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Full Length Article

US-China geopolitical tensions and Indian stock market dynamics: evidence from NARDL and wavelet coherence

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ABSTRACT

The geopolitical tension between China and the United States have increasingly shaped global financial markets; the exact impacts on emerging economies like India remain poorly explored. This study examines the impacts of changes in US-China tension on the Indian stock market based on the use of nonlinear Autoregressive Distributed Lag (NARDL) modeling and wavelet coherence analysis. With monthly observations and the newly developed U.S.-China Tension Index (UCT), the study finds asymmetric short-run effects: heightened tensions are likely to dampen sentiment and reduce returns, whereas reduced tensions offer limited relief. Interest rates are a key determinant in both the short run and long run, underscoring their inherent role in determining capital flows. Wavelet analysis captures a change in the nature of the relationship, from persistent co-movement in the early period to more prompt, temporary responses in subsequent years. These results underscore the growing significance of geopolitical attitudes to market action, especially for economies that are increasingly open to international capital flows.

The novelty of the paper arises from the application of a novel geopolitical risk metric (UCT) to an untapped economy (India) through a hybrid econometric-time-frequency method that captures hitherto unseen asymmetric and dynamic market responses.

Introduction

US-China tensions lie at the heart of determining global equity markets through the impact on economic growth, investor sentiment, and sectoral trends. Being the world's two largest economies, the evolution of their bilateral relationship, including trade wars, export bans, diplomatic moves, and military deployments, has spillover effects on global supply chains and capital flows, which subsequently influence companies one or two steps away from direct US-China tensions exposure [14]

Investor attitudes also fall with higher political uncertainty around the globe, making individuals more cautious to risk elsewhere and in other investments [10] Policy makers, investors, and large corporations closely observe Chinese and American diplomatic moves, trade negotiations, and Chinese and American policy shifts today. The technology and chip sectors are particularly vulnerable since they have globally networked supply chains, intellectual property concerns, and they are highly valuable assets, thus they are among the most vulnerable to increasing geopolitical tensions [6] The emerging nations and commodity-exporting nations are also more volatile since they respond to shifts in Chinese demand and changes in global trade flows [13]

This study pioneers the application of the U.S.–China Tension Index (UCT) to simulate and empirically analyze the impacts of geopolitical tension on stock markets. Developed by [14], the UCT index quantifies rising bilateral tension using text-based analysis of leading U.S. newspaper coverage. It classifies articles by whether they mention the U.S. and China, include contentious bilateral issues, and express sentiment indicative of tension, thus offering a validated, high-frequency measure tied closely to business-person and policy-maker perceptions. Higher UCT levels are empirically linked with lower U.S. corporate investment, especially by firms heavily exposed to China, and observable changes in supply chain arrangements away from China. Such effects are pre-trade-war, with uncertainty about future bilateral activity being more disturbing than de facto barriers themselves.

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In financial markets, the index manifests as cross-sectional patterns of stock returns, in accordance with investor expectations of shrinking economic opportunities at times of increased tension.

In addition, subsequent studies using methods such as time-varying quantile Granger causality and DCC-GARCH-MIDAS modeling indicate that UCT shocks significantly increase volatility and induce asymmetric co-movements among the equity markets of the United States and China situations that are easily observed in technology-centered and small-cap industries [20]

Overall, in applying the UCT index to macro-financial modeling, this research makes a methodological contribution by providing more accurate and detailed insight into how geopolitical tension is being converted into economic and financial market dynamics. It improves forecasting and risk analysis in an ever-changing world in which economic and financial market dynamics are becoming increasingly geopolitically motivated.

The Trend of Us-China Tension Index Post Liberalisation

Diagram 1 shows the evolution of the US-China Tension Index over three decades. Overall, the US-China tension index has steadily increased over time. There are significant rises in 2008, 2018, 2020, and 2022. These increases can be attributed to ongoing trade wars and geopolitical uncertainties. The 2008 rise was spurred by diplomatic tensions during the Subprime Crisis, and the substantial increase corresponds to the deepening of the US-China trade war. The 2020 peak is most likely due to tensions related to the COVID-19 pandemic. The peak in 2022 might be attributed to increased military rhetoric against Taiwan and the implementation of harsher technology export rules. Fig. 1.

Despite the observed changes, the constant raising of the index's baseline suggests that tensions have become more entrenched over time, rather than being episodic. This pattern reflects a structural shift in US-China ties, from one of collaboration to one of strategic competition.

