Examining the Effects of Global and Indian Geo-Political Risk Indices and Indian News-Based Policy Uncertainty Index on Stock Indices of India using ARDL Model

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Abstract

The study aims to analyze the effects of geopolitical risk on the return of growth/Major Indian stocks during expansionary and recessionary periods across a conditional distribution. We selected a sample covering the period between 01/2003–09/2023. ARDL Model were applied to examine the existence of impact of geopolitical risk and Indian News-Based Policy Uncertainty Index on major Indian stock indices. The present study employed a range of econometric techniques, including the ARDL bound-testing methodology and Johansen co-integration process, to ascertain the existence of a long-term co-integrating relationship among the variables. The findings indicate that there exists a detrimental impact of geopolitical risk on equities, with the magnitude of this impact varying based on the specific characteristics of the stock. The adverse impact is mitigated by the economic cycle; however, it gradually diminishes towards the bottom end of the stock return distribution. The results of this study provide further insight into investing methods employed by growth/value investors who seek to capitalize on opportunities that emerge throughout shifts in the economic cycle. This study offers evidence regarding the ways in which the economic cycle affects the relationship between geopolitical risk and growth/value and small/large stocks.

Keywords: Geo-political risk, Economic Policy Uncertainty (EPU), ARDL Co-integration, Uncertainty Index, NIFTY, SENSEX

JEL Classification: C22, C43, E32, F51, F52, H56, N40, 047

1. Introduction

Geo-political risk (GPR) refers to the potential impact of political, social, and economic factors on global or regional stability (Caldara & Iacoviello, 2022). These risks arise from the interactions between nations, governments, and international organizations, and can have significant implications for businesses, economies, and societies as a whole (Su et al., 2019)(Shaik et al., 2023)(Foglia et al., 2023)(Pang et al., 2023). In an increasingly interconnected world, geo-political risk has become a critical consideration for businesses operating across borders (Hartwell & Devinney, 2021). Factors such as political instability, trade disputes, terrorism threats, civil unrest, and changes in government policies can all contribute to heightened levels of uncertainty and volatility (Tabassam et al., 2016)(MengYun et al., 2018)(Khan et al., 2023). Understanding and managing geo-political risk is essential for organizations seeking to navigate the complexities of today's global landscape (Novelli & Lopes Cardozo, 2008). By assessing potential risks and developing strategies to mitigate their impact, businesses can safeguard their operations and make informed decisions that align with their long-term objectives (Rezaee, 2016).

India, as a rapidly growing economy and a major player in global affairs, is not immune to geo-political risks. These risks refer to the potential impact of political, economic, and social factors on a country's stability and security (Chacko, 2014) (Iwashita et al., 2023). In the case of India, several geo-political risks can be identified. One such risk is its complex relationship with neighboring countries like Pakistan and China, which have often led to tensions and conflicts (Thapliyal, 2023)(Majumdar, 2023). Additionally, India's diverse population and regional disparities pose challenges in maintaining social cohesion and political stability. Furthermore, the country's dependence on foreign energy sources and vulnerability to global economic fluctuations also contribute to its geo-political risk profile (Banna et al., 2023). It is crucial for policymakers and stakeholders in India to carefully navigate these risks in order to ensure sustainable development and safeguard national interests in an increasingly interconnected world (Liu et al., 2018). There are several indices that are related to GPR i.e. Global Daily or Monthly GPR, Historical Daily or Monthly GPR, GPR Acts and Threats, Historical GPR Acts and Threats, Country specific GPR: Percent of articles, Country specific GPR Historical: Percent of articles and likewise. These GPR indices are developed by Dario Caldara and Matteo Iacoviello (Caldara & Iacoviello, 2022).

On the other hand, (Ghosh & Bagchi, 2023) the Indian News-Based Policy Uncertainty Index is a comprehensive tool that aims to measure and analyze the level of uncertainty surrounding policy decisions in India. This index takes into account various elements to provide a holistic understanding of policy uncertainty. These elements include news articles, editorials, and opinion pieces from reputable sources that discuss government policies and their potential impact on the economy. By analyzing these sources, the index captures the sentiment and tone of discussions surrounding policy decisions, allowing policymakers, investors, and analysts to gauge the level of uncertainty in the Indian market. This index serves as a valuable resource for decision-makers looking to navigate through uncertain policy environments and make informed choices based on reliable data. These Global GPR Indices, Country specific GPR and Policy Uncertainty Index of India might have been affected by many macro-economic factors (Pratap & Priyaranjan, 2023). Similarly, such GPR and uncertainty indices might also affect the stock markets of India as geopolitical events and risks can influence investor sentiment, market volatility, and economic conditions, leading to fluctuations in stock prices (Hoque & Zaidi, 2020). Hence, it will be interesting to study the impact of such indices on the stock market reactions of India.

2. REVIEW OF LITERATURE

Using a time-frequency analysis, (Chen, 2023) determines whether or not the shocks from different uncertainties on the oil-stock correlation are comparable. The findings show that oil-stock correlations are affected differently by different time horizons and different degrees of exposure to economic policy uncertainty, the volatility index, and geopolitical risk. Notable uncertainty indexes include the volatility index, economic policy uncertainty, and geopolitical risk.

(Bossman et al., 2023) uses data from 2013 to 2022 to study the uneven impact of policy uncertainty, geopolitical risk, and market sentiment on stock prices in different economic sectors within the European Union. The findings demonstrate that economic policy uncertainty has a major role in the bear market's development. In times of economic decline, European Union stocks may provide investors with a buffer against the negative effects of geopolitical risk.

There are two main issues that (Lee, 2023) investigates in his work: (1) How much do geopolitical risk factors affect households' decisions to invest in the stock market, and (2) if they do, what economic process might account for the link? Results show that the GPR index, which is meant to measure geopolitical risk, is strongly and negatively related to choices to invest in the stock market. The findings are stable with respect to the breadth and depth of the decision-making margins involved in stock market involvement.

Investors consider geopolitical risk a significant factor when making financial commitments. (Zhang et al., 2023), who used dynamic panel data from 32 nations and regions in Asia, Europe, the Americas, Australia, Africa, and the Middle East, discovered that emerging economies, nations that export crude oil, and nations that are at peace are more likely to experience geopolitical risk on stock market volatility.

Regarding the categorical GPR indices, (M. Yang et al., 2021) use the conditional variance of the GARCH-MIDAS model in two parts (the short-run and the long-run components) to examine the explanatory and predictive power of GPR factors for volatility in the capitalization-weighted stock market index 300, and they find that GPR Treat generates a stronger and positive impact on the volatility in the capitalization-weighted stock market index.

