“Nexus between stock market and macroeconomic indicators: An NARDL approach”

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NEXUS BETWEEN STOCK MARKET AND MACROECONOMIC INDICATORS: AN NARDL APPROACH

Abstract

This study investigates the asymmetric short- and long-run effects of gold prices, crude oil prices, and the USD/INR exchange rate on India's Nifty 50 index. Drawing on daily data from 2022 through 2024, it employs the Nonlinear Autoregressive Distributed Lag (NARDL) model to uncover both long-term equilibrium relationships and short-term nonlinear dynamics among these key economic variables. Unit root tests reveal mixed orders of integration, reinforcing the suitability of the NARDL framework for this analysis. The long-run estimates indicate that only negative gold price shocks exert a statistically significant effect on the Nifty 50, while positive shocks appear inert. In contrast, the short-run results highlight that both USD/INR appreciations and depreciations adversely affect the index, underlining the stock market's heightened sensitivity to exchange rate volatility. Intriguingly, short-term declines in gold prices are associated with positive responses in equity markets, potentially reflecting hedging behavior or shifts in investor sentiment. Meanwhile, crude oil price fluctuations exert no statistically meaningful impact in either the short or long term. Diagnostic checks confirm a stable long-run cointegrating relationship among the studied variables. These findings offer robust, empirically grounded insights for investors and policymakers, particularly in crafting risk mitigation strategies and informed decision-making during periods of geopolitical turbulence and economic uncertainty.

Keywords equities, gold, oil, currency, asymmetry, cointegration, nonlinearity, geopolitics

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INTRODUCTION

The Russia–Ukraine war, which began in 2022, introduced a new wave of global economic disruption at a time when economies were still recovering from the COVID-19 pandemic. As major exporters of oil, agricultural products, fertilizers, and metals, both countries play vital roles in global supply chains. The war triggered sharp increases in energy and food prices, currency fluctuations, and financial market volatility, directly influencing key macroeconomic indicators such as crude oil prices, gold prices, and exchange rates. Given the sensitivity of stock markets to these variables, the crisis has raised critical questions about how macroeconomic shocks are transmitted to equity markets. Understanding this nexus is essential for policymakers and investors, particularly in emerging markets such as India, where the Nifty 50 index reflects the broader economic and financial environment.

In this context, the behavior of financial markets has come under heightened scrutiny. Stock markets, often regarded as forward-looking indicators of economic health, tend to respond quickly to geopolitical instability and macroeconomic shocks. Emerging markets, such as India, are particularly vulnerable to external pressures due to their dependence on imported energy and exposure to global capital movements. As a result, fluctuations in commodity prices and currency exchange rates can have significant and immediate effects on domestic equity markets.

Gold, crude oil, and foreign exchange rates are especially important during crises. Gold is widely viewed as a safe-haven asset, while oil prices directly affect inflation and business costs. Exchange rate volatility, particularly involving the United States dollar and Indian rupee, can influence trade competitiveness and investor sentiment. Understanding how these macroeconomic variables impact stock markets under conditions of geopolitical stress is essential for investors, analysts, and policymakers.

The increasing integration of financial markets has further amplified the sensitivity of domestic markets to global developments. In such an environment, traditional linear models may fail to capture the complex and often asymmetric relationships that emerge during times of crisis. This highlights a critical scientific problem: the need to explore how macroeconomic and geopolitical shocks asymmetrically affect financial markets, particularly in emerging economies. Addressing this problem is essential for developing more accurate tools to assess market behavior and enhance financial decision-making under uncertainty.

1. LITERATURE REVIEW

Numerous studies have investigated the interplay between macroeconomic variables and stock market performance, particularly during periods of global uncertainty. Geopolitical crises such as the Russia–Ukraine war have brought renewed attention to how fluctuations in commodity prices and currency exchange rates influence equity markets. Crude oil, gold, and foreign exchange rates are considered critical indicators of economic health and investor sentiment, especially in emerging economies like India. These variables tend to exhibit stronger and more complex dynamics during crises, highlighting the importance of exploring both symmetric and asymmetric relationships across time horizons.

Crude oil is among the most globally traded commodities, and its pricing, primarily in U.S. dollars, links it closely with international capital flows. Changes in oil prices affect input costs, inflation, and corporate profitability, and by extension, stock market movements. Studies have established that oil price volatility is a major source of financial instability, especially in oil-importing nations like India (Gao et al., 2014; Arouri et al., 2011; Bouri, 2015). Huang et al. (2017) found that exchange rates moderate the oil–stock market nexus, and the impact varies by country. Salisu and Isah (2017) applied a panel nonlinear ARDL model and revealed significant asymmetric effects of oil prices, especially for oil-importing nations. Similarly, Balcilar et al. (2019) used quantile regression to show that risk exposure to oil shocks differs across economies, with developing countries experiencing heightened sensitivity. Wang et al. (2020) observed that oil price changes exert greater influence during extreme market conditions, while Xie et al. (2021) concluded that supply and demand shocks in oil markets can significantly disrupt stock markets, albeit with market-dependent resilience.