Literature Review

Several studies have directly assessed the bilateral impact of US-China trade tensions on the stock markets of both countries. Using network-based models, [3] showed how the conflict leads to a weakening of cross-country market links and strengthens intra-country market clusters, indicating rising financial decoupling.

[12] employed time-varying quantile granger causality method and found that Chinese stock markets exhibited better reactivity to US-China tension (UCT). Furthermore, evidence revealed that the UCT's impact on Chinese stock markets was steadily growing and demonstrates notable time-varying characteristics and the asymmetric feature is evident in the US stock market's delayed reactions to worsening ties and greater susceptibility to good news about US-China relations.

[19] demonstrated how tensions between China and the US impacted the relationship between their stock markets and to what extent prices fluctuate through a DCC-DAGARCH-MIDAS model. The findings indicate that heightened tension increases the degree of return volatility changes, and the impacts of the trade war are realized sooner.

Another section of literature examines the uncertainty channel through the impact of uncertain policies on market responses [7] employed a trade policy uncertainty (TPU) index to link uncertainty during trade disputes with greater volatility in the market and lower Chinese stock returns [1] and [4] extend this concept further by demonstrating that markets respond more to words and announcements than to policy changes themselves. This indicates that words and signals are playing a greater role in the functioning of markets. This concept is evidenced by "Do words hurt more than actions?", demonstrating that threats in words and public comments can lead to sharp market declines even without the existence of actual policy changes.

[2] applied a TVP-VAR model (Time-Varying Parameter Vector Autoregression) to analyze the sensitivity of emerging market stock market returns, particularly in Asia, to US and China shocks. They affirmed that US shocks are more powerful and long-lasting than those of China, and the magnitude and direction of the shocks vary over time, particularly in times of crises [5] quantified China-US trade tensions with the application of machine learning. Their result was not sensitive to changes in global financial markets and was concurrent with extensively documented events in the US-China trade war. Local forecasts indicated that increasing trade tensions had a negative effect on stock market indices and exchange rates in China and emerging economies, but primarily did not influence US markets, except for firms more integrated with China [15], with the example of Turkey's Borsa Istanbul, affirmed that there exists a long-run relationship between Turkish stock prices and US-China trade shocks, revealing substantial third-party exposure [9] also analyzed further how stock market interlinkages increase worldwide during peak periods of the trade war, suggesting threats of far-reaching impacts.

Research such as [11] extends the context by examining the dynamics of exchange rate movements and stock market performance, particularly in the case of triangular economies like India. They show that exchange rate movements serve to disperse the effect of trade shocks on home markets, particularly in the context of countries with strong export sectors or foreign investment.

[8] elaborates that trade tensions are not merely economic phenomena; they are reflections of forms of strategic geopolitical re-alignment. Works such as "The Changing Fundamentals of US-China

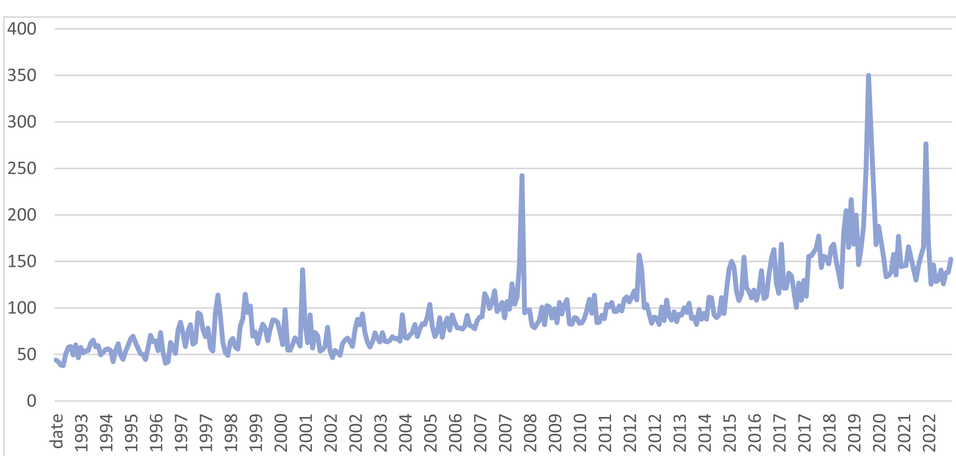

Fig. 1. Trend of US-China Tension.
Source: Author's Own

Relations" and "Is Globalisation Dead?" locate the trade war in the larger context of multilateralism and globalist pullback, which have far-reaching ramifications for global supply chains, investments, and decoupling patterns. These works emphasize the need to understand financial market responses in terms of dynamics of changing global power relations, and not just economic variables.