Using a standard linear regression model, (Raheem & le Roux, 2023) investigate the association between geopolitical risk and Travel and Leisure equities for six rising tourist attraction countries (Indonesia, South Korea, Malaysia, India, China, and Israel). The findings indicate that terrorism has no effect on stocks or that more significant terrorist actions have a minor impact on the travel and tourist industry when compared to less severe assaults. South Korea and Indonesia show weak results, whereas the remaining countries under examination show the opposite pattern.

(Zheng et al., 2023) build a time varying frequency financial risk spillover network model using the time varying parameter vector autoregression model's variance decomposition and frequency analysis to characterize the dynamic characteristics of risk spillover between geopolitical risk and global stock, foreign exchange, bond, and crude markets. The findings demonstrate a considerable asymmetry between the positive and negative risk spillovers that occur from changes in geopolitical risk and global financial markets.

Global portfolio diversification is becoming increasingly important as seen by the growing relevance of the term "stock market synchronization," which denotes significant degrees of co-movements of different national stock markets. The interdependence of the American, Chinese, and Russian stock markets means they are all vulnerable to the effects of geopolitical uncertainty. Except at the lowest and highest quantiles of synchronization and geopolitical risk, stock market synchronization between the United States and Russia responds negatively to geopolitical risk. When geopolitical risk is high and synchronization is

low, the US and Chinese stock markets are less connected than when both are low (Sohag et al., 2022).
The findings of (J. Yang & Yang, 2021) suggest that mixed-frequency geopolitical risk influences stock market returns significantly and contributes to more precise stock return forecasts.

3. RESEARCH GAP

Although there is existing literature on the impact of geopolitical risk indices and economic policy uncertainty on stock returns in developed countries, there is limited research specifically focused on the Indian context. This research gap presents an opportunity to explore the unique dynamics of the Indian stock market in relation to global and Indian geopolitical risk indices, as well as policy uncertainty. Additionally, while some studies have examined the impact of geopolitical risk indices and economic policy uncertainty on stock returns in other emerging markets, such as Egypt and China, there is a lack of research specifically focused on India This research paper could fill this gap by using the ARDL model to comprehensively examine the effects of global and Indian risk indices and policy uncertainty on Indian stock indices, taking into account various financial indicators as well.

3.1. Objective of the Study

The study examines the impact of Global and Country specific GPR Indices and Political Uncertainty Index on the major Stock Indices of India i.e. NIFTY50 and SENSEX.

4. NEED OF THE STUDY

In today's interconnected world, geopolitical risks and policy uncertainties have a profound impact on financial markets, particularly stock indices. This investigation aims to scrutinise the relationship between these factors and the stock indices of India using an ARDL model. Understanding how global and Indian geopolitical risk indices, along with news-based policy uncertainty, influence stock market performance can provide valuable insights for investors, policymakers, and financial institutions. By examining these relationships, this research can help in making informed investment decisions, managing risks effectively, and developing strategies to navigate volatile market conditions. Moreover, the outcomes of this investigation can contribute to enhancing the understanding of the complex dynamics between political events, policy uncertainties, and their impact on financial markets. This knowledge can assist policymakers in formulating effective economic policies that promote stability and growth. Overall, this research has the potential to benefit society by providing valuable insights into the interplay between geopolitical risks, policy uncertainties, and stock market performance in India. It offers a foundation for informed decision-making in investment strategies while also aiding policymakers in creating a conducive environment for economic development.

5. RESEARCH METHODOLOGY

5.1. Relevant Variables and Sources of Data

The initial stage was the identification of pertinent factors that may elucidate the geopolitical risk index. This empirical study aimed to investigate the dynamic relationships between, GPRC_IND = Country GPR: Percent of articles (India), GPRHC_IND = Country GPR Historical: Percent of articles (India), India News-Based Policy Uncertainty Index, GPRM, GPRH, GPRM_ACT, GPRH_ACT, GPRM_THREATS, GPRH_THREATS, and Indian stock index NIFTY50, and SENSEX using monthly data covering the period from 2003 to 2023. The data have been collected from the geopolitical risk index databased i.e. www.policyuncertainity.com/GPR and ww.matteoiacoviello.com/GPR.

5.2. Logarithmic Transformation and Model Used

For elasticity reporting, all variables underwent a logarithmic transformation. Table 1includes an overview of the descriptive statistics pertaining to the variables that were employed in this investigation.A bounds test was then performed to check for cointegration after which the ARDL model was estimated with a long and short-run estimation. ARDL modelling was employed as a technique for studying co-integrating relationships. The model, which is composed of two parts—the short run and long run—presents a balance testing methodology for analyising co-integration. One of the main advantages of the ARDL model is that it allows for the analysis of both long-run and short-run relationships between variables. The long-run relationship is captured by the DL component, while the short-run dynamics are captured by the AR component. The Autoregressive Distributed Lag (ARDL) model is a time series econometric model commonly used in economics and finance to analyze the long-run and short-run relationships between variables. It is particularly useful when you have non-stationary time series data, which means that the data doesn't have a constant mean and variance over time. The ARDL model combines autoregressive (AR) and distributed lag (DL) components. It's a versatile model that can handle both stationary and non-stationary variables and allows you to study the dynamics between these variables over time.

5.3. Components of ARDL Model

- **Autoregressive (AR) Component**: This component involves modeling the relationship between the variable of interest and its past values (lags). The AR component captures short-term dynamics and helps to account for the serial correlation in time series data.
- **Distributed Lag (DL) Component**: The DL component involves modeling the relationship between the variable of interest and lagged values of other variables. It allows us to study how changes in one variable affect the variable of interest over time, considering the lags in the relationship.

The ARDL model is typically estimated through regression analysis, and it can be used for various purposes, such as:

- **Co-integration Analysis:** ARDL can be used to test for co-integration, which is a long-run relationship between non-stationary variables. Co-integrated variables move together in the long run, even if they may diverge in the short run.
- **Granger Causality Testing:** ARDL can be used to test for Granger causality, which determines whether one variable can predict another variable in a time series context. The Granger causality test involves estimating two separate time series models and comparing their forecasting performance. Here's the basic equation for Granger causality testing:

Model 1 (Restricted Model): Estimate a model for γ_t that includes only its lagged values and possibly a constant term. This model is typically expressed as:

$$Y_t = \alpha_0 + \alpha_1\gamma_{t-1} + \alpha_2\gamma_{t-2} + \alpha_3\gamma_{t-3} + \alpha_p\gamma_{t-p} + \varepsilon_t$$

