

# THE INTERDEPENDENCE OF CRUDE OIL PRICES AND THE INDIAN STOCK MARKET DURING THE UKRAINE-RUSSIA WAR: A VAR-BASED APPROACH

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## ABSTRACT

*The study investigates the interrelationship between LWTI & LBRENT prices, considered major crude oil benchmarks at a global level, and the BSE index for stock prices in India, amidst the Ukraine-Russia war, for which the values of crude oil, Indian stocks, and the dollar from 1 February to 10 October have been considered on a daily basis. The correlation analysis shows the BSE index has a low and negative link with LWTI, LBRENT, and dollar value. The VAR-based Johansen test reveals no long-run cointegrating linkage among the BSE index, crude oil prices, and dollar value. According to the VAR test, both LWTI & LBRENT prices have a positive influence on the BSE index, while the BSE index impacts LWTI & LBRENT negatively. The IRF exhibits a shock to the WTI oil price, leading to a decline in the stock index value. The VDT analysis highlights the exogeneity nature of the BSE index and dollar value, whereas the Granger test reveals that both crude oil benchmarks cause the BSE index unidirectionally. Furthering the study would be more useful for the entities, especially those engaged in manufacturing activities, the investors, the central bank, and the government.*

**Keywords:** Crude Oil Prices, Indian Stock Market, Dollar Price, Johansen Test, VAR, Impulse Response, and Variance Decomposition.

## INTRODUCTION

In January 2021, President Zelensky requested NATO membership, leading to rising tensions between Ukraine, Russia, and the West. This culminated in Russia's invasion of Ukraine on February 24, 2022 (Aloisi & Daniel, 2022), causing global stock market fluctuations and unease among investors (Ngwakwe, 2022). Sanctions imposed by Ukraine's Western partners, particularly the EU, impacted global stock markets and induced volatility in the oil market (Ngwakwe, 2022). The conflict has far-reaching effects on international relations, business, sustainability, trade, and foreign investments (Stukalo & Simakhova, 2018). The COVID-19 pandemic continues to affect global economies, with Russia's invasion exacerbating supply chain disruptions and increasing commodity prices (Cohen & Ewing, 2022). Economic sanctions on Russia by the US and Europe are expected to significantly impact Russia's GDP (Pestova *et al.*, 2022). The EU, heavily reliant on Russian energy supplies, anticipates economic

challenges due to increased energy prices and decreased business confidence (Thomas & Strupczewski, 2022). The invasion has led to a rise in commodity prices, affecting companies dependent on crude oil, with potential repercussions for the global economy and increased inflation (Caldara & Iacoviello, 2022). Gas and oil prices surged, impacting the Russian financial system and causing a decline in the ruble's value (Khudaykulova *et al.*, 2022). The conflict may disrupt international trade but could accelerate the transition to cleaner energy sources (Simchi Levi & Haren, 2022). The increase in oil prices is pressuring Indian equity markets, affecting industries dependent on crude oil (Sharma & Shrivastava, 2021). Rising oil prices may lead to inflation, a weakened national currency, and a decline in the Indian equity market (Singh & Sharma, 2018). Exchange rate fluctuations impact global oil prices, with changes in the rupee-to-dollar rate linked to oil price variations (Brahmasrene *et al.*, 2014). Examining the dollar-rupee exchange rate alongside crude oil prices enhances the model's explanatory capacity (Sahu *et al.*, 2014).

According to the available literature, Russia's invasion of Ukraine will have serious and long-term consequences for the global economy. Any disruption in Russia's supply chain would reduce energy resources globally, impacting commodities reliant on crude oil. Since the war began on February 22, commodity prices have risen, affecting companies depending on crude oil. In this study, we examined the interdependence between crude oil benchmarks (LWTI & LBRENT), stock values of Indian companies, and the dollar value in terms of Indian rupees during the Ukraine-Russia war. The following research questions are listed below that the researcher wants to answer through his study:

- Is there any correlation that exists among the variables amidst the war period?
- Is there a long-run interrelationship between crude oil, the dollar, and stock prices during the war period?
- Is the price of crude oil influencing the value of the dollar and stocks, or vice versa?
- Is the future value of crude oil influencing the dollar and equity markets, or vice versa?
- Is there any exogenous variable among the variables chosen?

## REVIEW OF LITERATURE

Yousaf *et al.* (2022) utilized an event study method to assess the response of the Russian-Ukrainian crisis on G20 nations and selected financial markets. They discovered that the day Russia invaded Ukraine had a noticeable negative reaction on stock indices, particularly in Russia. Kretschmar & Müller (2021) looked at the stock market response of companies with ties to Russia following the invasion and found significant negative average abnormal returns ranging from -2.38 per cent to -0.90 per cent. Hoffman & Neuenkirch, (2017) similarly discovered that an escalation of the conflict is harmful to stock market investors in both countries, with Russian returns potentially falling by 21 basis points and Ukrainian returns up to 30 basis points after a 1-point escalation. Ahmed *et al.* (2022) found that Russia recognizing Ukrainian territories as autonomous had a substantial negative impact on European stocks. Federle *et al.* (2022) discovered that proximity to Ukraine leads to lower market returns in 66 nations, similar results were also seen by Boungo & Yatie, (2022) and Patel & Yaroyaya, (2022) who studied 94 European and Asian stock markets, respectively. Ngwakwe (2022) noted that the Russian invasion caused an increase in "stock market volatility" in the US, EU, and UK.