Gold is widely regarded as a safe-haven asset, often attracting investment during financial crises. It serves as a hedge against inflation and currency depreciation and tends to rise in value when stock markets become volatile (Hoang et al., 2015; Yeniley, 2025). The inverse relationship between gold and equities is well recognized, with investors shifting to gold during downturns (Hood & Malik, 2013). Empirical studies reinforce this role. For instance, Shiva and Sethi (2015) demonstrated a one-way causal link between gold and the Nifty index using VECM and Granger causality approaches. Gokmenoglu and Fazlollahi (2015) confirmed long-run relationships between gold, oil, and the S&P 500. Nguyen et al. (2016) found that gold acts as a refuge for several markets, though its effect is market-specific. Adewuyi et al. (2019) reported gold's portfolio diversification potential in the Nigerian context, while Mejri et al. (2023) emphasized the lead-lag dynamics between gold and indices like the DJIA and S&P 500, especially in turbulent times such as COVID-19 and the Russia–Ukraine war. Ahmed (2018) also highlighted the influence of energy commodities like natural gas on regional markets and warned against ignoring structural breaks in time-series analysis.

Exchange rate movements also significantly affect stock prices, particularly in open and capital-sensitive economies. Theoretically, three models

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frame this relationship: the product market hypothesis (Dornbusch & Fischer, 1980), the portfolio balance model (Frankel, 1983), and asset market models (Horne, 1983). Theoretical perspectives on the relationship between exchange rates and stock prices vary, with some suggesting causality from exchange rates to stock prices, while others find no long-term association. Empirical research also presents mixed findings. For instance, Kollias et al. (2010) found no cointegration between exchange rates and stock prices in European markets, although causality was observed under stressed conditions. Mroua and Trabelsi (2020) observed long- and short-run cointegration between exchange rates and BRICS stock markets. Lin (2012) confirmed that the link between exchange rates and Asian equities strengthens during crises and is more influenced by capital flows than trade. Ali et al. (2020) showed that simultaneous declines in gold and exchange rates negatively affect stock performance, emphasizing the dual role these variables play under uncertainty.

Pradhan et al. (2015), Tiwari et al. (2015), and Wickremasinghe (2011) have highlighted that, despite the extensive literature on the relationship between exchange rates and stock prices, several research gaps persist. A significant number of studies employ linear methodologies such as Vector Autoregression (VAR), Johansen cointegration, or traditional Autoregressive Distributed Lag (ARDL) models, which may not adequately capture the asymmetric characteristics inherent in financial relationships. Many studies overlook the possibility that stock markets may exhibit distinct responses to positive versus negative shocks. Moreover, no study to date has used the Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the asymmetric impact of oil prices, gold prices, and the USD/INR exchange rate on the Indian stock market during the Russia–Ukraine war, a period characterized by heightened economic uncertainty and market volatility.

Pradhan et al. (2015), Tiwari et al. (2015), and Wickremasinghe (2011) have highlighted that, despite extensive research on the relationships between macroeconomic variables and stock markets, several gaps remain. Notably, the asymmetric effects of macroeconomic variability on stock indices have not been adequately addressed in most studies. Instead, researchers have predominantly employed linear techniques such as Vector Autoregression (VAR), Johansen cointegration, and Autoregressive Distributed Lag (ARDL) models to examine the symmetric associations between gold, crude oil, the USD/INR exchange rate, and stock markets. Second, prior studies have largely assumed linearity in the relationships between stock indices and macroeconomic variables, potentially overlooking important asymmetric responses. Third, to the best of the authors' knowledge, no study has employed the Nonlinear Autoregressive Distributed Lag (NARDL) model to analyze how specific macroeconomic indicators affect the Indian stock market during the Russia–Ukraine war, a period characterized by heightened uncertainty and volatility.

This study aims to investigate the short- and long-term asymmetric impacts of gold prices, crude oil prices, and the USD/INR exchange rate on the Nifty 50 index during the Russia–Ukraine war, utilizing the Nonlinear Autoregressive Distributed Lag (NARDL) model. The NARDL approach, as developed by Shin et al. (2014) and Pesaran et al. (2001), is particularly effective in capturing nonlinear cointegration and distinguishing between the effects of positive and negative changes in independent variables. By incorporating both the direction and magnitude of shocks, this approach offers a more robust framework for understanding market behavior. This research seeks to fill a critical gap in the literature and contribute new empirical evidence regarding the asymmetric dynamics between selected macroeconomic variables and the Indian equity market during geopolitical crises. Drawing upon prior literature, the study formulates the following hypotheses:

H1: *Positive and negative changes in gold prices have asymmetric effects on the Nifty 50 index in the short and long run.*

H2: *Positive and negative changes in crude oil prices have asymmetric effects on the Nifty 50 index in the short and long run.*

H3: *Positive and negative changes in the USD/INR exchange rate have asymmetric effects on the Nifty 50 index in the short and long run.*

H4: There is a long-run cointegrating relationship between the Nifty 50 index and gold prices, crude oil prices, and the USD/INR exchange rate during the Russia–Ukraine war.

