investor reactions virtually instantaneously; the horizontal component (to the right) points toward an out-of-phase oscillation, where rises in TVEPU signal contemporaneous falls in tourism returns (inverse correlation). This dynamic is consistent with the "news-based uncertainty–sentiment" channel documented in the finance literature (Baker et al., 2016). Temporary TVEPU shocks abruptly shatter investors risk perceptions, but their impact vanishes within a short while after news flow normalizes. Indeed, the absence of significant white-contoured clusters beyond 8 months (medium and long bands) is a testament to temporary, volatility-excitation dynamics of media-induced uncertainty shocks. The economic process is as such: TV reporting exposes political instability, lowering expectations of tourism consumption and travel planning and triggering panic stock price selling. During times of high policy uncertainty, market makers widen spreads and liquidity disappears, increasing volatility in tourism stocks.

This intraday surge in volatility triggers deleveraging of risk-sensitive portfolios; although this feedback mechanism has the potential temporarily to magnify shocks, it will typically decay over a quarter to half-year. Consequently, our wavelet analysis demonstrates that TVEPU is a powerful but transient adverse risk factor for Chinese tourism equities it does not produce a lasting impact on trends in the long run, but significantly boosts volatility when the economy encounters crisis.

While the linear ARDL estimate suggests that TVEPU exerts a statistically significant but economically negligible positive long-run effect on tourism returns, the NARDL decomposition reveals that negative uncertainty shocks ($LTVEPU^{-}$) dominate, with a coefficient of –0.059. This asymmetry is corroborated by the wavelet coherence patterns in the 2–8-month band, where phase arrows point down-right, indicating that media-driven uncertainty spikes provoke short-run sell-offs in tourism equities and accumulate into long-run value losses. The insignificance of positive shocks further supports the hypothesis that "bad news" exerts disproportionately stronger pricing power than "good news".

Based on Figure 3, a prominent concentration of high power represented by intense dark red areas appears exclusively within the 8–16-month scale range between the tourism stock index and the UCT series. These zones, outlined by white contour lines, surpass the 5% significance threshold as determined by a Monte Carlo test with 1,000 permutations, indicating that the observed relationship is statistically meaningful rather than coincidental. In terms of timing, the peaks within these clusters align with the 2018–2019 trade conflict and its aftermath, implying that the observed fluctuations are closely linked to specific periods of geopolitical tension. The phase vectors in this analysis reveal a symmetrical, bidirectional pattern. Arrows pointing downward to the left (UCT ↑ → Tourism ↑/↓ reacting later) suggest a delayed impact of geopolitical tension, implying that the tourism market initially absorbs the flow of information and reflects it in prices over the following quarters. Conversely, arrows pointing upward to the left (Tourism ↑/↓ leading → UCT) indicate that, in certain periods, investors may have anticipated future volatility in the UCT, engaging in expectation-based pricing thus positioning the tourism index as a potential early indicator of geopolitical stress. This dual-phase behavior gives rise to a recurring "feedback loop" within approximately 12 to 18-month cycles. The initial shock, triggered by the announcement of tariffs, distorts expectations for tourism revenues. In turn, reduced travel flows and currency volatility exert pressure on tourism-related stocks. Depressed stock prices and potential lobbying efforts from the tourism sector may subsequently prompt diplomatic efforts. As a result, a reciprocal causality emerges between the tourism index and the UCT.

The statistical robustness of the white-contoured regions—located within the cone of influence and unaffected by edge effects confirms that this mechanism operates not as a short-term anomaly but as a consistent medium-term dynamic. In sum, the wavelet findings suggest that the UCT functions as a medium-horizon, cyclical, and bidirectional risk factor for Chinese tourism stocks, revealing a mutually reinforcing interaction between investor sentiment and geopolitical tensions.