Numerous studies have investigated the link between oil prices and stock indices in various nations. Cong *et al.*, (2008) found no discernible interlink between oil price shocks and the Chinese stock exchange. Rahman & Uddin (2009) found no causal or cointegrating link between currency rates and stock prices in Bangladesh, India, and Pakistan. Menedez-Carbajo (2011) discovered a direct relationship between gas prices and the Dominican peso. Chittedi (2012) found that oil price fluctuations influence volatility in stock prices in India, but stock prices are not impacted by changes in oil prices. Raheman *et al.*, (2012) found a short-run link between oil prices and stock returns in Asia-Pacific nations. Basher, Haug, & Sadorsky (2012) found a dynamic link between crude prices, currency exchange, and stock prices in developing markets. Sahu *et al.* (2014) found a long-term causal relationship between the Indian stock market and oil prices. Adam *et al.* (2015) found a positive impact of WTI crude oil price shocks on IHSG. Poornima & Reddy (2016) found one-way causal relationships between oil, gold, FX, and equity

markets. Giri & Joshi (2017) found a long-run link between share prices and economic factors, including oil prices. Kumar (2017) studied the effect of volatile changes in crude oil prices on the Indian equity index. He, Nakajima, & Hamori (2019) found that natural gas prices do not significantly affect the exchange rates of BRICS countries. B *et al.*, (2019) found a long-term relationship between the Vietnam stock market and crude oil prices. Polat, (2020) analyzed the time-varying transmission between oil price shocks and the Turkish stock market. Darmawan *et al.* (2020) discovered cointegration between the Brent oil benchmark and the IHSG. Agarwalla *et al.*, (2021) found a long-term linkage between prices of crude oil and India's energy index. Daradkah *et al.*, (2021) demonstrated a causal link between oil prices and stock market returns in Egypt, Morocco, and Jordan. Sharma & Shrivastava (2021) found oil prices to have a short-term causal relationship with variables and a long-term relationship with unemployment, industrial production, and inflation. Katsamp *et al.* (2022) explored the connections between stock returns and crude oil prices for European nations. Following a thorough literature review, we discovered no study has been conducted to analyse the interdependence between "crude oil prices and the Indian stock market," particularly during the Ukraine-Russian War. After following this research gap, we have formulated four research objectives, as follows:

- To investigate the direction of causality among the variables during the war period.
- To study the correlational relationship that existed among the variables during the war period.
- To study the impact of crude oil prices on the dollar's value and the Indian stock market during the war period.
- To study the impact of the shock on one variable on another.

## DATA DESCRIPTION, METHODOLOGY, AND MODEL SPECIFICATION

### DATA DESCRIPTION

Using a causality and VAR method, this research examines the interactions between the international crude oil benchmarks, i.e., LWTI & LBRENT, and the BSE index during the Ukraine-Russian war. The secondary data are the only source used in the

inquiry. For the analysis, daily data on the price of crude oil (WTI and Brent), the value of the US dollar relative to the Indian rupee, and the price of Indian stocks (S&P BSE Sensex) have been taken into account. The period from 1 February 2022 to 10 October 2022 is chosen since it is when tensions between Russia and Ukraine were at their height and when war actually began. The data for the study consists of 171 daily observations that have been translated into a log format. The US Energy Information Administration's official website has been used to acquire information on crude oil prices. The official websites of the RBI and S&P BSE SENSEX have been used to gather information on the exchange rate and Indian stock prices, respectively.

## METHODOLOGY

### Unit Root Test

The Augmented Dickey-Fuller (ADF) test, introduced by Dickey and Fuller in 1979... (1), extends the original Dickey-Fuller test to address autocorrelation and lag structures in time series data. The test assesses whether a time series possesses a unit root, signifying non-stationarity. It involves regressing the differenced series ( $\Delta y_t$ ) on lagged values of the level series ( $y_t$ ), potential lagged differences, and an error term ( $\varepsilon_t$ ) to determine the significance of the unit root coefficient ( $\phi_1$ ). The first equation specifies  $y_t$  as a random walk, where  $\Delta y_t$  is subject to regress to one period lag, i.e.,  $y_{t-1}$ , along with the error term  $\varepsilon_t$ . 2nd and 3rd equation, in which  $y_t$  is considered random with drift and drift with a deterministic trend, respectively.

$$\Delta y_t = (\phi_1 - 1)y_{t-1} + \sum_i \theta_i \Delta y_{t-i} + \varepsilon_t \quad \dots (1)$$

$$\Delta y_t = (\phi_1 - 1)y_{t-1} + \sum_i \theta_i \Delta y_{t-i} + \beta + \varepsilon_t$$

$$\Delta y_t = (\phi_1 - 1)y_{t-1} + \sum_i \theta_i \Delta y_{t-i} + \beta + \theta t + \varepsilon_t$$

The null hypothesis ( $H_0$ ) being followed here is that a unit root exists in a time series.

### Cointegration Test

In order to identify whether the series carries any kind of long-run integration, a cointegration test is used. The Johansen & Juselius, test 1990... (2) for tracing cointegration is displayed below, in which the first equation represents a system where  $\Delta y_t$  is

regressed on lagged levels of  $y_t$  and lagged differences of  $\Delta y_t$ .