Model 2 (Full Model): Estimate a model for γ_t(dependent variable) that includes its lagged values, possibly a constant term, and the lagged values ofX_t. This model is expressed as:

$$Y_t = \beta_0 + \beta_1\gamma_{t-1} + \beta_2\gamma_{t-2} + \cdots . + \beta_P\gamma_{t-P} + \gamma_1 X_{t-1} + \gamma_2 X_{t-2} + \cdots + \gamma_P X_{t-P} + \varepsilon_t$$

- **Error Correction Mechanism (ECM):** When co-integration is present, an ECM can be added to the ARDL model to capture the short-term dynamics that adjust the variables back to their long-run equilibrium after a shock. The ECM is typically added to the model when co-integration is detected among the variables. The ECM introduces the first difference of both variables, lagged values of the first differences, and possibly lagged values of the error term. The ECM equation is often written as:

$$\Delta Y_t = \alpha(Y_{t-1} - \beta_0 - \beta_1 X_{t-1}) + \sum_{i=1}^{p} \gamma_i \Delta Y_{t-i} + \sum_{j=1}^{q} \delta_j \Delta X_{t-j} + \varepsilon_t$$

Where, $\Delta Y_t$the first is difference of Y_t and ΔX_t is the first difference ofX_t, p and q represent the lag lengths of the first difference of both variables respectively, α is the coefficient of the error correction term and the ε_t is the error term.

ARDL models are commonly used in fields such as economics, finance, and social sciences to study the relationships between economic variables like GDP, inflation, interest rates, and more. They are especially valuable when dealing with non-stationary time series data, where other modeling techniques like ordinary least squares may not be appropriate due to the violation of assumptions like stationarity.

4.4. Multivariate Framework

The multivariate framework was established in equation as follows:

$$Y_t = \alpha_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + +\beta_9 X_9 + \varepsilon_t \dots \quad (1)$$

The relationship can be expressed as follows:

In the first equation we considered NIFTY as a dependent variable

$$Nifty_t = f\ (GPRC - Ind_t, GPRHC - Ind_t, GPRM_t, GPRH_t, GPRMact_t, GPRHact_t, GPRMT_t, GPRHT_t, PUI - NB_t, \dots. \quad (1)$$

In the next equation we considered SENSEX as a dependent variable

$$Sensex_t = f\ (GPRC - Ind_t, GPRHC - Ind_t,\ GPRM_t,\ GPRH_t,\ GPRMact_t,\ GPRHact_t, GPRMT_t, GPRHT_t, PUI - NB_t, \dots. \quad (2)$$

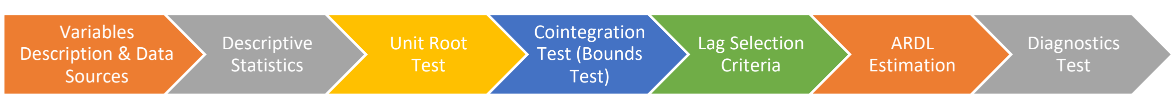
After the natural logarithm, equation (3) and (4) are expressed as follow:

$$InNifty_t = \alpha_0 + \beta_1 InGPRC - Ind_t + \beta_2 InGPRHC - Ind_t + \beta_3 InGPRM_t + \beta_4 InGPRH_t + \beta_5 InGPRMact_t + \beta_6 GPRHact_t + \beta_7 GPRMT_t + \beta_8 GPRHT_t + \beta_9 InPUI - NB_t + \varepsilon_t \quad \dots\dots\dots (3)$$

$$InSensex_t = \alpha_0 + \beta_1 InGPRC - Ind_t + \beta_2 InGPRHC - Ind_t + \beta_3 InGPRM_t + \beta_4 InGPRH_t + \beta_5 InGPRMact_t + \beta_6 GPRHact_t + \beta_7 GPRMT_t + \beta_8 GPRHT_t + \beta_9 InPUI - NB_t + \varepsilon_t \quad \dots\dots\dots (4)$$

For more clarity and precision, the step of econometric methodology is mentioned in the figure 1.

Figure 1. Flow Chart of the Econometric Methodology that is applied in this research



6. ANALYSIS, RESULTS AND DISCUSSION

First, we convert sample data into log returns value. Converting data into log returns is a common technique used in finance and statistics to analyze the relative change in a variable over time. To convert the periodic returns into log returns, we would use the natural logarithm. The formula for calculating the log return is: Log return = 1n (1+ periodic return).

In the next step, ADF and PP test have been employed to examine whether the data is stationarity in nature. The overview of descriptive statistics of 63 observations are exhibited in the Table 1 and the coefficient of correlation between the selected samples of the study are shown in the table 2.

Table 1. Descriptive statistics of data sources

Source: Authors' calculation using EVIEWS 12

	SENSEX	NIFTY	PUI-NB	GPRM_THREATS	GPRM_ACT	GPRM	GPRHC__INDIA_	GPRH_THREATS	GPRH_ACT	GPRH	GPRC_INDIA_
Mean	25484.75	7647.18	90.22	105.64	98.41	101.85	0.22	97.12	76.43	82.85	0.21
Median	19963.66	6023.83	78.08	95.45	88.92	92.44	0.22	89.49	71.36	77.18	0.19
Max	66527.67	19753.80	283.68	413.42	429.14	358.71	0.83	264.37	293.83	244.57	0.89
Min	2959.79	934.05	23.35	53.12	28.45	60.60	0.04	47.14	21.13	46.86	0.064
S.D.	16131.36	4790.80	48.12	43.82	45.42	35.35	0.09	30.69	33.85	23.46	0.09
Skew	0.84	0.82	1.44	3.46	2.76	3.54	1.49	2.12	2.18	2.46	2.12
Kurt	2.91	2.84	5.32	20.03	16.56	21.63	8.71	9.93	12.32	14.59	13.64
J.B.	29.45	27.91	141.04	3489.86	2216.9	4101.75	429.38	681.19	1093.78	1638.29	1354.03
Sum Sq. Dev.	6.43E+1	5.67E+0	571955.4	474297.7	509511.7	308586.8	2.45	232714.0	282972.5	135942.2	2.18
Obser	248	248	248	248	248	248	248	248	248	248	248