Despite widespread coverage, there are very few papers that have studied India. There is one paper [11] that covers India as a part of a model with two other economies but does not study how the Indian stock market responds to US-China tensions when India is economically and strategically important. The US-China trade tensions papers tell us about their influence on finance markets in the shape of volatility, uncertainty, contagion, and changes in geopolitical alignments. But there is a stark lack of papers on large non-aligned emerging economies like India, which need to be studied more intensely because they are becoming more and more part of global capital markets and foreign trade.

The study proposes the following testable hypothesis:

H1. US-China tension has a significant influence on the Indian stock market.

H2. Positive and negative changes in US-China tension index have asymmetric effect on the Indian stock market.

H3. The linkage between US-China tension and Indian stock market is time-varying and frequency-dependent.

Data and Methodology

This research uses monthly time-series data over 360 observations, from January 1993 to December 2022, to examine the effect of US-China geopolitical tensions on the Indian stock market. The major dependent variable is the Bombay Stock Exchange (BSE) Index that reflects the Indian equity market. The major explanatory variable is the US-China Tension Index (UCT) constructed by [14], which is a media-based measure of the intensity and frequency of bilateral tensions between the two countries. The data relating to US-China tension index is sourced from https://www.policyuncertainty.com/US_China_Tension.html.

Other control variables are as follows:

Exchange Rate (EXR) - INR/USD, to reflect currency movements and their effect on capital flows as well as investor sentiment.

Interest Rate (INT) - Defined by the Weighted Average Call Rate, reflecting domestic liquidity and borrowing cost.

Wholesale Price Index (WPI)- is an inflationary trend and cost pressures indicator.

India Geopolitical Risk Index (GPR_IND) -A measure of geopolitical risk for India that reflects local political uncertainty.

All series are log-transformed to ensure constancy of variance and facilitate elasticity-based interpretation.

In order to thoroughly investigate the impact of tensions between the United States and China on the Indian stock market, the present study utilizes a dual-methodological framework that combines the Non-Linear Autoregressive Distributed Lag (NLARDL) model and the Wavelet Coherence method. The NLARDL model allows the estimation of asymmetric long-run and short-run relationships between the Indian stock market and the corresponding explanatory variables. This technique is specifically useful in following the non-linear and possibly divergent transmission of positive and negative shocks in a multiple-variable setting. The Wavelet Coherence method also allows for a time-frequency decomposition of the co-movements among the variables. This method provides dynamic visualization of how the relationship between US-China tensions and the Indian stock market varies over different time horizons and frequencies, thereby determining times of high or low correlations and lead-lag relations. Utilizing these methodologies together, the study follows both the structural (long-run equilibrium and asymmetries) and temporal (time-varying co-movement) dimensions of the relationship, therefore providing rich and comprehensive understanding of the transmission of geopolitical tensions across borders to influence financial markets.

The NLARDL (Non-Linear Autoregressive Distributed Lag), developed by [16], methodology is an econometric approach used to analyze the relationship between time series variables, particularly in the context of cointegration and long-run equilibrium. It extends the traditional Autoregressive Distributed Lag (ARDL) model by allowing for non-linear relationships among variables, making it particularly useful in economic and financial studies where the effects of shocks can vary over time. The model typically includes both positive and negative changes of the independent variables to capture asymmetry.

In the present study, we intend to capture the asymmetric effect of US-China tension on Indian stock market in a multivariate framework. Thus, the functional relationship can be expressed as below:

$$BSE = f(EXR, WPI, INT, GPR - IND, UCT_{+}, UCT_{-})$$

The wavelet coherence method developed by [17] enables one to compute cross-wavelet power and therefore identify regions with higher covariance of time series variables across scales. The wavelet coherence confirms the periods during which co-movement of time series variables can be identified even though it is linked to low wavelet power. We adopt the method developed by [18], an extension of the method developed by [17]