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{k-1} \Gamma \Delta y_{t-i} + \mu + \varepsilon_t \quad \dots (2)$$

$$\dots (3)$$

$$\begin{aligned} \Delta \ln X_t &= \alpha_0 + \Sigma \beta_i \Delta \ln X_t + \Sigma \chi_j \Delta \ln Y_t + \Sigma \gamma_k \Delta \ln Z_t + \varepsilon_t \\ \Delta \ln Y_t &= \gamma_0 + \Sigma \sigma_i \Delta \ln Y_t + \Sigma \tau_j \Delta \ln X_t + \Sigma \theta_k \Delta \ln Z_t + \varepsilon_t \\ \Delta \ln Z_t &= \delta_0 + \Sigma \omega_i \Delta \ln Z_t + \Sigma v_j \Delta \ln Y_t + \Sigma \varphi_k \Delta \ln X_t + \varepsilon_t \end{aligned}$$

Whereas, equation... (3) represents a cointegration relationship involving the variable  $\Delta \ln X_t$ . It specifies that the change in the natural logarithm of X at time t is determined by a constant term ( $\alpha_0$ ), the lagged differences in the natural logarithm of X ( $\Sigma \beta_i \Delta \ln X_t$ ), the lagged differences in the natural logarithm of Y ( $\Sigma \chi_j \Delta \ln Y_t$ ), the lagged differences in the natural logarithm of Z ( $\Sigma \gamma_k \Delta \ln Z_t$ ), and an error term ( $\varepsilon_t$ ), which set the Null Hypothesis ( $H_0$ ): There is no long-run cointegrating equilibrium among the system variables.

**VAR and VECM**

VECM is preferred over VAR in the presence of cointegration, allowing examination of short- and long-term equilibrium. Sims (1980)... (4) popularized VAR models as an alternative to extensive Simultaneous Equations models, facilitating prediction of multiple time series using a single model.

$$\begin{aligned} Y_t &= \alpha_0 + \sum_{i=1}^k \alpha_i Y_{t-i} + \sum_{j=1}^k \beta_j X_{t-j} + \varepsilon_t \quad \dots(4) \\ X_t &= \gamma_0 + \sum_{i=1}^k \gamma_i X_{t-i} + \sum_{j=1}^k \delta_j Y_{t-j} + \varepsilon_t \end{aligned}$$

The VAR equation highlights  $\alpha_0$  and  $\gamma_0$  as the constant term;  $\alpha_i$  and  $\beta_j$  as the coefficient values that show the level at which  $Y_{t-i}$  explains  $Y_t$  and X past values explain  $Y_t$ , respectively;  $\gamma_i$  and  $\delta_j$  as the coefficient values that show the extent at which  $X_{t-i}$  explains  $X_t$  and Y past values explain  $X_t$ , respectively;  $\varepsilon_t$  as the white noise error term; and k as the lag order criteria.

In summary, these equations collectively define a VAR (k) model, where k represents the lag order of the model. This VAR model captures the contemporaneous relationships and dynamic interactions between the variables  $Y_t$  and  $X_t$  over time.

**Granger Causality Test**

The Granger causality test (Granger, 1969) ... (5) looked at the direction and strength of causation between the variables. It is used to determine whether one series can predict another.

$$\begin{aligned} Y_t &= \alpha_0 + \alpha_1 Y_{t-1} + \dots + \alpha_i Y_{t-i} + \beta_1 X_{t-1} + \dots + \beta_i X_{t-i} + \mu \quad \dots(5) \\ X_t &= \alpha_0 + \alpha_1 X_{t-1} + \dots + \alpha_i X_{t-i} + \beta_1 Y_{t-1} + \dots + \beta_i Y_{t-i} + \mu \end{aligned}$$

The equation above depicts  $Y_t$ , which may be caused by  $X_t$ , as well as  $X_t$ , which is caused by  $Y_t$ . Here both  $X_t$  and  $Y_t$  represents the respective variables taken in the study to perform a directional causality test. Therefore, the ( $H_0$ ) are that  $Y_t$  does not cause  $X_t$ , and  $X_t$  does not cause  $Y_t$ .

**Impulse Response Function and Variance Decomposition**

The Impulse Response Function (IRF) tracks system variable responses to shocks, applying a one standard deviation shock to each variable. The Variance Decomposition Test measures movements from own and other variables' shocks in the VAR system.

**MODEL SPECIFICATION**

There are four sub-models in the model, and they all regard all variables as endogenous. The details of each sub-model are as follows: Changes in LBRENT, LWTI, and LUSD cause changes in LBSE, the second model shows a change in LBRENT as a result of changes in LBSE, LWTI, and LUSD; the third model shows a change in LWTI as a result of changes in LBSE, LBRENT, and LUSD; and the fourth model shows a change in LUSD as a result of changes in LBSE, LBRENT, and LWTI. Each variable in the system is regarded as both a dependent and an independent variable at the same time since the VAR system sees all variables as endogenous. The system's variables are all changed to natural logarithms, and the model's functional form is as follows:

$$\begin{bmatrix} \Delta LBSE_t \\ \Delta LBRENT_t \\ \Delta LWTI_t \\ \Delta LUSD_t \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \beta_0 \\ \gamma_0 \\ \lambda_0 \end{bmatrix} + \sum_{j=1}^k \begin{bmatrix} \alpha_{1t-j} & \alpha_{2t-j} & \alpha_{3t-j} & \alpha_{4t-j} & \alpha_{5t-j} \\ \beta_{1t-j} & \beta_{2t-j} & \beta_{3t-j} & \beta_{4t-j} & \beta_{5t-j} \\ \gamma_{1t-j} & \gamma_{2t-j} & \gamma_{3t-j} & \gamma_{4t-j} & \gamma_{5t-j} \\ \lambda_{1t-j} & \lambda_{2t-j} & \lambda_{3t-j} & \lambda_{4t-j} & \lambda_{5t-j} \end{bmatrix} \times \begin{bmatrix} \Delta LBSE_t \\ \Delta LBRENT_t \\ \Delta LWTI_t \\ \Delta LUSD_t \end{bmatrix} + \begin{bmatrix} \varepsilon_{LBSE_t} \\ \varepsilon_{LBRENT_t} \\ \varepsilon_{LWTI_t} \\ \varepsilon_{LUSD_t} \end{bmatrix}$$

Where LBSE, LBRENT, LWTI, and LUSD are considered as variables that the researcher needs to study; L, should be considered a natural logarithm;  $\Delta$  is denoted as a change in the variable sign;  $\Sigma$  is the summation sign; t, it is considered a time trend;  $\alpha_0, \beta_0, \gamma_0$  and  $\lambda_0$  displays the constant terms of the

system variables;  $\alpha_j^{\text{th}}, \beta_j^{\text{th}}, \gamma_j^{\text{th}}$  and  $\lambda_j^{\text{th}}$  are treated as the short run coefficients of the VAR system; and  $\epsilon_t$ , is taken as error terms or white noise error.

$$(1) LBSE_t = \alpha + \sum_{j=1}^k B_i LBSE_{t-i} + \sum_{j=1}^k \phi_j LBRENT_{t-j} + \sum_{j=1}^k \varphi_m LWTI_{t-m} + \sum_{j=1}^k \delta_n LUSD_{t-n} + u_{1t}$$

$$(2) LBRENT_t = \sigma + \sum_{j=1}^k B_i LBSE_{t-i} + \sum_{j=1}^k \phi_j LBRENT_{t-j} + \sum_{j=1}^k \varphi_m LWTI_{t-m} + \sum_{j=1}^k \delta_n LUSD_{t-n} + u_{2t}$$

$$(3) LWTI_t = \vartheta + \sum_{j=1}^k B_i LBSE_{t-i} + \sum_{j=1}^k \phi_j LBRENT_{t-j} + \sum_{j=1}^k \varphi_m LWTI_{t-m} + \sum_{j=1}^k \delta_n LUSD_{t-n} + u_{3t}$$

$$(4) LUSD_t = \chi + \sum_{j=1}^k B_i LBSE_{t-i} + \sum_{j=1}^k \phi_j LBRENT_{t-j} + \sum_{j=1}^k \varphi_m LWTI_{t-m} + \sum_{j=1}^k \delta_n LUSD_{t-n} + u_{4t}$$

$LBSE_{t-i}$  is past lag Sensex Index;  $LBRENT_{t-j}$  is past lag Brent Crude Oil price;  $LWTI_{t-m}$  is past lag WTI oil price and  $LUSD_{t-n}$  is past lag Dollar exchange rate, where t, is time (days) and  $\alpha, \sigma, \vartheta$  and  $\chi$  are Constant values of the model, while,  $u_{1t}, u_{2t}, u_{3t}$  and  $u_{4t}$  depicts error terms of VAR equations.

**EMPIRICAL RESULTS**

Results shows visual representation (Figure 1), descriptive analysis (Table-1), unit root tests (Tables-2 and 3), correlation (Table-4), lag selection (Table-5), long-run cointegration (Table-6), VAR results (Table 7) and diagnostics (Table 8). Impulse response, variance decomposition, and Granger causality are depicted in Figure 2, 3 & Table 10 respectively.



**Figure 1: Depicting movement in variables i.e. Crude Oil Price, USD and Indian Stock Market**

The trend from January 1 to October 10, 2022, is depicted on the figure1 using the log values of BSE, BRENT, WTI, and USD. The graphical display reveals that LWTI and LBRENT exhibit a consistent pattern over the course of the sample period, whereas LUSD has a rising trend and LBSE exhibits significant variation. The most fluctuation and downward slope of LBSE could be seen on February 4th week due to beginning of the war and on may third and last week, when the war was on its peak.

**Descriptive Statistics**

Table 1 represents descriptive statistics for four variables during the Ukraine-Russia conflict. The BSE Sensex has a mean of approximately 56581 Indian rupees, Brent and WTI crude oil prices are around 107.50 and 101, respectively, and USD equals roughly 78 Indian rupees. Brent price is 6.4% higher than WTI. BSE Sensex's highest and lowest values are 60611.74 and 51360.42, with a standard deviation of nearly 2368, indicating significant fluctuation. Brent oil prices range between 82.55 and 133.18, with a standard deviation of 11.30, while WTI prices range from 77.17 to 123.64. USD shows less volatility with a standard deviation of roughly 2. Brent and WTI prices are normally distributed based on Jarque-Bera statistics (P-values > 0.05). Skewness indicates positive skewness for all variables except the BSE Sensex. Kurtosis values below 3 suggest lower risk and greater stability.