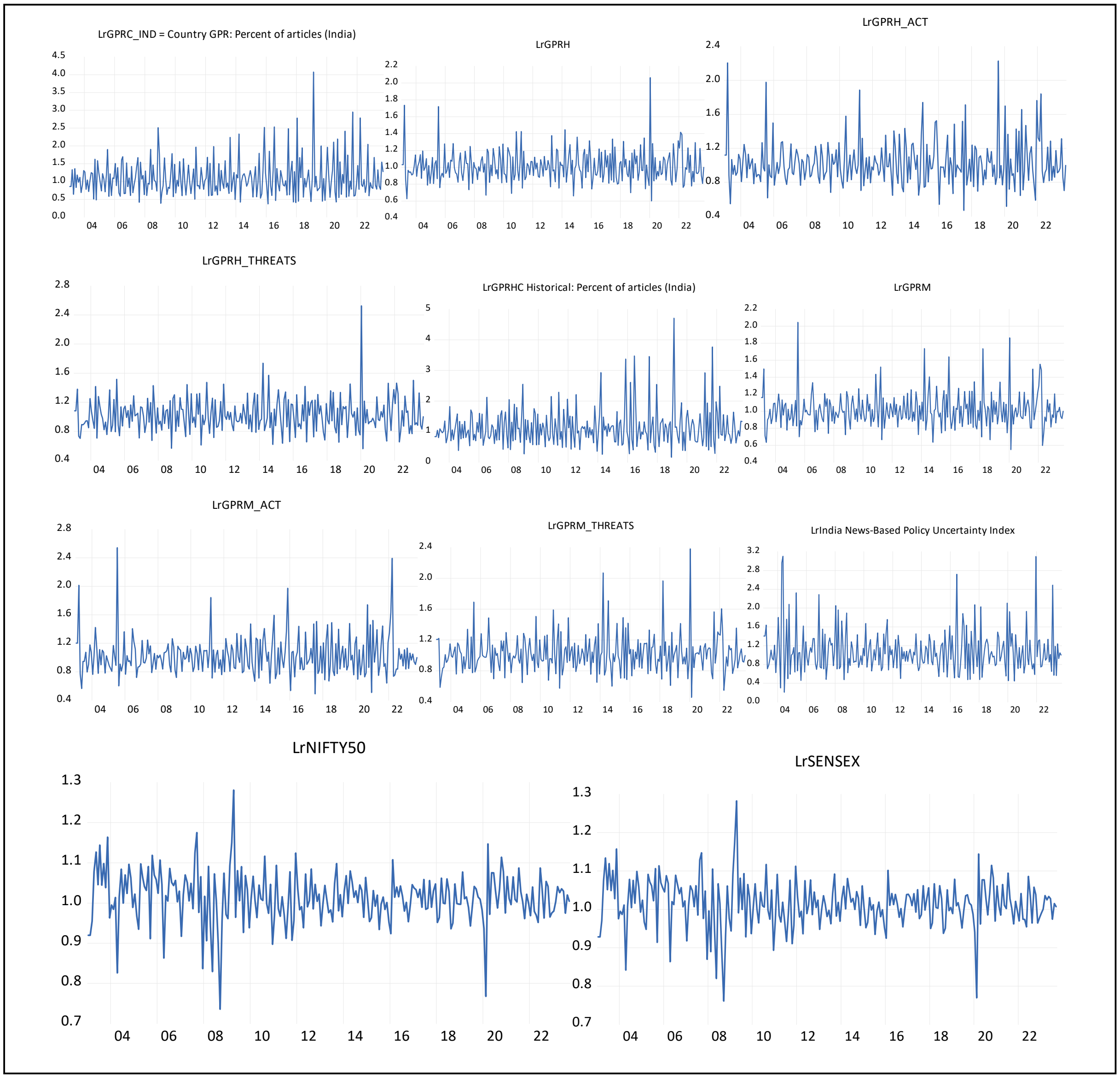
Table 2. Correlation Matrix of selected variables

Source: Authors' calculation using EVIEWS 12

	SENSEX	NIFTY	PUI-NB	GPRM_THREATS	GPRM ACT	GPRM	GPRHC INDIA	GPRH THREATS	GPRH_ACT	GPRH	GPRC INDIA
SENSEX	1										
NIFTY50	0.99	1									
PUI-NB	-0.17	-0.16	1								
GPRM_THREATS	0.31	0.31	-0.19	1							
GPRM_ACT	-0.36	-0.36	-0.117	0.50	1						
GPRM	-0.008	-0.005	-0.19	0.89	0.83	1					
GPRHC_ INDIA	0.016	0.015	-0.046	0.29	0.33	0.35	1				
GPRH_THREATS	0.34	0.34	-0.17	0.91	0.48	0.83	0.37	1			
GPRH_ACT	-0.44	-0.44	-0.14	0.38	0.96	0.74	0.34	0.41	1		
GPRH	-0.16	-0.16	-0.18	0.71	0.89	0.92	0.41	0.79	0.88	1	
GPRC_ __INDIA_	0.06	0.06	-0.12	0.31	0.29	0.33	0.85	0.28	0.25	0.29	1

Table 1 presents the descriptive analysis of 248 observations from the time series variables. All the variables exhibit a long right-tail (positive skewness) with Geopolitical risk monthly index (GPRM) and Geopolitical Threats (GPRT) having the longest right tail. While stock index i.e. SENSEX and NIFTY exhibit platkurtic distribution (value of kurtosis is less than three), the other variables exhibit leptokurtic distribution of the normal because in that case the value of kurtosis is greater than three. The independent variables GPRM threats, GPRHC-India, GPRH threats and GPRC India show a positive monotonic relationship with SENSEX and NIFTY (dependent variable) while other variables showed the negative correlation with the selected dependent variables. The tendencies of all selected variables are demonstrated in Figure 2.

Figure 2. Historical Log Returns Trend of the Variables
Source: Authors' calculation using EVIEWS 12



Unit Root Test

In order to minimize spurious regression, it is critical to conduct a unit root test, which verifies the stationarity of the variables involved in the regression through differentiation and estimation of the equation of interest using stationary processes (Kwiatkowski et al., 1992). Unit root test using Levin, Linand Chu test (Levin et al., 2002), Breitung t-stat (Moon et al., 2006), Im, Pesaran and Shin W-stat, Augmented Dickey Fuller—Fisher Chi-square, and Phillips Perron—Fisher Chi-square methods (Phillips & Perron, 1988) assume a common and individual unit root process as a null hypothesis of a unit root. However, we fail to accept the null hypothesis at level based on 5 % p value. The model proposed is not stationary at level as well as at first differences (Table 3). The model proposed is not stationary at level as well as at first differences (Table 3).

Table 3. Summary of Unit root test of selected samples.

Source: Authors' calculation using EVIEWS 12

Variables	ADF (In level)	ADF(at first difference)	Decision
GPRC- India	-14.86569**	-14.16751**	*I(0)*
GPRHC-India	-15.43322**	-13.53028**	*I(0)*
GPRM	-19.57756**	-12.76998**	*I(0)*
GPRH	-21.16736**	-11.62187**	*I(0)*
GPRM_ACT	-18.40150**	-9.677165**	*I(0)*
GPRH_ACT	-14.37318**	-12.43006**	*I(0)*
GPRM_THREATS	-22.29787**	-11.63999**	*I(0)*
GPRH_THREATS	-20.63129**	-9.559025**	*I(0)*
PUI-NB	-15.31346**	-10.01824**	*I(0)*
NIFTY50	-15.13125**	-12.58388**	*I(0)*
SENSEX	-14.75359**	-15.82192**	*I(0)*

Note: ADF refers to the augmented Dickey–Fuller unit root test. ** indicates significant P value

Here, the results of unit root test are statistically significant at level as well as at first difference, so we can employ the ARDL method to explore the long-term interrelationship among the various geopolitical risk index based on monthly, historical and country based indexes and with selected Indian stock indices i.e. Sensex and Nifty during the period of January 2003 to October 2023.