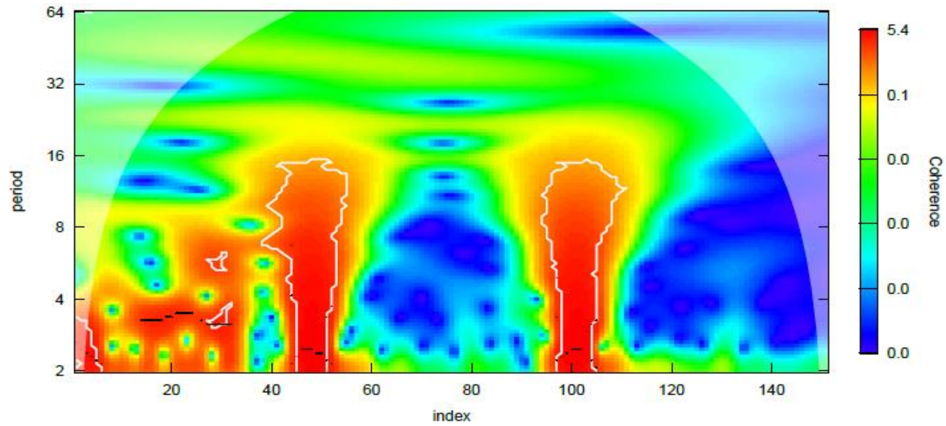


Figure 3. FTSE China and UCT (Note: Authors' wavelet calculations; data from Rogers et al. (2024) for UCT and Investing.com for the FTSE China A 600 – Travel & Leisure Index)

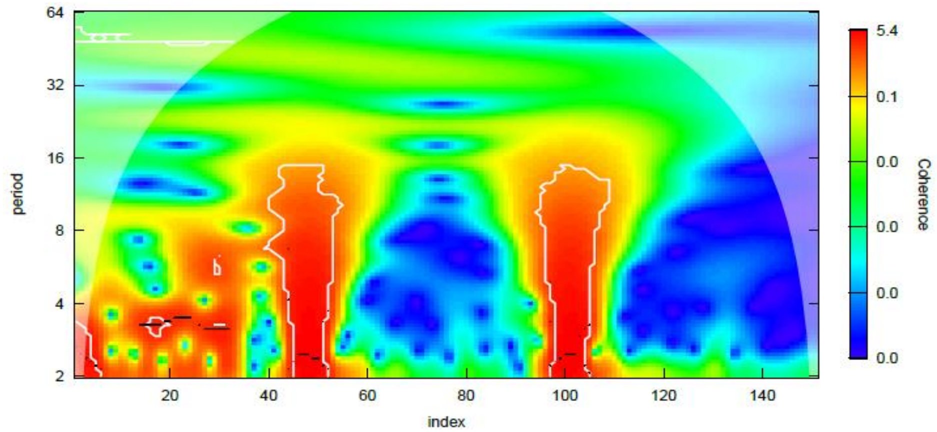


Figure 4. FTSE China and CWUI (Note: Authors' wavelet calculations; data from Ahir et al., (2018) for CWUI and Investing.com for the FTSE China a 600 – Travel & Leisure Index)

Figure 4 illustrates the relationship between the tourism stock index and the China-specific World Uncertainty Index (CWUI) across two distinct frequency bands. First, in the short-term range of 2–8 months, extensive and uninterrupted clusters of warm colors are evident, aligning with episodes such as the 2015 global growth concerns, the 2018 Fed balance sheet tightening rhetoric, and the initial shock of COVID-19 in 2020. These clusters, enclosed within white contour lines, surpass the 5% significance level based on a 1,000-permutation Monte Carlo simulation, indicating that the observed volatility in tourism stocks during periods of rising global uncertainty is not a random occurrence. The phase arrows predominantly point to the upper-right, suggesting that increases in the CWUI tend to lead movements in the tourism index and are in-phase, reflecting a positive correlation—i.e., as global risk appetite weakens, investors simultaneously withdraw from tourism equities. Second, in the medium-term band of 16–32 months, significant clusters appear during periods such as the 2016–2017 trade policy uncertainty and the post-2021 stagflation recovery phase. These areas are also statistically significant within the white contour lines, with phase vectors again directed to the upper-right. This indicates that the CWUI not only triggers short-term disruptions but also contributes to sustained co-movements in the tourism sector over cycles lasting approximately 1.5 to 2.5 years. The findings highlight that Chinese tourism stocks exhibit multi-scale sensitivity to developments such as shifts in global monetary policy (e.g., Fed tightening cycles) and pandemic-related or supply-chain disruptions.