**Table 1: Descriptive Statistics**

	BSE	BRENT	WTI	USD
Mean	56580.73	107.4819	101.1089	78.02281
Median	57060.87	107.19	101.31	77.787
Maximum	60611.74	133.18	123.64	82.4028
Minimum	51360.42	82.55	77.17	74.4797
Std. Dev.	2367.959	11.30185	10.39999	2.016778
Skewness	-0.31198	0.063863	0.037452	0.176066
Kurtosis	1.984445	2.212797	2.219503	2.152332
Jarque-Bera	10.12233	4.531521	4.380348	6.003081
Probability	0.006338	0.103751	0.111897	0.04971
Sum	9675304	18379.41	17289.63	13341.9
Sum Sq.Dev.	9.53E+08	21714.42	18387.18	691.457

Source: Author's work

**Unit Root Test**

ADF and PP tests from Tables 2 and 3 show that all the selected series, i.e., in log form, of BSE, BRENT, WTI, and USD are not stationary at their initial level, including at constant, constant and trend, and none.

**Table 2: Augmented Dickey Fuller Test**

Variable	At Level			At First Difference		
	Constant	Constant and Trend	None	Constant	Constant and Trend	None
LBSE	-1.96(0.31)	-2.067(0.56)	-0.102(0.65)	-13.25(0.00) *	-13.27(0.00) *	-13.29(0.00) *
LBRENT	-2.04(0.27)	-2.54(0.31)	-0.06(0.66)	-11.93(0.00) *	-12.01(0.00) *	-11.97(0.00) *
LWTI	-1.84(0.36)	-2.43(0.36)	-0.194(0.615)	-12.48(0.00) *	-12.57(0.00) *	-12.52(0.00) *
LUSD	-0.41(0.904)	-2.99(0.14)	2.32(0.995)	-14.45(0.00) *	-14.43(0.00) *	-14.03(0.00) *

Source: Author's work

As a result, we cannot reject the  $H_0$  of unit root present in all series at the level at the 5 per cent level of significance; however, the variables can be first differenced using the ADF and PP test, and stationarity can be achieved in all cases, i.e., at constant, constant, trend, and none; by doing first difference, the researcher can reject the  $H_0$  of unit root present in the variables.

**Table 3: Phillip Perron Test**

Variable	At Level			At First Difference		
	Constant	Constant and Trend	None	Constant	Constant and Trend	None
LBSE	-1.98(0.30)	-2.08(0.55)	-0.105(0.65)	-13.25(0.00) *	-13.27(0.00) *	-13.29(0.00) *
LBRENT	-2.12(0.24)	-2.54(0.31)	-0.06(0.66)	-11.88(0.00) *	-11.98(0.00) *	-11.92(0.00) *
LWTI	-1.87(0.34)	-2.48(0.34)	-0.20(0.61)	-12.47(0.00) *	-12.57(0.00) *	-12.50(0.00) *
LUSD	-0.25(0.93)	-2.995(0.13)	2.70(0.99)	-14.48(0.00) *	-14.47(0.00) *	-14.00(0.00) *

Source: Author's work

After determining the unit root and stationarity arranging all of the variables, the next step is to choose the ideal lag length for the cointegration study and for application into the VAR model using the Akaike and Schwarz information criterion.

**Table 4: Correlation**

	DLBSE	DLBRENT	DLWTI	DLUSD
DLBSE	1			
DLBRENT	-0.24071	1		
DLWTI	-0.25117	0.888018	1	
DLUSD	-0.13883	0.058115	0.044966	1

Source: Author's work

Table 4 shows a strong correlation between crude oil prices, i.e., DLBRENT and DLWTI, with a correlation value of +0.888; this can also be seen in Figure 1, where both variables move together during the study period; and a weak and negative correlation between DLBSE and the other three variables, with a correlation value ranging from -0.13 to -0.25. While the correlation between DLBRENT & DLUSD and DLWTI & DLUSD shows +0.058 and +0.045, respectively, there is a negligible relationship between these two series.

**Table 5: VAR Optimal Lag Selection**

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1229.723	NA	3.46E-12	-15.03954	-14.96362	-15.00872
1	1986.813	1467.734	3.89e-16*	-24.13268*	-23.75308*	-23.97857*
2	2001.65	28.0344	3.94E-16	-24.1184	-23.43512	-23.841
3	2012.526	20.01678	4.20E-16	-24.05553	-23.06856	-23.65483
4	2022.61	18.06573	4.53E-16	-23.98295	-22.6923	-23.45896
5	2032.58	17.37097	4.89E-16	-23.90896	-22.31463	-23.26168
6	2050.063	29.60224*	4.82E-16	-23.92715	-22.02914	-23.15658
7	2056.79	11.06177	5.43E-16	-23.81338	-21.61169	-22.91952
8	2060.463	5.857594	6.36E-16	-23.66212	-21.15675	-22.64497

Source: Author's work

To run further analysis such as cointegration in accordance with the Johansen test and to run a VAR model, it is prescribed to have an optimal lag length; thus, table 5, which assists in selecting the appropriate lag order suggested by AIC, FPE, HQ, and SIC, where AIC, FPE, HQ, and SIC all suggest selecting a lag of order 1, can also be called the optimal lag for the analysis.