2. DATA AND RESEARCH METHODOLOGY

This study utilizes the Nonlinear Autoregressive Distributed Lag (NARDL) model to explore the relationship between gold prices, crude oil prices, the USD/INR exchange rate, and the Nifty 50 index during the Russia–Ukraine war. The analysis is based on daily spot prices for all variables, covering the period from February 24, 2022, to October 2024, totaling 705 observations. The start date corresponds to the onset of Russia's full-scale invasion of Ukraine, marked by the announcement of a "special military operation" on February 24, 2022. Data on all the variables were taken from Bloomberg, and gold is measured in USD/oz. NSE is measured in INR. Crude oil is measured in USD/barrel. The rationale behind taking these variables for this study is that the R-U conflict has profoundly affected global markets, especially supplies such as crude oil and gold. Russia is a significant supplier of crude oil, and interruptions in its supply chain may result in swings in crude oil prices, subsequently affecting global financial markets, including the Nifty 50 (Yousuf & Hassan, 2019). Moreover, the USD/INR currency rate is influenced by geopolitical tensions, which may impact foreign investment and economic stability in developing economies such as India. A declining INR relative to the USD may result in increased import expenses, impacting company profitability and the stock market (Walid et al., 2011). Therefore, this study examines the association among gold, crude oil, USD/INR rate, and Nifty 50 during the R-U war by employing the NARDL model.

The primary advantage of using the NARDL model is that it captures the nonlinear characteristics of the data. Using the ADF and PP approach at the level of first difference, we verified that the dataset was stationarity-free before using the NARDL model. Moreover, we checked the necessary conditions for applying the NARDL model. For instance, the Berusch-Pegan test for heteroskedasticity and the CUSUM test for stability diagnostics were applied. According to Shin et al. (2014), the NARDL model accounts for possible nonlinear linkages by separating explanatory variables into their positive and negative variations. This enables the NARDL model to distinguish between the impacts of increases and reductions in the factors that influence the outcome of an experiment. Furthermore, the NARDL model exhibits flexibility regarding the lag structure, permitting distinct delays for various variables. Since all the variables are in different measurements. Thus, to normalize data, equation (1) was used, and the general equation of the NARDL model is given in equation (2)

$$R_t = ln\frac{P_t}{P_{t-1}}, \tag{1}$$

$$\Delta y_t = \varphi + \sum_{j=1}^{p}\omega_i \Delta y_{t-i} + \sum_{j=0}^{q}\delta_i^+ \Delta x_{t-i}^+ + \sum_{i=0}^{r}\delta_i^- \Delta x_{t-i}^- + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \varepsilon_t, \tag{2}$$

where φ is the constant term, Δ is the difference operator, y_t and x_t characterize the dependent and the independent factors, respectively. x_t^+ and x_t^- are the negative and positive changes in the independent variable x_t. ρ, θ^+, θ^- are the long-run coefficients and ω_i, δ_i^+, and δ_i^- are the coefficients of the dependent and independent factors. ε_t is the error term.

$$\begin{aligned}\Delta NSE_t &= \varphi_0 + \varphi_1 NSE_{t-1} + \varphi_2 GD_{t-1}^+ \\ &+ \varphi_3 GD_{t-1}^- + \varphi_4 CO_{t-1}^+ + \varphi_5 CO_{t-1}^- + \varphi_6 FX_{t-1}^+ \\ &+ \varphi_7 FX_{t-1}^- + \sum_{j=1}^{p}\omega_{1i}\Delta NSE_{t-1} + \sum_{j=0}^{q}\omega_{2i}\Delta GD_{t-1}^+ \\ &+ \sum_{j=0}^{r}\omega_{3i}\Delta GD_{t-1}^- + \sum_{j=0}^{s}\omega_{4i}\Delta CO_{t-1}^+ \\ &+ \sum_{j=0}^{u}\omega_{5i}\Delta CO_{t-1}^- + \sum_{j=0}^{v}\omega_{6i}\Delta FX_{t-1}^+ \\ &+ \sum_{j=0}^{x}\omega_{7i}\Delta FX_{t-1}^- + \varepsilon_{1t}.\end{aligned} \tag{3}$$

The null hypothesis of the above equations is given.

$$\varphi_0 = \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = \varphi_5 = \varphi_6 = \varphi_7 = 0.$$

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Kumar et al. (2020), Sheikh et al. (2020), and Ajaz et al. (2017) emphasized the relevance of assessing long-term cointegration among variables through the F-statistic. When the computed F-statistic is greater than the upper critical value, the null hypothesis of no cointegration is rejected, which suggests the existence of a long-run association between the variables. Alternatively, if the F-statistic lies below the lower bound, the null hypothesis cannot be rejected, indicating a lack of evidence for cointegration.