Cointegration test

The existence of a long-term link between endogenous and exogenous variables is determined using the boundaries test. In contrast to(Engle & Granger, 1987), and(Johansen & Juselius, 1990) tests, which call for variables integrated of the same order, the ARDL bounds test can evaluate the cointegration of variables of different orders, the bound test has desirable qualities. The value of the F statistic governs the cointegration's decision rule.

The measurements produce a critical value with a lower and upper bound. It is possible to reject the null hypothesis that there is no cointegration if the F values are higher than the lower and upper values. Cointegration is regarded as being inconclusive if the F-value is indecisive or between the bottom and upper limits. Results of an ARDL bounds test are shown in Table 4.

Table 4. Results of F bond test of ARDL

Source: Authors' calculation using EVIEWS 12

F-Bounds Test Statistics					Decision
Test Statistic	Value	Signif.	Lower critical bounds I(0)	Upper critical bounds I(1)	
F-statistic	**37**.08939	10%	2.07	3.16	
K	10	5%	2.33	3.46	
		2.5%	2.56	3.76	
		1%	2.84	4.1	
t-Bounds Test Statistics					Cointegration
Test Statistic	Value	Signif.	I(0)	I(1)	
t-statistic	-19.68857	10%	-3.13	-4.96	
		5%	-3.41	-5.29	
		2.5%	-3.65	-5.59	
		1%	-3.96	-5.94	

Results indicates that the calculated F-statistics (37.0893) is greater that the UCB- I (1) (Table 1) and significant, the null hypothesis of no long-run relationship among the variables can be rejected in this case. Therefore, we conclude a long-run relationship between geopolitical risk indices and Indian stock prices in India over the period 2003-2023.The ARDL model can be used to estimate a long run and an error correction model.

In addition, Table 5 reports the estimated results of Trace and Max-Eigen statistics. The Johansen cointegration approach outcomes validate a long-run cointegration linkage between selected sample and the determinants as geopolitical risk which confirm the outcomes of the ARDL-bounds technique.

Table 5. Results of the Johansen cointegration method.

Source: Authors' calculation using EVIEWS 12

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	Critical Value	Prob.**
None	0.458637	842.4852	285.1425	<0.01
At most 1	0.364105	692.7509	239.2354	<0.01
2	0.322071	582.2868	197.3709	<0.01
3	0.295474	487.4408	159.5297	<0.01
4	0.287044	401.9848	125.6154	<0.01
5	0.248081	319.4308	95.75366	<0.01
6	0.228823	249.8599	69.81889	<0.01
7	0.192541	186.4594	47.85613	<0.01
8	0.177056	134.2768	29.79707	<0.01
9	0.175457	86.72936	15.49471	<0.01
10	0.150003	39.65548	3.841465	<0.01
Maximum Eigenvalue				
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None	0.458637	149.7342	70.53513	<0.01
At most 1	0.364105	110.4641	64.50472	<0.01
2	0.322071	94.84602	58.43354	<0.01
3	0.295474	85.45598	52.36261	<0.01
4	0.287044	82.55402	46.23142	<0.01
5	0.248081	69.57092	40.07757	<0.01
6	0.228823	63.40044	33.87687	<0.01
7	0.192541	52.18259	27.58434	<0.01
8	0.177056	47.54746	21.13162	<0.01
9	0.175457	47.07388	14.26460	<0.01
10	0.150003	39.65548	3.841465	<0.01

After testing the integration orders, For the ARDL model, a suitable amount of lags must be chosen. The ideal lag order is determined to be one based on LR, FRE, and AIC, as shown in Table 6.

Table 6. Lag selection criteria

Source: Authors' calculation using EVIEWS 12

Lag	LogL	LR	FPE	AIC	SC	HQ
0	2086.535	NA	1.21e-21	-16.94315	-16.78595*	-16.87984
1	2296.757	399.8507	5.87e-22*	-17.67149*	-15.78510	-16.91184*
2	2388.443	166.1576	7.49e-22	-17.43219	-13.81660	-15.97620
3	2498.773	190.0380*	8.29e-22	-17.34509	-12.00031	-15.19275
4	2576.058	126.1785	1.22e-21	-16.98823	-9.914256	-14.13954

Note: * Indicates lag order selected by the criterion.

Model 1- ARDL Error Correction and Long-Run Results taking SENSEX as a dependent variable.

The present study engaged the ARDL method to find the long run interrelationships amongst the selected variables. A constrained constant indicates that the intercept takes an active role in long-term associations, which would be more appropriate for the variables under consideration. In the present model, the explained variable is NIFTY and SENSEX, while the explanatory variables (explanatory variables) are different phenomenon of the geopolitical risk index of historical and monthly data along with the country based geopolitical risk index with economic policy uncertainty data. In the first model we explain the behavior of the SENSEX with the geopolitical risks and in the second model we explain the behavior of the NIFTY with the geopolitical risk data. In Table 8 the findings of the long-term relationship estimations are reported. For the model one considering the Sensex as the explained variables. Most of the long-run (equilibrium) coefficients are statistically significant, as shown by the T-statistic values and p-values (prob.), and the implications are consistent with economic theory.

These findings indicate that the higher GPR causes stock price crashes to occur more frequently. The results indicated that the geopolitical risk index monthly significantly (at 5% level) and negatively affects Indian stock price (SENSEX). In the long term, a 1% increase in Geopolitical risk index the Indian stock price negatively affected by the -0.23%, and by the -0.169% negatively affect in the short run. Result also reviled that geopolitical risk index historical (GPRH) has significantly negative impact on the Sensex price with -0.118687% in the long run, and -0.157616% in the short run periods based on the results of the Error Correction Regression model. In the next results also reflex that the country based geopolitical risk index historical of India (GPRHC_HIST INDIA) also negatively affected the selected Indian stock index. Similar to this, geopolitical risk index historical threats (GPRH THRETAS) also negatively (-0.128%) affected the Indian stock price (statistically significant at 10@ level). 1 % increase in the geopolitical risk index historical threats stock price decreases by the 0.128%.