**Table 6: Johansen Cointegration Test**

<b>Johansen cointegration (Trace &amp; Eigen Value)</b>						
<b>Obs</b>	<b>NullHypothesis</b>	<b>Eigenvalue</b>	<b>Trace Statistics</b>		<b>Max Eigen Value Statistics</b>	
			<b>Statistics</b>	<b>P-value</b>	<b>Statistics</b>	<b>P-value</b>
169	r=0(none)	0.098567	36.11896 (47.85613)	0.3904	17.53713 (27.58434)	0.534
	r#1(atmost1)	0.070517	18.58183 (29.79707)	0.5233	12.35839 (21.131620)	0.5127
	r#2(atmost2)	0.034804	6.223438 (15.49471)	0.6691	5.98671 (14.26460)	0.6149
	r#3(atmost3)	0.00140	0.236728 (3.841466)	0.6266	0.236728 (3.841466)	0.6266

Source: Author's work

Table 6 reports Johansen cointegration analysis, with "trace statistics" and "max eigenvalue" at 36.12 and 17.54, respectively. Critical values at 5% significance are 47.85 and 27.58. Since both test values are below their critical benchmarks, and with a P-value > 0.05, the null hypothesis of "no cointegration" among variables cannot be rejected. This suggests no equilibrium relationship in the long run, recommending the use of a VAR system for short-run equilibrium modelling.

**Table 7: Vector-Autoregressive System of Equation**

<b>Variables</b>	<b>Dependent Variable</b>							
	<b>LBSE</b>		<b>LBRENT</b>		<b>LWTI</b>		<b>LUSD</b>	
	<b>Coefficient</b>	<b>Probability</b>	<b>Coefficient</b>	<b>Probability</b>	<b>Coefficient</b>	<b>Probability</b>	<b>Coefficient</b>	<b>Probability</b>
LBSE (-1)	0.940	0.000*	-0.187	0.031**	-0.171	0.046**	-0.008	0.351
LBRENT (-1)	0.066	0.057***	0.883	0.000*	0.053	0.563	-0.002	0.797
LWTI (-1)	-0.075	0.049**	0.007	0.940	0.835	0.000*	-0.004	0.691
LUSD (-1)	0.694	0.152	-0.204	0.067***	-0.249	0.024**	0.989	0.000*
R-squared	0.921471		0.907211		0.905187		0.983634	
Adj. R-squared	0.919567		0.904962		0.902889		0.983237	
Sum sq. resids	0.023624		0.174026		0.171523		0.001819	
S.E. equation	0.011966		0.032476		0.032242		0.00332	
F-statistic	484.0345		403.3071		393.8176		2479.247	
Log likelihood	513.6909		343.9499		345.1815		731.6498	
Akaike AIC	-5.9846		-3.98765		-4.00214		-8.54882	
Schwarz SC	-5.89237		-3.89542		-3.90991		-8.45659	
Mean dependent	10.94231		4.67278		4.611661		4.356937	
S.D dependent	0.042191		0.105345		0.103463		0.025642	
Determinant resid covariance (dof adj.)			3.23E-16					
Determinant resid covariance			2.87E-16					
log likelihood			2077.1					
AIC			-24.2012					
SC			-23.8323					
NO. of Coefficients			20					

Source: Author's work



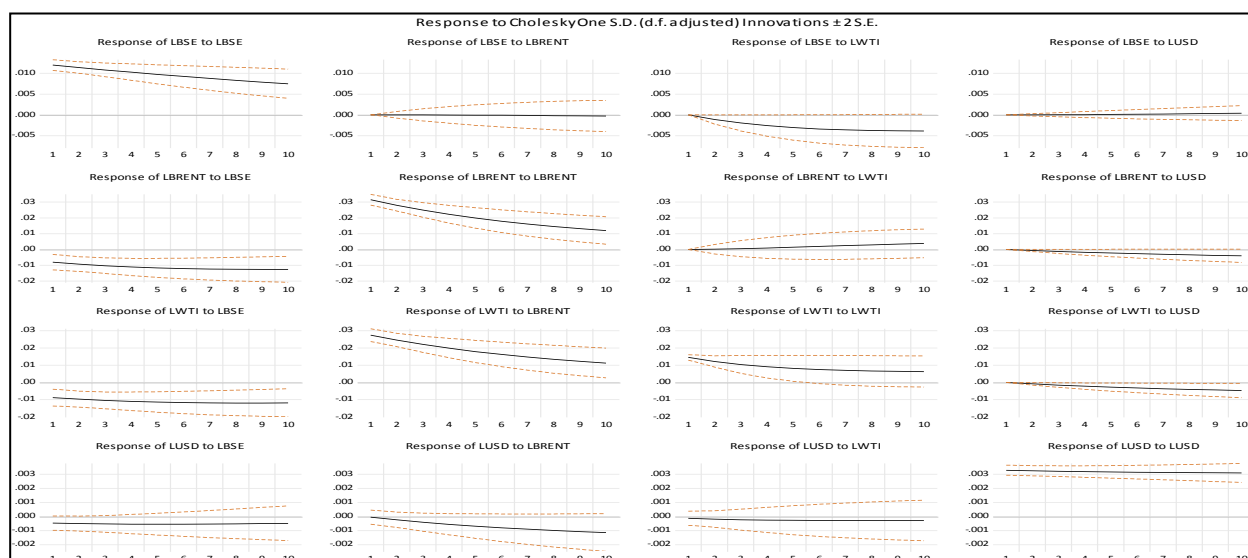
From table 7, the VAR system, post Johansen test, indicates "no long-run cointegrating relationship." Optimal lag selection has been completed. In Equation 1, where LBSE is dependent, lag values of LBSE, LBRENT, and LWTI show positive relationships, suggesting increases in these variables lead to an increase in LBSE. Equation 2, with LBRENT as dependent, shows negative effects of LBSE and LUSD at lag 1, indicating their rise causes a drop in LBRENT, while LBRENT's own lag has a positive impact. Equation 3, where LWTI is dependent, reveals a negative relationship with LBSE and LUSD at lag 1, signifying their growth leads to a decline in LWTI. Equation 4, with LUSD as dependent, shows no significant impact from other variables, indicating its exogenous nature, with an R-Square of approximately 0.99.