In conclusion, the CWUI emerges as a systematic and multi-scale risk factor for Chinese tourism equities, exerting persistent pricing influence both through short-lived global news shocks and broader macro-financial cycles. As such, it should be considered an independent dimension of uncertainty in strategic portfolio construction and policy design.

2. The US

The unit root tests (Table 7) indicate that all variables are either I(0) or I(1), with none found to be I(2); this validates the suitability of employing ARDL and NARDL modeling approaches. Since wavelet coherence analysis operates independently of integration order, the stationarity characteristics of the series do not restrict its application.

Strong coherence regions observed in the longer time scale (≥16 months) are interpreted as shared low-frequency oscillations, without asserting any formal cointegration relationship. Under the ARDL (6, 0, 4, 1, 0) framework for Equation 3, the computed F-statistic of 8.37 exceeds the upper-bound critical thresholds at both the 5 % and 10 % significance levels. Accordingly, the null of no cointegration is rejected and H_1 is upheld, confirming that the variables are cointegrated and maintain a meaningful long-run equilibrium (Table 8). The ARDL bounds analysis assesses the long-run connection between the DJUSTT index and four uncertainty measures TVEPU, UCT, UWUI, and UCPU.

In the long-run estimates, the UCT coefficient is 0.4492 (p = 0.02), indicating a significant positive effect on DJUSTT. The error-correction term for Equation 3 is –0.96, negative and highly significant, confirming a stable equilibrium and showing that deviations are swiftly corrected. The computed F-statistic of 8.37 surpasses the I(0) and I(1) critical thresholds for both asymptotic and finite samples, thereby substantiating cointegration among the variables (Table 9).

Table 7. Unit Root Test[1] ([1]L shows natural logarithms of all series have been taken; [2]Based on Schwartz Info Criterion; [3]Based on Bartlett Kernel

Variables	ADF[2]		PP[3]	
	Constant	Constant and trend	Constant	Constant and trend
LDJUSTT	-6.27	-6.80	-11.63	-11.99
LTVEPU	-5.98	-6.07	-12.68	-12.75
LUCT	-16.40	-16.35	-25.98	-26.58
LUWUI	-12.37	-12.39	-12.38	-12.39
LUCPU	-17.35	-17.30	-20.56	-20.52

Table 8. Bounds Test for ARDL Model

Dependent Variable: LDJUSTT	Value	Signif.	I(0)	I(1)
F-statistic	8.37	%10	2.2	3.09
		%5	2.56	3.49

Table 9. ARDL Long-Term Test Results

Variable	Coefficient	t-Statistic	Prob.
LTVEPU	0.0021	0.40	0.68
LUCT	0.4492	2.22	0.02
LUWUI	-0.0005	-1.43	0.15
LUCPU	-0.0287	-1.32	0.18
C	0.5770	2.82	0.00
[4]ECT_{t-1}	-0.961940	-7.23	0.00
Diagnostic Test Statistics			
Breusch-Godfrey LM Testi Prob.			0.0670
Heteroskedasticity Test			0.1261
CUSUM Test			Stability

[4]EC = DJUSTT - (0.0021*LTVEPU + 0.4492*LUCT -0.0005*LUWUI -0.0287*LUCPU + 0.5771)

Using the NARDL specification (6, 0, 2, 4, 4, 0, 4, 0, 1) for Equation 3 produces an F-statistic of 7.10, which exceeds the upper-bound critical thresholds at the 5 % and 10 % significance levels.