The result of a cross-wavelet coherence analysis generally appears in the form of a graphical display comprising five main components: black arrows with eight direction marks (←, →, ↑, ↓, ↘, ↗, ↙, ↖), warm and cold color maps, black contours, two coordinate axes, and the cone. The right-pointing arrows (→) and left-pointing arrows (←) represent an in-phase and an out-of-phase relationship, respectively, and this is synonymous with positive and negative correlations. The up-right-pointing arrows (↗) and down-left-pointing arrows (↙) represent that the first and the second series have a leading effect, respectively. For example, in the wavelet coherence plots, the '↘' pointing black arrows represent an in-phase relationship or positive comovement of the two-time series, with the second time series having a leading effect. On the other hand, the '↖' pointing black arrows represent an out-of-phase relationship or negative comovement of the two-time series, with the first time series leading. A phase difference of zero means that both time series are moving in tandem. The black curves exhibited in the plots represent areas where the coherence is statistically significant at the 5% level, and the solid white bell-shaped line in the wavelet coherence plots represents the cone of influence.

The present study is guided by Evaluatology framework. Rather than solely relying on statistical significance, the framework focuses on effect isolation, incremental information validation and performance comparison. Thus, the research design of the present study is not only to estimate the linkage but also to evaluate whether US-China tension add significant information and predictive content beyond traditional domestic macroeconomic determinants of the Indian stock market.

One of the core principles of the Evaluatology framework is effect isolation of the phenomenon under investigation. Thus, the analysis first specifies a baseline model which consists of domestic macroeconomic variables. This model serves as a benchmark representation of the dynamics of Indian stock market in the absence of external geopolitical factor. In the second stage, the US-China tension index is included to form the augmented model to see whether the addition alters the estimated dynamics and strengthens explanatory power of the model. In doing so, the research moves beyond correlation assessment and evaluates the incremental contribution of the US-China tension.

Evaluatology also stresses that effects in complex system may be asymmetric and context dependent. Stock markets respond differently to adverse and favorable shocks. Following this principle, we employ the NARDL model which allows the decomposition of the tension index into positive and negative components.

Results

Table 1 show the descriptive statistics of the variables in the study, which covers 360 months of data. The BSE index averaged around 17,196, but it jumped around a lot, from a low of 2,122 to a high of 63,100. This indicates that the Indian stock market grew extensively but also witnessed turbulent periods during the period. The exchange rate (EXR) varied a bit, averaging 51.14, and ranging from 31.20 to 82.77. This shows that the Indian rupee has generally lost value against the USD over time.

The interest rate (INT), which we measured using the weighted average call rate, had a big range (0.73 to 34.83). It also had high skewness (3.53) and kurtosis (25.11), which means it doesn't follow a normal distribution and might have some outliers. These outliers are possibly due to high liquidity rates during crisis periods. The wholesale price index (WPI) averaged 610.3. Its skewness and kurtosis were mild, suggesting inflation was relatively stable compared to the other variables. The India-specific geopolitical risk index (GPR_IND) and the US-China Tension Index (UCT) both had high skewness and kurtosis. This suggests that there were some rare but big geopolitical shocks during the period. The Jarque-Bera test says that all the series aren't normally distributed. That's why we used econometric models like the NARDL model, which can deal with data that isn't linear or normally distributed. Table 2.

The unit root test determines the stationarity status of the logged variables in our model, which is needed before we use the NARDL method. For the study Augmented Dickey-Fuller test is used. The test results show that LNBSE, LNEXR, and LNWPI aren't stationary at-level, but they do become stationary after the first-differenced, meaning they're I(1). On the other hand, LNINT, LNGPR_IND, and LNUCT are stationary at level, so they're I(0).

This mix of I(0) and I(1) variables is valid condition for applying NARDL. It can handle both stationary and non-stationary variables even if they aren't all in the same order. It's important that none of the variables are I(2), because it would compromise the integrity of the NARDL model and render the bounds testing ineffective. The next step is to determine the number of lags to execute the NARDL model which is followed by the BDS-test. Table 3

The BDS test helps to determine whether the US-China tension index shows pattern over time. These patterns are significant as they help to evaluate whether the market will react differently to good and bad news about the US-China relations. The results of the BDS test, reported in Table 4, suggests the presence of non-linearity in the series. In other words, the results indicates that the US-China tension index shows systematic temporal dependence and not random behavior. This reinforces the use of non-linear econometric model in the subsequent analysis. Table 5.