To evaluate the presence of a long-term relationship further, an Error Correction Model (ECM) is employed. A statistically significant and negative coefficient of the ECM term confirms the existence of cointegration, indicating that the system corrects short-term imbalances to restore equilibrium over time. The NARDL framework, developed by Shin et al. (2014), is particularly suitable for capturing nonlinear cointegration effects and identifying differences between the impacts of positive and negative changes in explanatory variables.

3. RESULTS AND DISCUSSION

This study utilizes the NARDL model to look at how the Nifty 50 index, which is a proxy for the NSE, relates to crude oil, gold, and the USD/INR rate, which are all measures of the foreign currency. In 2014, Shin et al. proposed this method. The symmetric and asymmetric long-term and short-term interactions between variables may be captured by the NARDL model, which is its main advantage.

Table 1 displays outcomes from a BDS Test (Brock, Dechert, Scheinkman Test), often used to identify nonlinearity or dependency in a model's residuals. This test is used to determine the association between the National Stock Exchange (Nifty 50) as the dependent variable and Gold (GD), Crude Oil (CO), and the USD/INR exchange rate (FX) as independent variables. The BDS statistic for all variables and dimensions is significant, as shown by p-values of 0. This firmly refutes the null hypothesis of independent and identically distributed residuals, suggesting that the associations between Nifty 50 and the chosen independent variables are nonlinear and demonstrate a degree of dependency. Moreover, the findings indicate that the residuals of the regression model, including Nifty 50 and the independent variables (gold, crude oil, and exchange rates), are nonlinear and demonstrate dependency. This suggests that a linear model may inadequately represent the dynamics, and using more sophisticated econometric techniques, such as nonlinear time series models, such as the NARDL model, might be better suited for effectively modeling these interactions. Thus, the researchers apply the NARDL model to determine the association between the NSE and the chosen macroeconomic factors during the Russian invasion.

Further, the BDS test results indicate significant nonlinearity and dependence across the examined variables. This suggests that the NARDL model is indeed appropriate for capturing the asymmetric relationships. For instance, compared to previous studies such as those by Shin et al. (2014), the findings of this study similarly confirm that nonlinear adjustments are crucial when examining the impact of macroeconomic shocks on the Nifty 50 index.

Table 2 demonstrates an overview of important statistical features for the variables Foreign Exchange (FX), Gold (GD), Nifty 50 (NSE), and Crude Oil (CO), each with 705 observations. The

Table 1. BDS test results

Dimension	GD (BDS Statistic, Std. Error, Normal Prob., Bootstrap Prob.)	FX (BDS Statistic, Std. Error, Normal Prob., Bootstrap Prob.)	CO (BDS Statistic, Std. Error, Normal Prob., Bootstrap Prob.)
2	(0.1963, 0.0027, 0.00, 0.00*)	(0.2014, 0.0040, 0.00, 0.00*)	(0.1853, 0.0031, 0.00, 0.00*)
3	(0.3330, 0.0043, 0.00, 0.00*)	(0.3435, 0.0064, 0.00, 0.00*)	(0.3151, 0.0049, 0.00, 0.00*)
4	(0.4281, 0.0052, 0.00, 0.00*)	(0.4432, 0.0077, 0.00, 0.00*)	(0.4042, 0.0058, 0.00, 0.00*)
5	(0.4938, 0.0054, 0.00, 0.00*)	(0.5127, 0.0080, 0.00, 0.00*)	(0.4653, 0.0061, 0.00, 0.00*)
6	(0.5392, 0.0051, 0.00, 0.00*)	(0.5609, 0.0078, 0.00, 0.00*)	(0.5071, 0.0058, 0.00, 0.00*)

Note: * denotes significant values at 1%.