Hence, the null of no cointegration is rejected and H_1 is upheld, establishing that the variables are cointegrated. Table 10 therefore highlights a robust, long-run connection among the model's variables.

Table 10. Results of Bounds Testing Based on the NARDL Model for UD

LDJUSTT	**Value**	**Signif.**	**I(0)**	**I(1)**
F-statistic	7.10	%10	1.85	2.85
		%5	2.11	3.15

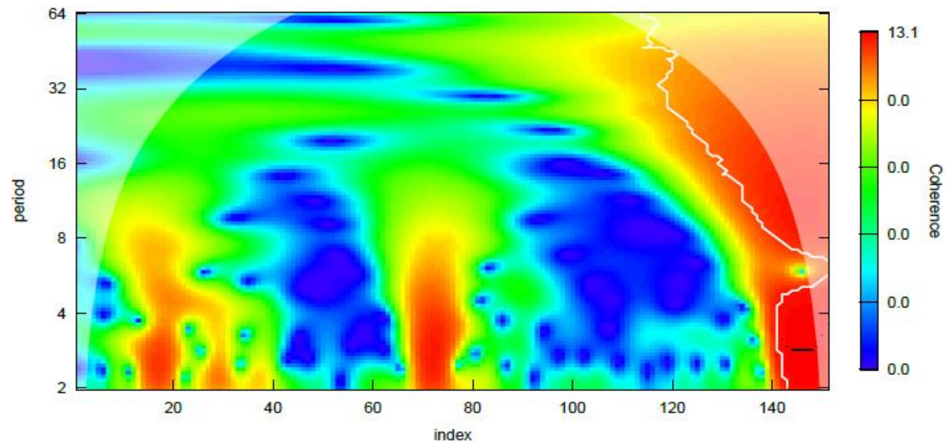
Table 11. NARDL Long-Term Test Results

Variable	Coefficient	t-Statistic	Prob.
$LTVEPU^{poz}$	0.0035	0.86	0.38
$LTVEPU^{neg}$	0.0058	1.38	0.16
$LUCT^{poz}$	0.4154	2.42	0.01
$LUCT^{neg}$	0.4008	2.36	0.02
$LUWUI^{poz}$	-0.0001	-0.76	0.44
$LUWUI^{neg}$	-0.0002	-0.81	0.41
$LUCPU^{poz}$	-0.0495	-2.24	0.02
$LUCPU^{neg}$	-0.0456	-2.15	0.03
C	1.0705	28.97	0.00
[5]ECT_{t-1}	-1.27	-8.78	0.00
Diagnostic Test Statistics			
Breusch-Godfrey LM Testi Prob.			0.3912
Heteroskedasticity Test			0.3021
CUSUM Test			Stationary

[5]EC = DJUSTT - (0.0035*$LTVEPU^{poz}$+ 0.0058*$LTVEPU^{neg}$+ 0.4154 *$LUCT^{poz}$+ 0.4008*$LUCT^{neg}$-0.0001* $LUWUI^{poz}$-0.0002 *$LUWUI^{neg}$-0.0495*$LCPU^{poz}$-0.0456*$LCPU^{neg}$+ 1.0705)

Using the NARDL approach, the symmetric effects of the AI Cable News-based EPU Index (TVEPU), the US-China Tension Index (UCT), US World Uncertainty Index (UWUI), and US Climate Policy Uncertainty Index (UCPU) on LDJUSTT have also been tested. The results of the NARDL model are presented in Table 11. Accordingly, from Table 14, the coefficient of the error correction term (ECT) falls within the accepted interval, ($-1 < ECT < 0$), and is statistically significant, which also indicates its statistical significance revealed by the ARDL model. According to Table 11, the coefficients of $LUCT^{poz}$ and $LUCT^{neg}$are positive indicating that the impact of positive shocks is more dominant. $LUCPU^{poz}$ and $LUCPU^{neg}$ negative, indicating that the impact of negative shocks is more dominant. These coefficients are statistically significant.