At first, we conduct the F-bounds test within the NARDL framework to establish cointegration among Indian stock market, US-China tension index and domestic macroeconomic factors. The test yields a F-statistic of 5.685, which exceeds the I(1) critical bounds at the 10%, 5%, 2.5% and 1% significance level. This confirms the presence of cointegration or long-run equilibrium relationship among the variables. The presence of cointegration also validates the use of NARDL approach to model the dynamic and asymmetric effects of US-China tension and domestic macroeconomic factor on the Indian stock market.

Table 2
Unit Root Test.

	At Level		At First-Differenced		Status
	Test statistic	p-value	Test statistic	p-value	
LNBSE	-2.575639	0.2918	-18.31225	0.0000	I(1)
LNEXR	-2.049307	0.5717	-5.154889	0.0001	I(1)
LNINT	-4.608002	0.0011	—	—	I(0)
LNWPI	-2.487307	0.3343	-11.16801	0.0000	I(1)
LNGPR_IND	-5.054153	0.0002	—	—	I(0)
LNUCT	-6.787446	0.0000	—	—	I(0)

Source: Author's Own

The short-run parameters, long-run parameters and the residual diagnostic tests are reported in Table 6. The short-run parameters based on the NARDL error correction model clearly shows that domestic macroeconomic variables like interest rate and exchange rate have significant effect on the Indian stock market. A depreciation of the Indian rupee by 1% has a significant positive impact on stock market returns by 1.526%. The positive linkage reflects the fact that depreciation in Indian rupee against USD enhances the rupee-value earnings of exporting firms which lifts the equity prices of such firms listed in the Indian stock market. The linkage also captures investors' responses to anticipated capital flight and imported inflation alongside expectations of supportive policy measures. Together, these dynamics explain the positive linkage between INR-USD exchange rate and Indian stock market returns in the short-run.

On the other hand, an increase in interest rate has a significant negative impact on the Indian stock market returns. This negative association can be attributed higher borrowing cost which leads to lower corporate profitability and discouragement in new investment. For investors, a regime of higher interest rate makes assets with fixed-income more attractive as compared to equity. Factors like inflation and past performance of BSE do not indicate statistically significant short-run effects.

The short-run parameters further show that domestic geopolitical risk and US-China tension exert a strong influence on Indian stock market in the short-run.

One month lag of domestic geopolitical risk has a positive linkage with the BSE index in the short-run. This effect can be attributed to capturing of market expectations of reform following domestic turmoil and political transition. The results shows that the US-China tension dynamics are more complicated. It is observed that positive changes in US-China tension with one month lag, which captures increasing tension, have a significant negative impact on the Indian stock market. The result captures the anxiety of the investors regarding global trade volatility and regional economic impacts. The negative changes, which captures declining tension between US and China, have a positive influence on the Indian stock market with one month and two-month lags. The implication of the result is that de-escalation by powerful leaders of US and China restores investor confidence in emerging markets like

Table 1
Descriptive Statistics.

	BSE	EXR	INT	WPI	GPR_IND	UCT
Mean	17195.94	51.14207	6.948914	610.3019	0.205840	98.16300
Maximum	63099.65	82.77000	34.83000	1196.105	1.125609	349.9455
Minimum	2122.300	31.20100	0.730000	231.6000	0.044387	37.98329
Skewness	1.109017	0.476248	3.532141	0.340659	3.296180	1.699077
Kurtosis	3.474772	2.129039	25.11400	1.906766	18.05435	8.100995
Jarque-Bera	77.17619	24.98731	8083.996	24.89030	4051.391	563.5140
Probability	0.000000	0.000004	0.000000	0.000004	0.000000	0.000000
Observations	360	360	360	360	360	360

Source: Author's Own

Table 3
Lag Selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-239.1041	NA	1.62e-07	1.392637	1.458494	1.418845
1	2620.977	5606.409	1.74e-14	-14.65328	-14.19228*	-14.46982
2	2690.932	134.7426	1.44e-14*	-14.84620*	-13.99006	-14.50550*
3	2724.984	64.42930*	1.45e-14	-14.83514	-13.58385	-14.33719
4	2744.286	35.86066	1.60e-14	-14.74026	-13.09382	-14.08506
5	2758.451	25.83643	1.81e-14	-14.61620	-12.57462	-13.80375
6	2776.863	32.95225	2.01e-14	-14.51627	-12.07954	-13.54657
7	2799.868	40.39057	2.17e-14	-14.44243	-11.61057	-13.31549
8	2818.037	31.27821	2.41e-14	-14.34112	-11.11411	-13.05692

* indicates optimal lag

Table 4
BDS Test.