Table 2. Descriptive statistics

Variables	FX	GD	NSE	CO
Mean	4.40417	7.603113	9.881903	4.461491
Median	4.415355	7.577531	9.854678	4.423888
Maximum	4.432018	7.929415	10.17413	4.891702
Minimum	4.318819	7.395568	9.635183	4.200655
Std. Dev.	0.027701	0.122563	0.136155	0.14514
Skewness	–1.488171	0.743978	0.416708	0.940571
Kurtosis	4.09742	2.843899	2.037055	3.204094
Jarque-Bera	295.5989	65.75248	47.64169	105.1727
Probability	0	0	0	0
Sum Sq. Dev.	0.540212	10.57527	13.05094	14.83027
Observations	705	705	705	705

mean values show that FX has an average of 4.40417, GD averages 7.603113, NSE has a mean of 9.881903, and CO averages 4.461491, representing their central tendencies. The median values approximate the means for the majority of variables, suggesting highly symmetric distributions, except for FX, which shows a more pronounced difference. The maximum and minimum values highlight the range of each variable, with CO exhibiting the widest spread between 4.200655 and 4.891702, indicating higher volatility compared to the others. This is further supported by CO having the highest standard deviation (0.14514), while FX shows the least variation with a standard deviation of 0.027701. FX has a pronounced negative skew (–1.488171), indicating an extended left tail, whereas GD, NSE, and CO have positive skewness, signifying extended right tails. The skewness of the NSE (0.416708) is the lowest, indicating a somewhat symmetrical distribution. The kurtosis results indicate that FX has a leptokurtic distribution (4.09742), characterized by heavier tails and sharper peaks, while GD and CO approximate a normal distribution, and NSE displays a platykurtic (flatter) distribution (2.037055). The results of the Jarque-Bera test, with a p-value of 0, indicate that none of the variables follow a normal distribution. The significant volatility observed in crude oil prices, coupled with the non-normality and asymmetric distributions of all variables, suggests that advanced econometric models, like the Nonlinear Autoregressive Distributed Lag (NARDL) model, are essential for accurate modeling. The NARDL model is well-suited to handle nonlinearity and heavy-tailed distributions, making it appropriate for this analysis.

The descriptive analysis revealed considerable asymmetries, volatility, and non-normality across the financial variables, highlighting the complex dynamics within the dataset. Notably, crude oil (CO) exhibited the highest standard deviation and positive skewness, consistent with previous findings that oil markets are inherently volatile due to geopolitical shocks and supply-demand imbalances (Zhang & Broadstock, 2020). Similarly, the foreign exchange rate (FX) showed significant negative skewness and leptokurtic behavior, suggesting frequent extreme left-tail outcomes, an observation that aligns with the stylized facts of exchange rate distributions as documented by Baillie and Bollerslev (1989). The Jarque-Bera statistics confirmed that all variables deviate from normality, reinforcing the appropriateness of nonlinear modeling techniques. In particular, the presence of skewed and heavy-tailed distributions supports the application of the Nonlinear Autoregressive Distributed Lag (NARDL) model, which allows for asymmetric adjustments and is robust under mixed orders of integration (Shin et al., 2014). Empirical studies using NARDL have demonstrated its efficacy in modeling financial and macroeconomic time series with asymmetric responses to positive and negative shocks (Shahbaz et al., 2018). Therefore, the nonlinearity and distributional irregularities observed in the data not only justify but necessitate the use of the NARDL approach to better capture the true dynamics between the Nifty 50 index and macroeconomic indicators.

Figure 1 presents time series plots depicting the daily spot price fluctuations for Nifty 50 (NSE), Gold (GD), Foreign Exchange (FX), and Crude Oil (CO) throughout the period from 2022 to 2024. The NSE graph shows an overall increasing trajectory, accompanied by significant variations within the observed time. It shows phases of expansion interspersed with slight regressions, indicative of