In the wavelet coherence map between the U.S. tourism stock index and the Climate Policy Uncertainty (CPU) index, notable clusters of warm colors appear exclusively within the 8–32 month scale band. The white contour lines confirm that these clusters are statistically significant at the 5% level based on Monte Carlo simulation. The concentration of these high-coherence regions corresponds with two key periods: the aftermath of the 2016 Paris Agreement's entry into force and the 2021–2022 period when the "Clean Energy for America" package was under legislative consideration in Congress. The phase arrows predominantly point to the upper-right, suggesting that increases in CPU tend to lead the movements of the tourism index and that both series move in-phase with a positive correlation—indicating that as regulatory uncertainty rises, tourism stocks are simultaneously and negatively repriced. Unlike the China case, no statistically significant clusters are observed in the longer 32–64 month band, implying that U.S. markets absorb climate-related uncertainty over a more intermediate time horizon. This finding suggests that in the U.S. tourism sector, the risk premium associated with climate policy is priced not through prolonged structural shifts, but rather through medium-term (1–3 year) cycles. During periods of intensified regulatory discourse—specifically in 2016–2017 and 2021–2022—rising CPU likely disrupted investment planning horizons, prompting hotel, airline, and cruise operators to revise cash flow projections. This uncertainty manifested in upward revisions of equity risk premiums and higher borrowing costs, leading to a decline in the index that was simultaneous with CPU spikes but confined to a limited frequency band (Figure 5).



.Figure 5. DJUSTT and UCPU (Note: Authors' wavelet calculations; data from Gavriilidis, (2021) for UCPU and Investing.com for the Dow Jones Travel & Leisure Index)

The wavelet coherence map between the TV-based Economic Policy Uncertainty Index (TVEPU) and the U.S. tourism stock index reveals prominent clusters of warm colors solely within the 2–8 month frequency band. The presence of white contour lines confirms that these regions exceed the 5% statistical significance threshold based on a 1,000-permutation Monte Carlo test. The peaks of these clusters align with two major episodes: the heightened media focus on China's economic slowdown in 2015 and the first quarter of 2020, when COVID-19 began to spread within the United States. The distinct orientation of phase arrows—pointing to the lower-right—conveys two critical insights. First, the rightward direction indicates that fluctuations in TVEPU precede changes in the tourism stock index, suggesting that uncertainty signals emerging from television news coverage are quickly transmitted to the market. Second, the downward tilt reveals that the two series move in opposite phases: as TVEPU increases, tourism stock returns simultaneously decline. This negative correlation highlights how news-driven uncertainty shocks can exert immediate pressure on investor sentiment, although the effect is temporally confined. The disappearance of statistically significant clusters beyond the 8-month scale confirms that TVEPU primarily acts as a short-term volatility trigger rather than a source of sustained influence. In summary, wavelet analysis identifies TVEPU as a risk factor that imposes sharp but short-lived downward pricing pressure on U.S. tourism stocks, without altering long-term market trajectories (Figure 6).