**Table 8: Diagnostic Test of Models**

Dependent Variables	LM TEST				BREUSCH PAGAN GODFREY			
	F-statistic	P-value	Obs*R-squared	P-value	F-statistic	P-value	Obs*R-squared	P-value
LBSE	0.167205	0.8462	0.348056	0.8403	2.415284	0.0509	9.403313	0.0518
LBRENT	1.689326	0.1879	3.452191	0.178	2.552731	0.041*	9.907241	0.042*
LWTI	1.689326	0.4574	1.623943	0.444	2.169412	0.0746	8.493898	0.0751
LUSD	1.265437	0.2849	2.599204	0.2726	0.708243	0.5874	2.869552	0.5799

Source: Author's work

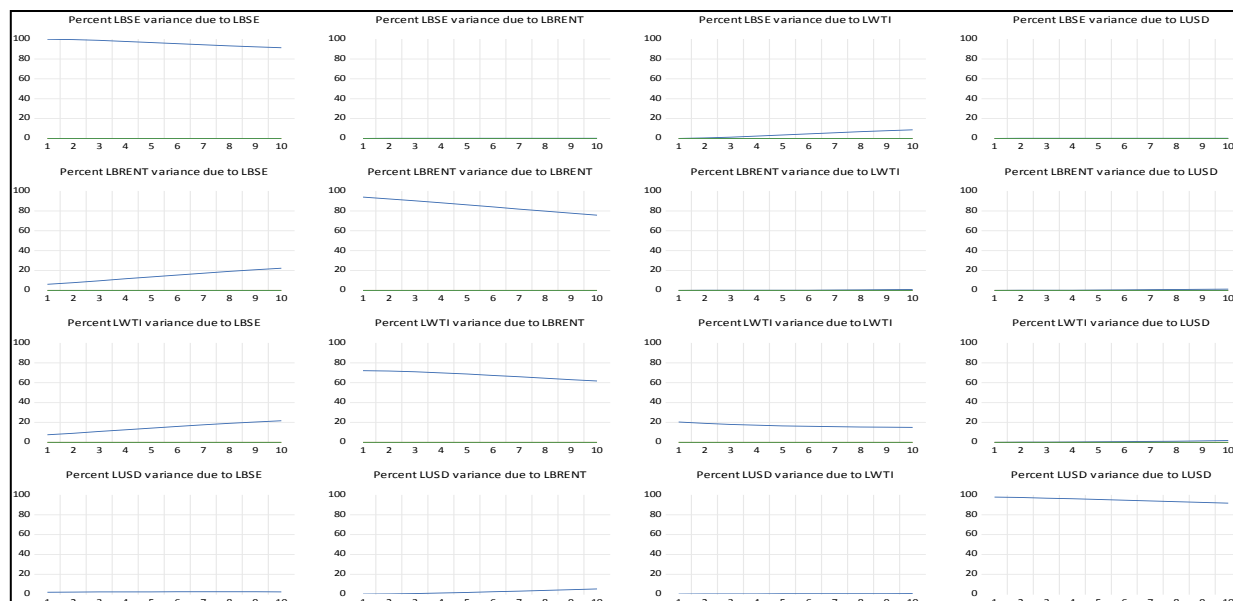
Table 8 shows diagnostic tests of VAR models for serial correlation, heteroscedasticity, and normality. The serial correlation LM test reveals that all models are free of autocorrelation, whereas the heteroscedasticity test reveals that all models are homoscedastic except for equation 2, where LBRENT is a dependent variable. The normality test fails to satisfy the Gaussian distribution assumption in the residuals. As a result, it is recommended to accept the null hypothesis of serial correlation and reject the  $H_0$  of normality. The results also suggest not rejecting the null hypothesis of homoscedasticity except in the case of Model 2.



**Figure 2: Impulse Response Function**

Figure 2 depicts the impulse response results in the VAR framework, applying a 1 standard deviation shock to each variable over a 10-period duration. In Model 1, a shock to LBSE significantly and continuously decreases LBSE, with negligible responses from LBRENT and LUSD. In Model 2, an LBSE shock causes a slight decline in LBRENT, while shocks to LUSD and LWTI lead to small changes. Model 3 shows a minimal decline in LWTI from an LBSE shock, and LBRENT, LWTI, and LUSD shocks result in moderate, low, and very small declines in LWTI, respectively. In Model 4, LBSE and LWTI shocks have negligible effects on LUSD, while an LBRENT shock induces a low, negative decline over time.