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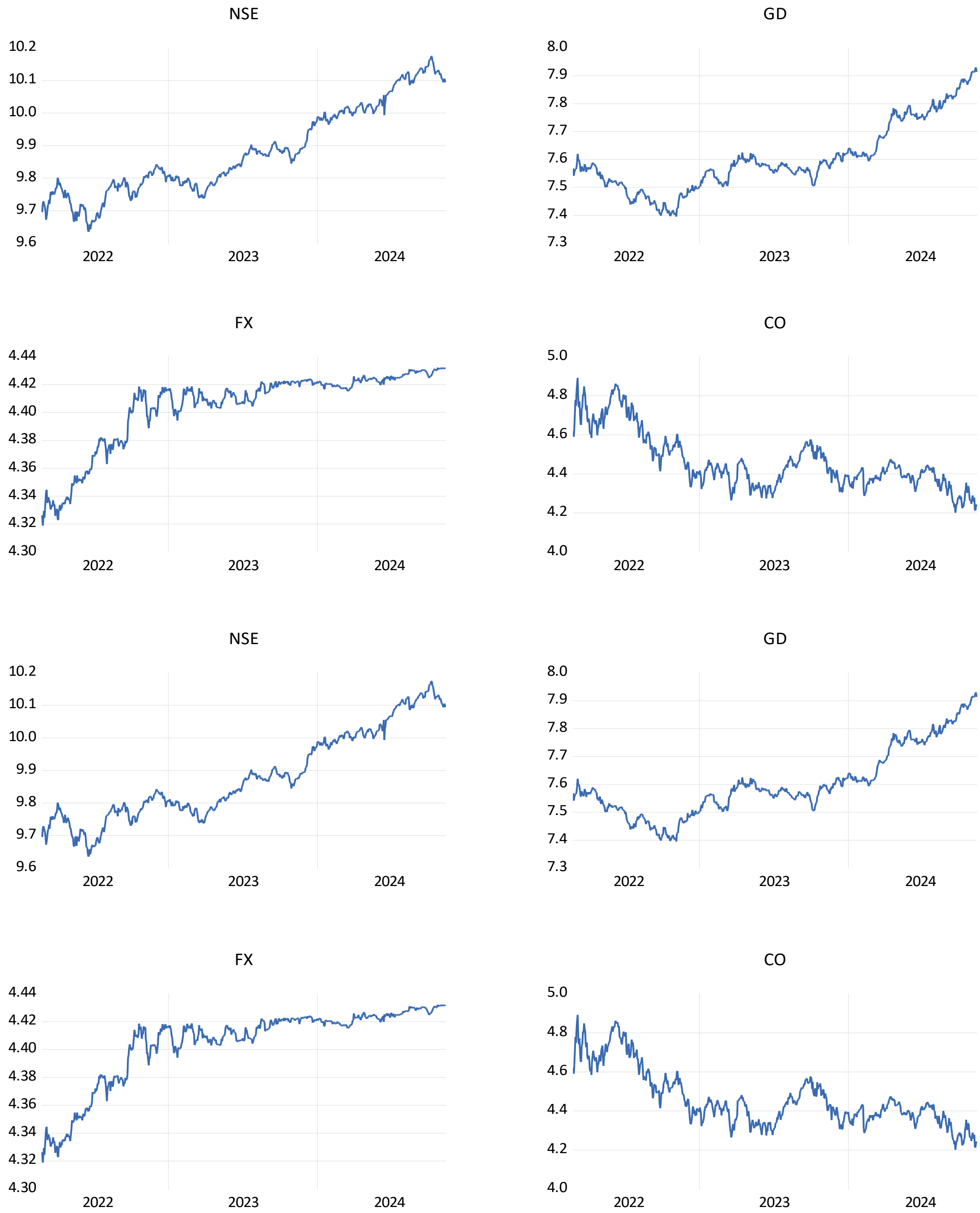

Figure 1. Time variation in daily spot prices of NSE, GD, FX, and CO

market instability. A high is anticipated in early 2024, followed by a minor correction. This signifies dynamic fluctuations driven by macroeconomic variables and market sentiment.

The trajectory of Gold (GD) exhibits a consistent increasing trend accompanied by distinct cyclical fluctuations. Following a period of relative stability in 2022, prices exhibit persistent increases from mid-2023, indicative of rising demand or economic worries propelling gold as a safe-haven asset. Conversely, the graph for FX (USD/INR) shows relative stability, followed by a slightly upward trajectory. The fluctuation range is limited, indicating low volatility. Nonetheless, little but regular escalations in the exchange rate are evident, signifying a progressive depreciation of the INR relative to the USD. The graph for Crude Oil (CO) shows a clear declining trajectory. The sequence starts with a maximum in early 2022, followed by a steep decrease and fluctuations, indicative of the global energy market dynamics, alterations in supply-demand equilibrium, and geopolitical occurrences. By 2024, crude oil prices had reached their lowest levels in the recorded period, signifying persistent downward pressure on oil prices.

Results from the unit root test, as shown in Table 3, provide light on the stationarity properties of the NSE, GD, FX, and CO variables, as established by the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests. To find out whether a time series is stationary, these tests look for a unit root. Level and first-difference formats, as well as the degree of integration, are used to show the results for each variable. The majority of the variables are first-order integrated according to the PP test, as the null hypothesis stating that there is a unit root is supported at the 1% significance level. Nevertheless, the foreign exchange rate (USD/INR) remains fixed at the level, indicating that the null hypothesis may be rejected at the 5% level of significance. Similarly, all variables in the ADF test are integrated of first order except for foreign exchange. Therefore, it follows that there is no second-order integrated variable. Following this reasoning, the NARDL model is the best instrument for studying the correlation between the variables.

Table 3. Unit root test results

Phillips-Perron Test Results			
Variables	**At Level (t-Statistic, Prob.)**	**At First Difference (t-Statistic, Prob.)**	**Level of Integration**
NSE	(–0.6023, 0.8674)	(–26.8099, 0.00*)	I(0)
GD	(0.895, 0.9955)	(–27.0861, 0.00*)	I(0)
FX	(–2.7676, 0.0435**)	(–27.4847, 0.00*)	I(1)
CO	(–1.6782, 0.4419)	(–26.1514, 0.00*)	I(0)
ADF test Results			
Variables	**At Level (t-Statistic, Prob.)**	**At First Difference (t-Statistic, Prob.)**	**Level of Integration**
NSE	(–0.6032, 0.8671)	(–11.4501, 0.00*)	I(0)
GD	(0.807, 0.9942)	(–10.4387, 0.00*)	I(0)
FX	(–2.3793, 0.008*)	(–11.9191, 0.00*)	I(1)
CO	(–2.0616, 0.2606)	(–19.513, 0.00*)	I(0)

Note: ** indicates significant results at 5 %. * indicates significant results at 1%.