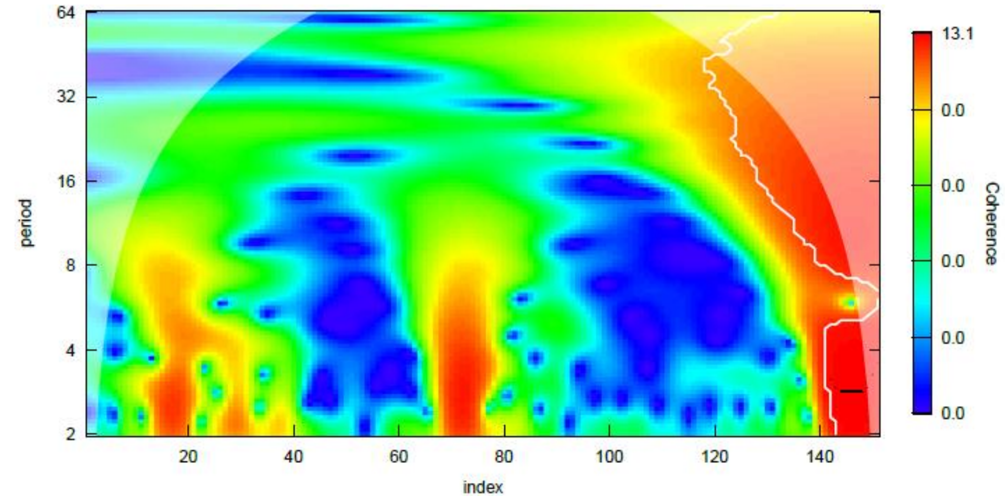


Figure 6. DJUSTT and TVEPU (Note: Authors' wavelet calculations; data from Bergbrant and Bradley, 2022; Hong et al., (2021) for TVEPU and Investing.com for the Dow Jones Travel & Leisure Index)

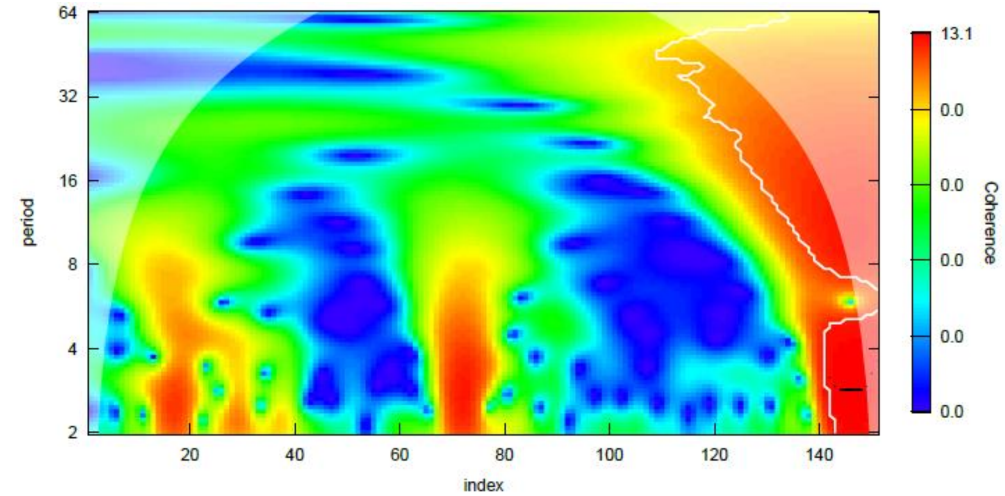


Figure 7. DJUSTT and UCT (Note: Authors' wavelet calculations; data from Rogers (2024) for UCT and Investing.com for the Dow Jones Travel & Leisure Index)

The wavelet coherence map between the U.S. tourism index and the UCT reveals concentrated clusters of warm colors confined to the 8–16 month scale band. White contour lines confirm that these clusters surpass the 5% significance threshold based on 1,000 Monte Carlo permutations. The peaks of these clusters align precisely with the 2018–2019 tariff conflict and subsequent negotiation rounds, indicating that the observed fluctuations are closely tied to concrete geopolitical tensions. Phase arrows in this segment are distributed in both upper-left and lower-left directions. Arrows pointing to the upper-left suggest that during certain sub-periods, the tourism index anticipated future increases in UCT, reflecting an expectations-driven pricing channel. In contrast, arrows directed to the lower-left indicate that UCT shocks had a lagged, downward effect on the index, pointing to a realized shock transmission mechanism.