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.1219	0.0031	39.338	0.0000
3	0.2081	0.0049	42.375	0.0000
4	0.2642	0.0058	45.343	0.0000
5	0.2984	0.0060	49.310	0.0000
6	0.3162	0.0058	54.402	0.0000

Source: Author's Own

Table 5
F-Bounds Test.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	5.685285	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

Source: Author's Own

India.

In the long-run, the geopolitical variables (domestic geopolitical risk and US-China tension) are insignificant suggesting that their influence is mainly short-run in nature and sentiment driven. Additionally, interest rate has a significant negative influence even in the long-run, thus, capturing the structural role in the determination of capital and investment prices. The presence of a statistically significant and negative error correction term (-0.0361) captures a long-run equilibrium condition, where there is a significantly low adjustment rate of 3.6% per period towards this equilibrium due to short-run shocks. Furthermore, diagnostic tests confirm the stability of the model showing no serial correlation or heteroskedasticity and ensuring that the system is stable in the long run, thus confirming that the estimated relationships are indeed consistent and correctly specified.

To check whether the US-China tension index enhance the predictability of the Indian stock market, a baseline model (excluding the UCT variable) is also determined. The study adopts a structured evaluatology-based approach [21] in model parsimony, incremental information testing and forecast comparison theory

The functional baseline model is presented below:

$$BSE = f(EXR, WPI, INT, GPR\_IND)$$

Out of sample forecasts for the dependent variable were generated for both models to check the predictive accuracy of the models. The predictive accuracy of the baseline models and the UCT augmented model are compared using measures like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Symmetric Mean Absolute Percentage Error (SAME), Theil's U statistic and Diebold-Mariano (DM) test.

As discussed above, the evaluation of the forecasting relevance of the

Table 6
Short-run and Long-run Parameters.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNBSE(-1))	-0.0300	0.0530	-0.5669	0.5711
D(LNEXR)	-1.5268	0.1670	-9.1422	0.0000
D(LNEXR(-1))	-0.0727	0.1889	-0.3852	0.7003
D(LNINT)	-0.0473	0.0128	-3.6957	0.0003
D(LNWPI)	-0.5285	0.5481	-0.9643	0.3356
D(LNWPI(-1))	-0.1030	0.5490	-0.1877	0.8512
D(LNDGPR)	0.0049	0.0071	0.6971	0.4862
D(LNDGPR(-1))	0.0163	0.0076	2.1423	0.0329
D(LNDGPR(-2))	-0.0036	0.0071	-0.5048	0.6140
D(LNUCT_POS)	-0.0331	0.0299	-1.1058	0.2696
D(LNUCT_POS(-1))	-0.1005	0.0340	-2.9559	0.0033
D(LNUCT_POS(-2))	-0.0384	0.0359	-1.0711	0.2849
D(LNUCT_NEG)	-0.0026	0.0347	-0.0751	0.9401
D(LNUCT_NEG(-1))	0.0705	0.0342	2.0741	0.0388
D(LNUCT_NEG(-2))	0.0629	0.0307	2.0455	0.0416
C	0.0094	0.0092	1.0269	0.3052
EC(-1)	-0.0361	0.0094	-3.8336	0.0002
Long-run Parameters				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNEXR	-0.8949	0.9028	-0.9912	0.3223
LNINT	-0.8789	0.4089	-2.1493	0.0323
LNWPI	3.4614	1.8098	1.9125	0.0566
LNDGPR	-0.2535	0.2270	-1.1166	0.2649
LNUCT_POS	0.7453	0.4852	1.5358	0.1255
LNUCT_NEG	0.8502	0.5290	1.6072	0.1089
C	-6.2877	10.086	-0.6233	0.5334
			Test statistic	p-value
Breusch-Godfrey Serial Correlation LM Test			1.929683	0.1468
ARCH			0.336483	0.5622
RAMSEY RESET Test			1.533370	0.1261
CUSUM Plot			Stable	
CUSUM Sum of Sqaures			Stable	

Source: Author's Own

US-China tension index we have first estimated a baseline model (without the index) and a full model (with the index). The forecasts of both the models are compared for the accuracy metrics such as RMSE, MAE, MAPE, SMAPE, Theil's U1 and U2 (See Table 7). All the metrics suggests that the full model is marginally better than the baseline model. To formally compare the forecasts of both the model, we further employ Diebold-Mariano test. The result, under the squared error loss function, indicates the rejection of the null of hypothesis of predictive accuracy. This clearly indicates that the full model provides significantly superior forecasts.