Geopolitical risks can create market sentiment swings. Positive news, like the resolution of a geopolitical conflict, can lead to a rally in the stock market, while negative developments can lead to a sell-off. During times of heightened geopolitical risk, investors may seek safer assets like government bonds or precious metals, causing a shift away from equities. This can lead to a decrease in demand for stocks and, consequently, a decline in the SENSEX. It's important to note that the impact of geopolitical risks on the SENSEX can be both short-term and long-term, depending on the nature and duration of the specific risk. In current scenario the Geopolitical risks have a significant impact on the SENSEX, which is the benchmark stock market index of India. These risks can create uncertainty and volatility in the financial markets, leading to fluctuations in stock prices. Geopolitical risks, such as tensions between nations, conflicts, or political instability, can erode investor confidence. Geopolitical events often introduce uncertainty and unpredictability into the markets. Investors dislike uncertainty because it makes it difficult to gauge the future outlook for companies and industries. This can lead to a more cautious and risk-averse approach, causing investors to sell stocks, which can result in lower stock prices. These risk can deter foreign investors from putting their money into the Indian stock market. A decrease in foreign investment can lead to a decline in stock prices, as foreign capital often plays a significant role in the Indian stock market. Similarly, the Geopolitical events can also impact currency exchange rates. If a geopolitical event leads to a depreciation of the Indian Rupee, it can affect the earnings of Indian companies that do business internationally. This can influence stock prices and, consequently, the SENSEX and NIFTY.

Table 7. Estimates of long-run coefficients using the selected ARDL model (for SENSEX).
Source: Authors' calculation using EVIEWS 12

Dependent Variable: LOG_RETURNS_SENSEX, method ARDL				
Selected Model: ARDL(1, 1, 0, 2, 0, 3, 4, 0, 2, 4)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LOG_RETURNS_SENSEX(-1)	0.135889	0.066825	2.033499	0.0432
LOG_RETURNS_INDIA_NEWS_BASED_PUI	-0.003644	0.009529	-0.382393	0.7025
LOG_RETURNS_INDIA_NEWS_BASED_PUI(-1)	0.016798	0.009326	1.801175	0.0731
LOG_RETURNS_GPRH_THREATS	-0.128008	0.076857	-1.665534	0.0972**
LOG_RETURN_GPRM_THREATS	0.117129	0.097979	1.195442	0.2332
LOG_RETURN_GPRM_THREATS(-1)	-0.000438	0.037085	-0.011824	0.9906
LOG_RETURN_GPRM_THREATS(-2)	0.088517	0.035501	2.493360	0.0134*
LOG_RETURN_GPRM_ACT	0.024309	0.061856	0.392991	0.6947
LOG_RETURN_GPRM	-0.169964	0.161525	-1.052247	0.2939
LOG_RETURN_GPRM(-1)	0.063739	0.057824	1.102301	0.2716
LOG_RETURN_GPRM(-2)	**-0.233531**	**0.057275**	**-4.077362**	**0.0001***
LOG_RETURN_GPRM(-3)	0.035926	0.021909	1.639811	0.1025
LOG_RETURN_GPRHC_HISTORICA_INDIA	0.006752	0.010605	0.636671	0.5250
LOG_RETURN_GPRHC_HIST_INDIA(-1)	-0.019657	0.011495	-1.710045	0.0887**
LOG_RETURN_GPRHC_HIST_INDIA(-2)	-0.012998	0.011570	-1.123473	0.2625
LOG_RETURN_GPRHC_HIST INDIA_(-3)	0.013524	0.011616	1.164292	0.2456
LOG_RETURN_GPRHC_HIST INDIA_(-4)	-0.020870	0.010683	-1.953548	0.0520*
LOG_RETURN_GPRH_ACT	-0.004762	0.050111	-0.095037	0.9244
LOG_RETURN_GPRH	0.142378	0.133810	1.064030	0.2885
LOG_RETURN_GPRH(-1)	**-0.118687**	**0.051639**	**-2.298418**	**0.0225***
LOG_RETURN_GPRC_IND___COUNTRY_GPR__ PERCENT_OF_ARTICLES__INDIA_	-0.001100	0.014154	-0.077702	0.9381
LOG_RETURN_GPRC INDIA_(-1)	0.028187	0.015777	1.786642	0.0754**
LOG_RETURN_GPRC INDIA_(-2)	0.007368	0.015946	0.462076	0.6445
LOG_RETURN_GPRC_INDIA_(-3)	-0.016964	0.016018	-1.059053	0.2908
LOG_RETURN_GPRC_INDIA_(-4)	0.030860	0.013633	2.263674	0.0246*
C	0.881630	0.105473	8.358817	0.0000*
@TREND	-7.55E-05	5.56E-05	-1.357787	0.1759
• R^2	0.227615	$\bar{x}$ dependent var		1.014419
• Adjusted R^2	0.131512	σ dependent var		0.062260
• S.E. of regression	0.058021	AIC		-2.748798
• Sum squared resid	0.730527	SIC		-2.348654
• LLH	364.7278	HQC		-2.587661
• F-statistic	2.368445	DWS		1.993620
• Prob(F-statistic)	0.000339			

The short-term association between agricultural growth and the major determinates in India was also examined in this study using an error correction model.

Table 8. Estimates of ARDL Error Correction Regression

Source: Authors' calculation using EVIEWS 12

Dependent Variable: D(LRSENSEX)				
Selected Model: ARDL(1, 1, 2, 3, 0, 4, 0, 0, 2, 4)				
ECM Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.881630	0.059557	14.80313	0.0000
@TREND	-7.55E-05	5.17E-05	-1.461456	0.1453
D(LR PUI NB INDEX IND)	-0.003644	0.005626	-0.647635	0.5179
D(LRGPRM_THREATS)	0.117129	0.027157	4.312977	0.0000
D(LRGPRM_THREATS(-1)	-0.088517	0.024808	-3.568152	0.0004
D(LRGPRM)	-0.169964	0.042055	-4.041498	0.0001
D(LRGPRM(-2))	-0.035926	0.016860	-2.130916	0.0342
D(LRGPRHC_INDIA_)	0.006752	0.008886	0.759870	0.4482
D(LRGPRHC INDIA_(-1))	0.020344	0.012422	1.637668	0.1029
D(LRGPRHC INDIA_(-2))	0.007345	0.012206	0.601797	0.5479
D(LRGPRHC_INDIA_(-3))	0.020870	0.008872	2.352208	0.0196
D(LRGPRH(-1))	-0.157616	0.033787	-4.665000	0.0000
D(LRGPRC_INDIA_)	-0.001100	0.010903	-0.100864	0.9198
D(LRGPRC INDIA_(-1))	-0.021265	0.015092	-1.408998	0.1603
D(LRGPRC_INDIA_(-2))	-0.013897	0.014832	-0.936912	0.3498
D(LRGPRC_INDIA_(-3))	-0.030860	0.010472	-2.946931	0.0036
CointEq(-1)*	-0.864111	0.057815	-14.94624	0.0000
• R^2	0.588894	• x dependent var		-0.000277
• Adjusted R^2	0.556151	• σ dependent var		0.085339
• S.E. of regression	0.056854	• AIC		-2.822268
• Sum squared resid	0.730527	• SIC		-2.550742
• Log likelihood	364.7278	• HQC		-2.712924
• F-statistic	17.98537	• DWS		1.993620
• Prob(F-statistic)	0.000000			

Model 2- ARDL Error Correction and Long-Run Results taking NIFTY as a dependent variable.