This bidirectional phase pattern gives rise to a feedback pricing cycle, recurring in roughly 12- to 18-month intervals and involving mutual causality between the two series. Compared to the broader frequency coverage observed in the

Chinese tourism index (8–16 months plus 16–32 months), the U.S. case is more narrowly concentrated. As geopolitical tensions subside, the statistically significant coherence zones quickly dissipate. Once the wave intensity fades, markets appear to digest the flow of information, and UCT-induced shocks gradually revert to the mean (Figure 7).

An analysis of Figure 8 reveals that the wavelet coherence output between the U.S. tourism stock index and the U.S.-origin World Uncertainty Index (UWUI) displays broad and continuous clusters of warm colors across two distinct frequency bands—2–8 months (short term) and 16–32 months (medium term). Both bands are enclosed by white contour lines and exceed the 5% significance level based on 1,000-permutation Monte Carlo testing, indicating that the influence of global uncertainty shocks on tourism stocks is statistically meaningful and not due to chance.

Phase vectors consistently point to the upper-right, suggesting that increases in UWUI precede movements in the tourism index and that the two series oscillate in-phase—demonstrating a positive correlation. This implies that when global uncertainty rises, investors tend to exit tourism-related assets simultaneously. The short-term coherence clusters align with the 2018 Federal Reserve rate hike cycle, marked by tightening global liquidity, and the initial shock of the COVID-19 pandemic in early 2020. Meanwhile, the medium-term clusters correspond to the 2020–2021 variant-driven waves and the aggressive Fed tightening measures of 2022. In contrast to the Chinese case—where UWUI influence extends into the 32–64 month range the absence of statistically significant coherence in the U.S. market beyond 32 months suggests that global shocks are digested more rapidly, with prices returning to equilibrium in the longer term.

This distinction aligns with the United States' status as a global financial hub and its strong information-processing capacity. In summary, the UWUI emerges as a multi-scale but relatively short-lived uncertainty driver for U.S. tourism equities. While it exerts pronounced pricing pressure in the short and medium term, its impact statistically dissipates beyond the 32-month horizon. This highlights the U.S. market's ability to swiftly absorb and reprice global shocks and underscores the need for investors to adjust their risk management horizons according to the nature of the uncertainty faced.

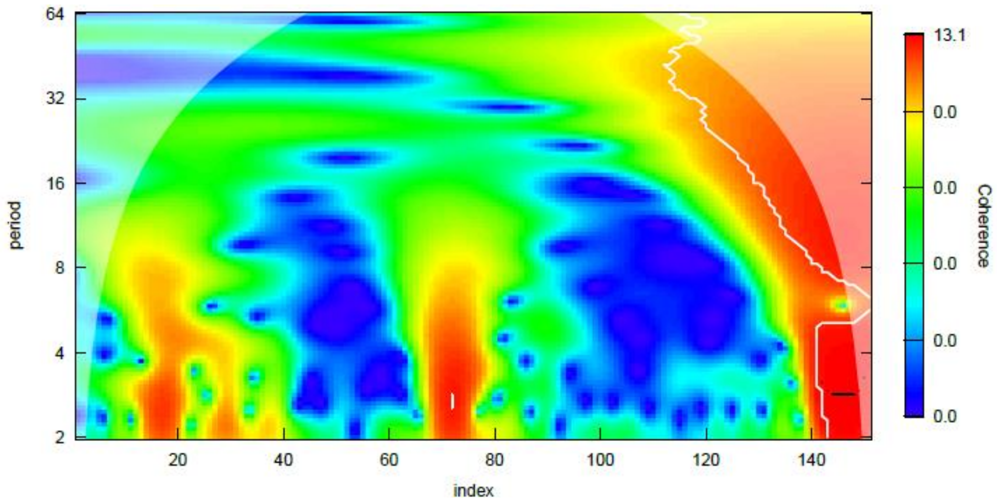


Figure 8. DJUSTT and UWUI (Note**:** Authors' wavelet calculations;
data from Ahir et al., (2018) for UWUI and Investing.com for the Dow Jones Travel & Leisure Index)