Table 4. Error correction description for the NARDL model cointegration results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.340593	0.096115	3.543613	0.0004*
GD_POS	–0.004768	0.006633	–0.718932	0.4724
GD_NEG(–1)	–0.038312	0.016969	–2.257721	0.0243**
FX_POS(–1)	–0.046846	0.041368	–1.132416	0.2579
FX_NEG(–1)	–0.017788	0.043973	–0.404516	0.686
CO_POS	–0.003893	0.005079	–0.76658	0.4436
CO_NEG	0.00151	0.004372	0.345278	0.73
D(GD_NEG)	0.147899	0.060721	2.435689	0.0151**
D(FX_POS)	–0.484063	0.221537	–2.185024	0.0292**
D(FX_POS(–1))	–0.657538	0.206859	–3.178682	0.0015*
D(FX_NEG)	–0.781087	0.251815	–3.101824	0.002*
ECM(–1)	–0.034898	0.009895	–3.526709	0.0004*

Note: ** and * denote significant results at 5% and 1%, respectively.

Table 4 presents the findings of an Error Correction Model (ECM) inside an NARDL framework, emphasizing the cointegration connections between the Nifty 50 and gold, crude oil, and foreign exchange (USD/INR) during the Russia-Ukraine armed conflict. The observed outcomes reveal that the positive shock on gold is statistically significant in determining the fluctuations in the dependent variable, i.e., Nifty 50 (NSE), in the long run. With a p-value of 0.0243 and a coefficient of -0.038312, the negative effect on gold is significant. This indicates that the NSE is significantly impacted by past negative GD changes over the long term. Further, the outcomes also show that all other explanatory variables do not impact the de-

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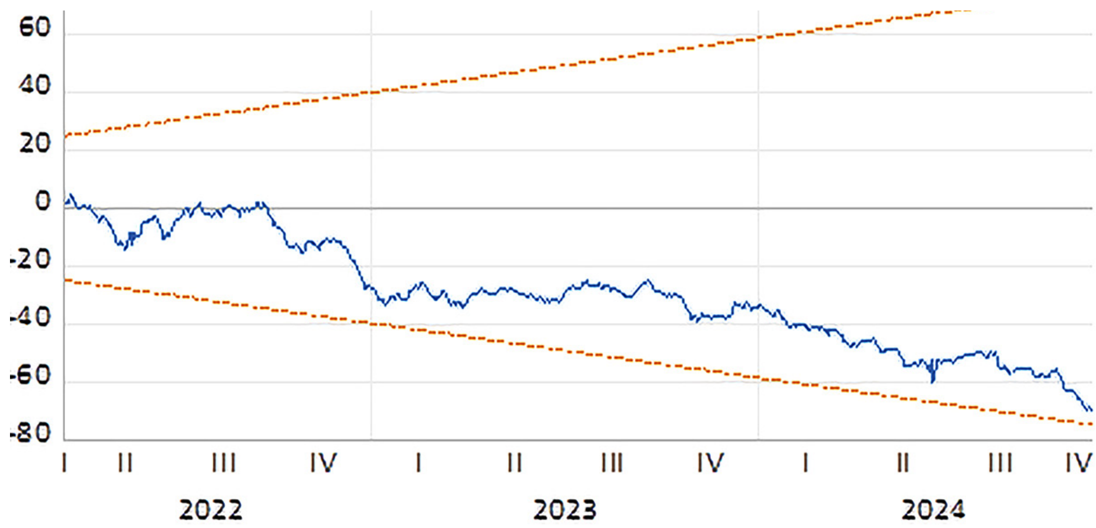

Figure 2. CUSUM plot

Table 5. Estimated long-run coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GD_POS	–0.136638	0.192437	–0.710038	0.4779
GD_NEG	–1.097823	0.461155	–2.380592	0.0176**
FX_POS	–1.342353	1.087722	–1.234096	0.2176
FX_NEG	–0.509701	1.241037	–0.410706	0.6814
CO_POS	–0.111563	0.140867	–0.791978	0.4286
CO_NEG	0.043255	0.128044	0.337812	0.7356
C	9.759635	0.048029	203.2019	0

Note: ** denotes significant results at the 5% level of significance.

pendent variable in the long run. A short-term negative shock in GD positively affects the NSE, as shown by a coefficient of 0.147899 and a p-value of 0.0151, suggesting that gold has a positive and considerable influence in the short run. Conversely, foreign exchange, which is denoted by the USD/INR rate, has an adverse effect on the Nifty 50. Furthermore, the error correction component has a negative coefficient of –0.034898, which is very significant (p = 0.0004). This verifies the presence of a long-term equilibrium connection, and the coefficient indicates that around 3.49% of the divergence from equilibrium is rectified in each time interval. Put simply, the findings emphasize the erratic impacts of both temporary and permanent shocks. Negative changes in GD in the long term significantly influence the dependent variable, while short-term dynamics are driven largely by FX shocks, both positive and negative.