In the model 2, the explained variable is NIFTY while the explanatory variables (explanatory variables) are different phenomenon of the geopolitical risk index of historical and monthly data. In this model we explain the behavior of the NIFTY with the geopolitical risks and in the second model we explain the behavior of the NIFTY with the geopolitical risk data. In Table 8 the findings of the long-term relationship estimations are reported. For the model one considering the Sensex as the explained variables. 2 major long-run (equilibrium) coefficients are statistically significant, as shown by the T-statistic values and p-values (prob.), and the implications are consistent with economic theory. The results indicated that the geopolitical risk index monthly significantly (at 5% level) and negatively affects Indian stock price (NFITY). In the long term, a 1% increase in monthly Geopolitical risk index the Indian stock price negatively affected by the -0.21%. Result also reviled that geopolitical risk index historical (GPRH) has significantly negative impact on the Nifty stock price with -0.083312% in the long run, and -0.124401% in the short run periods based on the results of the Error Correction Regression model. In the next results also reflex that the monthly geopolitical risk threats (GPRM_THREATS) also negatively affected the selected Indian stock index Nifty in the short run.

Table 9. Estimates of long-run coefficients using the selected ARDL model (for NIFTY).

Source: Authors' calculation using EVIEWS 12

Dependent Variable: LRNIFTY50				
Selected Model: ARDL (1, 1, 2, 0, 0, 0, 0, 2, 0, 2)				
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LRNIFTY50(-1)	0.070612	0.066985	1.054138	0.2929
LRINDIA_NEWS_BASED_PUI	-0.002325	0.009772	-0.237905	0.8122
LRINDIA_NEWS_BASED_PUI (-1)	0.013744	0.009101	1.510161	0.1324
LRGPRM	-0.050411	0.158771	-0.317507	0.7511
LRGPRM(-1)	0.054884	0.057872	0.948366	0.3439
LRGPRM(-2)	-0.219584	0.056410	-3.892683	0.0001**
LRGPRHC_HISTORICALINDIA_	0.012345	0.010286	1.200163	0.2313
LRGPRH_THREATS	-0.093320	0.076884	-1.213775	0.2261
LRGPRH_ACT	0.029897	0.050372	0.593521	0.5534
LRGPRC_ INDIA_	-0.003845	0.013213	-0.291021	0.7713
LRGPRH	0.055702	0.129568	0.429903	0.6677
LRGPRH(-1)	-0.083312	0.050064	-1.664095	0.0975**
LRGPRM_ACT	-0.025203	0.061205	-0.411773	0.6809
LRGPRM_THREATS	0.053355	0.097754	0.545812	0.5857
LRGPRM_THREATS(-1)	-0.021763	0.037022	-0.587820	0.5572
LRGPRM_THREATS(-2)	0.091762	0.036463	2.516570	0.0125
C	1.014596	0.093323	10.87192	0.0000
@TREND	-7.51E-05	5.51E-05	-1.363872	0.1740
R^2	0.156678	$\bar{x}$ dependent var		1.014259
Adjusted R^2	0.090100	σ dependent var		0.063318
S.E. of regression	0.060398	AIC		-2.701915
Sum squared resid	0.831728	SIC		-2.431962
Log likelihood	352.6865	HQC		-2.593230
F-statistic	2.353295	DWS		1.959801
Prob(F-statistic)	0.001968			

Table 10. Estimates of ARDL Error Correction Regression

Source: Authors' calculation using EVIEWS 12

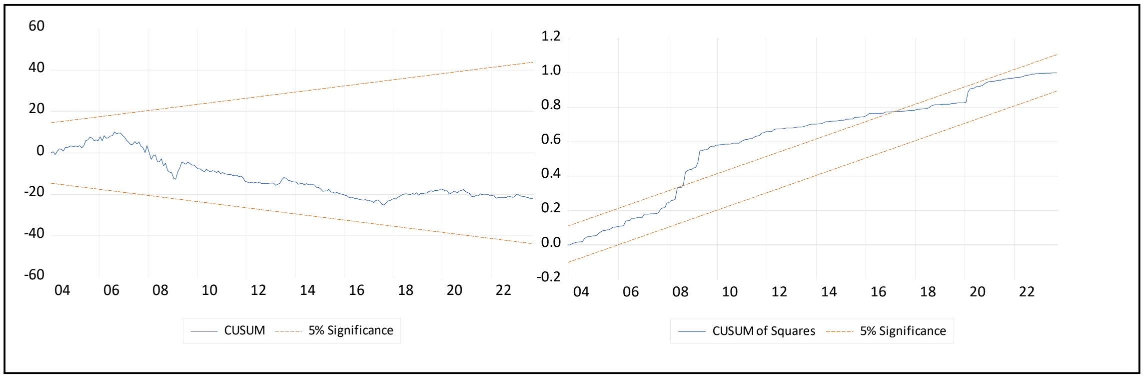
Dependent Variable: D(LRNIFTY50)				
Selected Model: ARDL(1, 1, 2, 0, 0, 0, 0, 2, 0, 2)				
ECM Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.014596	0.064320	15.77420	0.0000
@TREND	-7.51E-05	5.30E-05	-1.417331	0.1578
D(LR- PUI NB Ind	-0.002325	0.005372	-0.432771	0.6656
D(LRGPRM)	-0.050411	0.040026	-1.259441	0.2092
D(LRGPRM(-1))	0.219584	0.040264	5.453613	0.0000
D(LRGPRH)	0.055702	0.032703	1.703260	0.0899
D(LRGPRH(-1))	-0.124401	0.032837	-3.788426	0.0002
D(LRGPRM_THREATS)	0.053355	0.026233	2.033906	0.0431
D(LRGPRM_THREATS(-1)	-0.091762	0.025274	-3.630675	0.0003
CointEq(-1)*	-0.929388	0.058614	-15.85611	0.0000
• R^2	0.564523	$\bar{x}$ dependent var		0.000343
• Adjusted R^2	0.547986	σ dependent var		0.088113
• S.E. of regression	0.059240	AIC		-2.774789
• Sum squared resid	0.831728	SIC		-2.632709
• Log likelihood	352.6865	HQC		-2.717587
• F-statistic	34.13671	DWS		1.959801
• Prob(F-statistic)	0.000000			

Diagnostic Test

Various diagnostic tests are typically employed to evaluate the model's stability. The stability structure of the model utilizing cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) is shown in Figure 3. We can see that the blue line lies within the red line that is the blue line lies within the 5 % critical line, which prove that the residual variances stable.