CONCLUSİON AND RECOMMENDATİONS

This study introduces a multi-layered analytical framework that integrates level-asymmetric ((N)ARDL) and time–frequency (wavelet) methods to assess how various uncertainty shocks impact tourism equity performance in China and the United States. Three key findings emerge:

First, the existence of a differentiated long-run risk premium across sources of uncertainty. Although both markets exhibit cointegration, China's tourism stocks respond mildly to media-based uncertainty (TVEPU), while geopolitical (UCT) and climate-policy (CPU) effects are statistically weak. In contrast, U.S. tourism equities demonstrate a strong positive long-run linkage with UCT, implying that geopolitical tension commands a structural risk premium.

Second, asymmetric behavioral responses are evident. In China, negative TVEPU shocks have a stronger impact than positive ones, highlighting the market's vulnerability to fear-driven sentiment. In the U.S., positive UCT shocks—indicative of geopolitical de-escalation are priced favorably, consistent with institutional investors interpreting tension relief as a buying opportunity. Third, the wavelet analysis unveils frequency-specific and directionally heterogeneous shock transmission. In China, TVEPU produces short-term inverse co-movements (2–8 months), whereas CPU induces persistent long-cycle synchronization (16–64 months). For the U.S., UCT dominates the 8–16-month band with a bidirectional phase pattern, while UWUI exerts a two-tiered impact that fades beyond the 32-month threshold.

These results suggest tailored policy and investment responses. In China, regulatory transparency and fast-response pricing campaigns may help offset media-driven sentiment shocks. CPU's long-horizon effect implies that green bonds and sustainable infrastructure can act as cost-efficient hedging mechanisms. In the U.S., UCT-related geopolitical cycles call for portfolio diversification and derivative-based hedging. The multi-band sensitivity to UWUI in both countries suggests that tourism firms should maintain flexible liquidity buffers and dynamic credit lines. Overall, this study contributes to the literature by mapping the heterogeneous, source-specific, and frequency-dependent architecture of uncertainty risk in tourism finance, offering both methodological innovations and actionable insights for policy and investment design. Despite its comprehensive scope, this study is subject to several limitations.

First, the analysis relies on monthly data, which may not capture high-frequency volatility or intraday market reactions to uncertainty shocks.

Second, the uncertainty framework is limited to four indices; other dimensions such as financial stress, pandemic-related uncertainty, or social sentiment indicators remain unexplored.

Third, the tourism equity indices employed represent broad sector aggregates, preventing disaggregated insights across subsectors like hotels, airlines, and leisure services.

Future research could address these gaps by employing higher-frequency data to examine short-run volatility transmission mechanisms, decomposing the tourism sector into sub-industries to uncover differentiated risk sensitivities, and exploring nonlinear causal networks among multiple uncertainty indicators using advanced econometric tools such as time-varying Granger causality or machine learning-based forecasting models.

Author Contributions: Conceptualization, Ö.D., N.I.D.; methodology, Ö.D., N.I.D. and M.O.; software, Ö.D., N.I.D. and M.O.; validation, Ö.D., N.I.D. and M.O.; formal analysis, Ö.D., N.I.D. and M.O.; investigation, Ö.D., N.I.D.; data curation, Ö.D., N.I.D. and M.O.; writing—original draft preparation, Ö.D., N.I.D. and M.O.; writing—review and editing, Ö.D., N.I.D. and M.O.; visualization, Ö.D., N.I.D. and M.O.; supervision, Ö.D., N.I.D. and M.O.; project administration, Ö.D., N.I.D. and M.O. All authors have read and agreed to the published version of the manuscript.

Funding: Not applicable.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study may be obtained on request from the corresponding author.

Acknowledgements: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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Article history: Received: 19.09.2025 Revised: 12.01.2026 Accepted: 28.03.2026 Available online: 08.05.2026