These findings highlight the asymmetric and time-varying impact of macroeconomic factors consistent with earlier research that emphasizes nonlinear financial market responses to commodity and currency shocks (Shin et al., 2014; Narayan et al., 2020). The results validate the use of NARDL in modeling such relationships during crisis periods.

Table 5 presents the estimated long-run coefficients for the selected dependent and explanatory variables. The empirical findings reveal that positive changes in gold prices (GD) do not significantly influence the Nifty 50 index in the long term, as indicated by a p-value exceeding the conventional significance threshold. Conversely, negative shocks in GD exhibit a significant long-run impact on the index, evidenced by a p-value of 0.0176, which is below the standard level of significance. In contrast, the dependent variable is unaffected by the other selected explanatory factors during the course of the R-U crisis. Parameter stability verification after the NARDL model estimate is of utmost importance. As shown in Figure 2, the CUSUM test (Brown et al., 1975) was used to verify the parameters' robustness. Both the parameters and the findings are shown to be consistent and reliable.

In summary, the results provide strong evidence supporting *H1* and *H4*, with partial support for *H3*, and no support for *H2*. Gold prices, particularly negative shocks, appear to be the most influential variable across both time horizons. The exchange rate also plays a significant short-term role, while crude oil prices show limited influence on the Indian stock market during the Russia–Ukraine war. These findings highlight the importance of modeling asymmetric behavior and reinforce the role of gold and currency movements during geopolitical uncertainty.

CONCLUSION

This study explored the asymmetric short- and long-term effects of gold prices, crude oil prices, and the USD/INR exchange rate on India's Nifty 50 index amid the geopolitical instability stemming from the Russia–Ukraine war. To analyze these dynamics, the study employed the Nonlinear Autoregressive Distributed Lag (NARDL) framework and utilized daily data from February 2022 to October 2024. The analysis captured how both positive and negative movements in each variable relate to stock market behavior in a nonlinear fashion. The stationarity tests indicated that the series were integrated at mixed levels, supporting the appropriateness of the NARDL model. Results from the long-run estimates showed that only negative fluctuations in gold prices had a statistically meaningful influence on the Nifty 50 index, while positive changes did not exhibit significance.

In the short term, fluctuations in the stock index were largely linked to volatility in the exchange rate. Both increases and decreases in the USD/INR rate had adverse effects on market performance. Gold, in contrast, demonstrated a favorable short-run response to negative shifts in its price, implying that such declines often led to gains in the Nifty 50. Meanwhile, crude oil prices appeared to have no substantial effect in either the short or long term.

The error correction term was found to be negative and statistically significant, indicating the presence of a stable long-run relationship. Approximately 3.49% of the previous period's disequilibrium is adjusted in each subsequent period. These findings emphasize the relevance of incorporating asymmetric responses and geopolitical influences when assessing stock market behavior. This research adds to the existing body of knowledge by being one of the earliest to employ the NARDL framework in analyzing the Indian stock market amid the Russia–Ukraine war, providing key insights for investors, market observers, and policymakers during times of international uncertainty.

LIMITATIONS AND FUTURE SCOPE

This study offers interesting insights; however, several limitations need additional investigation. The omission of other macroeconomic indicators, like interest rates, inflation, and global market indices, may have disregarded other elements affecting Nifty 50 fluctuations. Subsequently, further studies can broaden their focus to include these elements and investigate sector-specific effects.

The research concentrated on the era of the Russia-Ukraine conflict, marked by increased global uncertainty. Although this offered a distinctive backdrop, analyzing further geopolitical or economic crises might affirm the results' resilience across many situations. Utilizing other models, such as GARCH or machine learning techniques, may enhance the study.

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IMPLICATIONS

The findings of this study carry important consequences for regulators, market participants, and investment professionals. Policymakers can utilize the insights to design strategies focused on stabilizing financial systems during geopolitical disturbances. From an investment perspective, the results help market participants understand asset interlinkages, enabling more effective risk management and portfolio diversification. Furthermore, this study advances the academic discourse by highlighting the role of asymmetric responses in interconnected markets, particularly during crises. By applying the NARDL model to explore cointegration amid the Russia–Ukraine war, the study provides a comprehensive analytical tool for understanding market behavior and guiding informed decision-making in volatile global environments.

AUTHOR CONTRIBUTIONS

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