Figure 3- The stability structure of the model utilizing cumulative sum.

Source: Authors' calculation using EVIEWS 12



7. CONCLUSION AND SUGGESTIONS

Geopolitical risk is one of the key determinants of investment decisions made by market participants. As a result of the Israel-Palestine conflict (risk of war), Global energy security, Russian-Ukrainian war, Russia-NATO tensions, Cyberattacks, Climate risk the global GPR is now higher than ever. Beside that country based geopolitical risk is also a major concern during these periods. The influence of GPR on financial markets is a matter of greater concern for governments, investors, and researchers. Consequently, this study aims to examine the influence of several Global Pandemic Response (GPR) measures on stock market volatility in the context of India, drawing on the GPR index developed by Caldara and Iacoviello (2022). The financial markets will definitely see a drop-in economic activity as a consequence of the geopolitical risk shock. India is currently undergoing a significant geopolitical realignment, characterized by the abandonment of its previous non-aligned movement rhetoric. Instead, it is adopting a pragmatic approach centered on national interests, thereby forging robust strategic partnerships with various nations, notably the United States and its regional allies, particularly Japan. Geopolitical risks can create market sentiment swings. Positive news, like the resolution of a geopolitical conflict, can lead to a rally in the stock market, while negative developments can lead to a sell-off. During times of heightened geopolitical risk, investors may seek safer assets like government bonds or precious metals, causing a shift away from equities. This can lead to a decrease in demand for stocks.

This paper reviews the long-term impact of Geopolitical risk monthly and historical index, along with other control variables, including GPRC_IND = Country GPR: Percent of articles (India), GPRHC_IND = Country GPR Historical: Percent of articles (India), Geopolitical Risk Monthly Index Acts, Geopolitical Risk Historical Index Acts, Geopolitical Risk Monthly Index Threats, Geopolitical Risk Historical Index Threats and India News-Based Policy Uncertainty Index on the Indian stock prices. The Augmented Dickey-Fuller and Phillips-Perron unit root tests were utilized to assess the stationarity of the variables. This research employed many econometric techniques, including the ARDL bound-testing methodology and Johansen co-integration process, to ascertain the long-term co-integrating relationship among the variables. The empirical results obtained by the ARDL bound-testing approach provide confirmation of the existence of a long-term co-integrating relationship among the variables.Long-term studies showed that more frequent stock price collapses are caused by higher GPRs. The findings showed that the Indian stock market (SENSEX and NIFTY) is negatively impacted by the monthly geopolitical risk index significantly (at a 5% level). The Indian stock price was negatively impacted by a 1% increase in the geopolitical risk index in the long run by -0.23%, and in the short run by -0.169%. The results also showed that, according to the Error Correction Regression model, the geopolitical risk index historical (GPRH) had a considerably negative impact on the price of the Sensex, with a long-term impact of -0.118687% and a short-term impact of -0.157616%. The subsequent findings further indicate that the chosen Indian stock index was adversely impacted by the historical country-based geopolitical risk index of India (GPRHC_HIST INDIA). The Indian stock price was similarly negatively impacted (-0.128%) by the geopolitical risk index historical threats (GPRH THRETAS), which was statistically significant at the 10@ level. Historical risks to the geopolitical risk index cause a 1% gain in stock price to drop by 0.128%.

Conversely, the findings showed that the monthly geopolitical risk index has a significant (at 5% level) negative impact on the price of Indian stocks (NFITY). Over an extended period, a 1% rise in the monthly Geopolitical Risk Index has a negative impact of -0.21% on the price of Indian stocks. Based on the findings of the Error Correction Regression model, the results also revealed that the geopolitical risk index historical (GPRH) has a significantly negative impact on the Nifty stock price, with long-term values of -0.083312% and short-term values of -0.124401%. The following data also indicate that the short-term performance of the chosen Indian stock index, Nifty, was adversely impacted by the monthly geopolitical risk threats (GPRM_THREATS).

In addition to other macroeconomic variables, these results indicate that policymakers in India and around the world should implement more effective measures to mitigate the impact of the geopolitical risk index on financial assets. It is a complex task, as it involves addressing various political, economic, and social factors that contribute to instability and uncertainty.Geopolitical risks can have a significant impact on Indian stock prices, and mitigating this impact requires a combination of strategic measures. Investors can focus on the fundamental analysis of stocks rather than short-term market sentiment to avoid the major risk. A company's financial health, management quality, and growth prospects are often more important in the long run so investors of financial stocks market may adopt a long-term investment perspective. Geopolitical events may lead to short-term fluctuations, but a long-term investment horizon can help mitigate the impact of short-term volatility. Defensive stocks, such as those in sectors like healthcare, utilities, and consumer staples, tend to be less sensitive to economic and geopolitical volatility. Investing in these sectors can provide stability during uncertain times. In the last but not the least the stakeholders of the financial market may adjust their asset allocation based on the prevailing geopolitical climate. For example, during periods of heightened geopolitical risk, consider reducing exposure to equities and increasing allocations to safer assets like bonds or gold.

On the other hands we can said that the Governments and businesses should conduct thorough risk assessments to understand the specific geopolitical challenges they face. This includes evaluating country-specific risks, regulatory environments, and the potential impact on their operations. Political risk insurance provides coverage against losses resulting from political events like expropriation, political violence, or currency inconvertibility. This can protect businesses with international operations from sudden geopolitical shocks. Building strong relationships with governments, local partners, and international organizations can help navigate geopolitical challenges. Engaging in dialogues and negotiations with relevant stakeholders can be instrumental in finding solutions. Institutions can utilize financial instruments like options and futures to hedge against currency exchange rate fluctuations and other financial risks caused by geopolitical events.

7.1. Future area of research

Nevertheless, the study's conclusions were constrained due to the use of Indian stock indexes in the model. Future research endeavors might potentially enhance the study by incorporating more factors, so expanding upon the existing knowledge. Furthermore, the study might potentially use sophisticated methodologies. Long term and short term impact of the Geopolitical risks can be measure on the prices of commodities, such as oil and gas energy resources, country's inflation rate and the profitability of companies etc.

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