Fig. 2 portrays the wavelet coherence plot between the Indian stock market index (BSE) and the US-China tension index. It can be observed that there is significant high coherence zone, which is highlighted in red and enclosed by black contour lines, between time points 130 to 340 (roughly corresponding to 2003-2021). The arrows in this area point to the left, signifying a long-term negative correlation between the variables (time points 130 to 220). It is noteworthy to point out that after time point 220 the left-pointing arrows go slightly downward, suggesting that the BSE index is the leading variable of the negative association.

Table 7
Accuracy Measures and Predictive Superiority Tests for Baseline Versus Full Model.

Diebold-Mariano test (HLN adjusted)						
Null hypothesis: Both forecasts have the same accuracy						
Accuracy	Statistic	<> prob	> prog	< prob		
Abs Error	1.504272	0.1334	0.9333	0.0667		
Sq Error	3.449359	0.0006	0.9997	0.0003		
Evaluation statistics						
Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
EQ_BASE	0.186374	0.150185	1.695310	1.692223	0.009946	2.816482
EQ_FULL	0.185655	0.149828	1.691398	1.688342	0.009908	2.805448
Simple mean	0.186001	0.149995	1.693244	1.690172	0.009926	2.810797

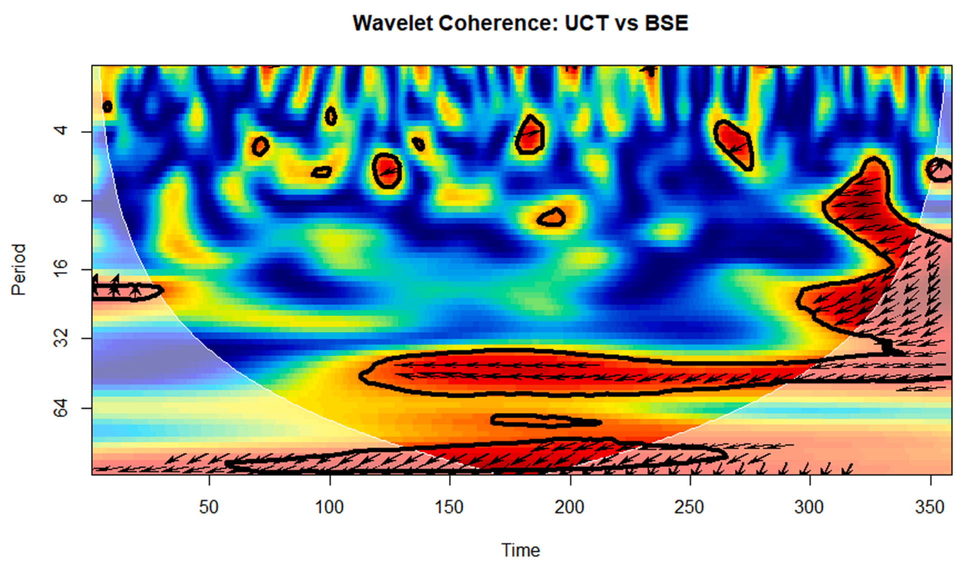

Fig. 2. Wavelet Coherence between UCT and BSE.
Source: Author's Own

Very few isolated areas of the high coherence zone are visible in the short-term, although the association is unstable. It is also interesting to see how the relationships between the two variables changed from long-term in the initial period to short-term in the latter period, particularly since 2017. The apparent change from lower to higher frequency in the wavelet coherence diagram indicates that the Indian stock market's reaction to US-China tensions became increasingly short-term but instantaneously developed with the passage of time. While previous stages (low frequency) are capturing long-run, structural market responses to US-China tension events, later periods of high-frequency coherence suggest that the market started responding more rapidly, presumably to investor sentiment, news shocks, and short-term capital flows, although these influences never in general lasted across longer horizons. The Wavelet Coherence plot is further explained with the help of Table 8.