**Figure 3: Variance Decomposition Test**

Figure 3 presents the variance decomposition results for LBSE, LBRENT, LWTI, and LUSD over a 10-day period. LBSE is primarily explained by its own shock, accounting for approximately 100% on the first day and 91% on the 10th day. LUSD is mainly influenced by its own shock, explaining nearly 98% initially and 92% by the end, with the remaining variance attributed to LBRENT, LWTI, and LBSE. LBRENT is influenced by its own shock (76%) and to a lesser extent by LBSE (22%), while LWTI is primarily explained by LBRENT (62%) and partially by LBSE and LUSD. In summary, LBSE and LUSD appear to be exogenous, while crude oil prices are less impacted by future shocks in the Indian stock market, with approximately 22% of the variation in crude oil prices attributed to the stock market's shock.

**Table 9: Granger Causality Test**

Pairwise Granger Causality Tests			
Null Hypothesis:	Obs	F-Statistic	Prob.
DLBRENT → DLBSE	168	2.84649	0.0609
DLBSE → DLBRENT		0.32005	0.7266
DLWTI → DLBSE	168	3.13113	0.0463
DLBSE → DLWTI		0.73886	0.4792
DLUSD → DLBSE	168	3.87896	0.0226
DLBSE → DLUSD		0.33903	0.713
DLWTI → DLBRENT	168	0.08828	0.9155
DLBRENT → DLWTI		2.06769	0.1298
DLUSD → DLBRENT	168	3.36801	0.0369
DLBRENT → DLUSD		0.01019	0.9899
DLUSD → DLWTI	168	2.68216	0.0714
DLWTI → DLUSD		0.11813	0.8887

Source: Author's work

Table 9 presents the Granger causality test results, indicating one-directional causality from DLUSD to DLBSE, DLBRENT, and DLWTI at a 5% significance level. Additionally, DLWTI exhibits unidirectional causality to DLBSE, while DLBRENT demonstrates unidirectional causality to DLBSE and DLUSD, both at a 10% significance level. However, there is no causality observed from DLBSE to DLBRENT, DLWTI, and DLUSD, as well as from DLBRENT and DLWTI to DLUSD. The findings suggest that India's BSE index does not exert short-term causality on crude oil benchmarks (LWTI & LBRENT) and dollar prices, and there is no short-term causality from crude oil prices to dollar prices, partially rejecting  $H_0$ . These results align with the earlier VAR findings.

## DISCUSSION

The study analysed the connection between crude oil prices and the Indian stock market during the time of the Ukraine-Russia conflict. The findings revealed a strong relationship between the crude oil benchmarks, LWTI and LBRENT, and the stock market, which was highly unstable during the war; this is the same finding reported by Ngwakwe (2022) in his study, which reveals high volatility in the US, UK, EU, and Asian stock markets during the war. The results showed that there is no long-run equilibrium between the BSE index and oil prices, which is inconsistent with the outcomes of Chittedi (2012) and Agarwalla *et al.* (2021), which highlight long-term cointegration. The results also show crude oil prices had a significant positive impact on the Indian stock market, which is symmetrical to the findings of Sharma & Shrivastava (2021), while this is opposite as per Singh & Sharma's (2018) results, which say there is a negative link between these two variables, while on the other side, USD value and the Indian stock market had a negative impact on crude oil prices, which is partially compatible with Samanta & Zudeh's (2012) findings, who found a shock to the exchange rate has a profoundly negative impact on crude oil prices. The impulse response analysis and variance decomposition further confirmed the independence of the Indian stock market and the dollar's value. The Granger causality test results showed that crude oil prices had a one-way relationship with the Indian stock market commensurate with Agarwalla *et al.* (2021).

## CONCLUSION

The study examines the relationship between crude oil prices and the Indian stock market during the Ukraine-Russia war using daily data from February 1, 2022, to October 10, 2022. Analysing through unit root, causality, cointegration, VAR, impulse response, and variance decomposition tests, the research reveals the interplay between these variables. With India being a significant crude oil importer, any geopolitical disturbance, like the Ukraine-Russia conflict, may impact its economy, particularly the stock market. Results show a positive influence of crude oil prices on the Indian stock market during the war, suggesting it as a safe asset amidst global uncertainty. However, during this period, the USD value and the Indian stock market negatively affect crude oil prices. The study recommends expanding the research to include different war periods, additional variables, and specific sectors impacted by the conflict. Further exploration of the direct impact of the war on the Indian economy and the consideration of other commodities is suggested for future studies.

## RECOMMENDATIONS

Investors in the Indian stock market is urged to diversify their portfolios amidst volatile crude oil prices. Focusing on sectors less dependent on oil, such as technology, healthcare, and renewable energy, is recommended. Manufacturing businesses should proactively address oil price risks, considering initiatives like integrating renewable energy and collaborating on strategic oil reserves. During geopolitical tensions like the Ukraine-Russia conflict, cautious investment in stocks less exposed to risks and oil price fluctuations is advised. Monitoring currency values is crucial, and implementing risk-mitigating measures like currency swap agreements can help alleviate foreign exchange risk. The central bank and government should explore currency swap agreements with major oil-exporting nations to stabilize the national currency and manage foreign exchange risk for economic stability.

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