The Table 8 displays a wavelet coherence examination of the dynamic connection between the BSE Index and US-China geopolitical tensions across time, which provides different patterns across three periods. From 2003–2013 (Time Points ~130–220), the coherence is low frequency, indicating a long-run negative connection without lead or lag, implying tensions influenced market sentiment but directionality was unclear. The period witnessed China's increasing global footprint, the 2008 global financial crisis, and continuous South China Sea tensions, which imposed relentless but indirect pressure on the Indian market. From 2013–2017 (~220–270), the pattern is mixed frequency with the BSE Index starting to lead the geopolitical tension index. This may suggest Indian markets were becoming increasingly forward-looking, potentially responding ahead of time to international macro signals such as the Yuan devaluation and Trump's Trumpian hawkish trade rhetoric, reflecting increasing market confidence and deeper integration with international capital flows. Lastly, from 2017–2021 (~270–340), the connection has high-frequency coherence, and the BSE responds instantaneously and sporadically to US-China tensions. This change is in line with extremely volatile global events such as the US-China Trade War, the COVID-19 outbreak, and news-driven capital flows, and captures the Indian stock market becoming more responsive to global geopolitical shocks and the prevalence of short-run investor sentiment in an increasingly fast-evolving world.

Table 8
Temporal Dynamics of Wavelet Coherence Between US-China Tensions and Indian Stock Market: Frequency, Relationship, and Key Events (2003–2021).

Time Period	Time Points	Frequency	Relationship Pattern	Key Events Driving It
2003-2013	~130-220	Low (long-term)	No clear lead or lag (negative)	China's global rise, 2008 crisis, South China Sea tensions
2013-2017	~220-270	Mixed	BSE begins to lead	Yuan devaluation, Trump trade rhetoric, market anticipation
2017-2021	~270-340	High (short-term)	BSE reacts immediately, inconsistently	US-China Trade War, COVID-19, news shocks, short-term capital flows

Source: Author's Own

Conclusion

This study presents new empirical evidence of how US-China geopolitical tensions influence the Indian stock market using econometric modeling (NARDL) and wavelet coherence. The evidence reveals that, although long-run impacts of US-China tensions on the Bombay Stock Exchange (BSE) are not significant, short-run reactions are statistically and economically significant. That is, when tensions increase (positive shocks to US-China tensions), Indian stock returns decrease, and when tensions decrease (negative shocks to US-China tensions), market sentiment is better. Secondly, interest rates are a salient variable explaining the volatility of BSE in the short run and the long run, and domestic geopolitical risks have a lagged, sentiment-based effect.

Wavelet coherence also observes a temporal development of this correlation, from a long-run correlation (2003-2013), to a future-oriented period in which BSE created tensions (2013-2017), to a high-frequency, sentiment-based reaction phase (2017-2021). This transition reflects the growing responsiveness of emerging economies such as India to changing global geopolitics, especially in the post-liberalization period of free capital movements and computerized trading systems.

It is important that policymakers understand the importance of financial stability during geopolitical crises. Exchange and interest rate volatility play a critical role in investor confidence in India. Coordination of fiscal and monetary policies during international or diplomatic crises would, therefore, be helpful in avoiding excessive market reactions. Additionally, the creation of early warning systems that track global geopolitical risks, such as the measurement of media sentiment tools like the UCT Index, would be wise in taking preventive measures before the expected problems arise.

Investors and corporate leaders must consider geopolitical risks in investment decisions and strategic planning. Asset managers can use adaptive protection measures or diversify regionally to mitigate short-term difficulties resulting from U.S.-China relations. Scenario planning and the ability to adapt operations-i.e., restructuring supply chains-are essential for firms and particularly firms in trade-volatile industries. Market participants should be aware that political rhetoric can influence prices without seemingly changing policies.

This study suggests a few areas of further research. First, sector-level analysis would reveal which Indian industries were most exposed to United States-China geopolitics. Second, use of investor sentiment indices or news-based proxies for uncertainty would be able to better inform our understanding of the transmission mechanisms involved. Third, as India continues to rise as a principal global manufacturing hub and geopolitics flashpoint, bidirectional relations could be studied, i.e., how India's foreign policy alignment and strategic choices affect regional market behaviors. Comparative studies with other major non-aligned economies, e.g., Brazil and Indonesia, would give a fuller picture of how superpower rivalries shape Global South markets. Incorporating region-specific strategic indicators like QUAD-related indices may enrich future research work. Finally, future research may explore the application of machine learning techniques to complement time-series econometric models and enhance forecasting performance under highly volatile geo-political regimes.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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