The Causal Relationship Between Volatility in Crude Oil Price, Exchange Rate, and Stock Price in India : GARCH Estimation of Spillover Effects

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Abstract

The macroeconomic variable: crude oil price, gold price, exchange rate, inflation, and stock returns are highly volatile and are highly correlated to each other. The volatility in one market spills over to other markets. This paper examined the dynamic causality between crude oil price, exchange rate, and BSE Sensex and their volatilities in India. The daily data on macro variables for 14 years between January 2006 and March 2019 were used in the GARCH estimation of causal effects of volatility spillovers. The GARCH estimates showed that one market's volatility and volatility spillover caused volatility and volatility spillovers in other markets in India. Crude oil price, exchange rate volatility, and volatility spillovers caused volatility in the BSE Sensex. The volatility in BSE Sensex was highly overdone by internal shocks of the stock market.

Keywords : Oil price, exchange rate, stock market, volatility, causal effect, GARCH estimation

JEL Classification Codes : B23, C22, C58, E44

Paper Submission Date : May 13, 2021 ; Paper sent back for Revision : July 6, 2021 ; Paper Acceptance Date : July 20, 2021

Macroeconomic stability plays a vital role in determining the economic strength and growth of an economy. A stable exchange rate, crude oil price, and domestic inflation are crucial for a stable stock market. The stability of these markets is also important for maintaining living standards and investments in the country. India is among the fast-growing economies globally, and much of its manufacturing industry depends on crude oil. India also ranks third among the biggest crude oil consumers of the world countries. Therefore, any volatility in the crude oil price will have a significant effect not only on the cost of production and the price of commodities but also on the cost of living in India. With increasing globalization and international trade, the exchange rate, too, plays a significant role in economic growth. Any exchange rate volatility not only affects exports, imports, and commodity prices, but it also affects the domestic financial sector, most importantly the interest rate and the value of the domestic currency. The uncertainty caused due to the instability of the financial sector and the stock market volatility poses a grave problem to policy planning that may hinder economic growth. Stock market volatility often leads to booms, crises, and even stock market crashes. The volatility in these markets often spills over to other markets and sectors of the economy, affecting both the real and financial sectors.

Studies on the causal relationship between macro variables pointed out the volatility in each market. However, the results varied and showed a wide disparity. While some studies supported long-run causality among the macro variables, others contradicted the same. Most studies generally analyzed the causality between the macroeconomic variables, the element of volatility in each variable, and its spillover. But the effect on the other

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DOI : https://doi.org/10.17010/ijrcm/2021/v8i3/167954

variables was largely less studied. To fill this gap, this study attempts to understand the dynamic causal relationship and the effects of volatility spillovers between three important macroeconomic variables, viz., crude oil price, exchange rate, and stock prices in India. The daily data from January 2006 to March 2019 were used for the empirical analysis. The causal relationship between the macro variables and the direction of causality was identified by the Johnsen cointegration and Granger causality tests. The effects of volatility spillovers of the individual markets over other markets were estimated by the GARCH method.

Review of Literature

Sujit and Kumar (2011) examined the dynamic relationship between oil price, gold price, exchange rate, and stock returns across countries using periodic data from January 2, 1998 to June 5, 2011 consisting of 3485 observations. The cointegration and the VAR methods validated the periodic relationship between these variables. The estimated results identified that the exchange rate directly influenced the gold price, stock market index returns, and oil price. However, the influence of the stock market on the exchange rate was somewhat lesser relative to the other variables. The variance decomposition showed that crude oil price and gold price explained a significant portion of the exchange rate variation. Moreover, the fluctuation in the gold price was largely dependent on the gold price itself than on other variables.

Ugurlu (2014) investigated the volatility in the Bucharest Exchange Trading Index (BET) of the Bucharest stock exchange using daily data for the period May 1, 2000 to October 6, 2014. The volatility of BET returns was estimated using the most popular volatility models like GARCH, EGARCH, TARCH, and PARCH, and the volatility forecast performance of these models was analyzed using GED distribution for the return of BET. The paper identified that ARMA (2, 2) model was the best model for investigating a variable by which GARCH models were estimated. The EGARCH (1, 2) model provided the best forecasting performance.

Kumar and Khanna (2018) studied the behavior of stock market volatility and its spillover in four Asian economies - India, China, Hong Kong, and Japan – applying the ARCH and GARCH models. They established that the Chinese financial market was the most volatile and the Indian financial market was more stable. The results further revealed that past volatility had more impact on current volatility relative to the shocks. While the Japanese stock market was more sensitive to its past shocks, the Chinese stock market was less sensitive to its past shocks, implying persistent volatility in the Chinese stock market. To varying degrees, the cross-market volatility was shared between the country stock markets, more strongly between China and Japan, and weakly between China and India.

Ali et al. (2020) analyzed the long-run relationship between exchange rate, gold price, and stock market returns and the effects of exchange rate and gold price of volatilities on the stock market volatility in Pakistan between 2001 and 2018 using the GARCH model. The correlation analysis showed a negative association between equity returns, crude oil price, and gold price. The Johansen cointegration test revealed no long-run relationship between the stock returns, crude oil price, and gold price. The Granger causality test identified one-way causation from oil price to stock returns. The GARCH (1,1) estimates showed that the exchange rate and gold price volatilities negatively influenced the stock market returns in Pakistan.

In the Indian context, Ghosh (2011) analyzed the nexus of the extreme oil price volatility with the exchange rate. The results of GARCH and EGARCH methods, applied over the period July 2, 2007 to November 28, 2008, observed that the Indian currency depreciated with respect to the US dollar with rising oil price returns. The EGARCH model provided the best assessment of the data when compared to other GARCH models. The estimate of the asymmetric term was found to be negative and significant, showing the existence of asymmetric response in the data. The study also revealed that the negative effect of oil price shocks on exchange volatility was similar in magnitude to the positive effect of oil price volatility. Moreover, the oil price shock permanently affected exchange rate volatility in India.

Singh and Ahmed (2011) explored the financial market risk in India, fitting GARCH family models to forecast the conditional variance of the S&P CNX Nifty Index using daily return data series. The forecasting performance of the models was examined along with robustness checks using alternative distributional assumptions. The study provided evidence that the TGARCH and PGARCH specifications described the Nifty Index volatility processes more reliably.

Sahu et al. (2014) investigated the dynamic relationship between crude oil price, exchange rate, and the stock price in India using daily data for the period April 1993 to March 2013. The results of the VECM method of estimation showed a long-run relationship between crude oil price and stock price, and the changes in the exchange rate had no significant impact on either stock price or oil price. Higher crude oil prices caused a rise in the cost of production, which eventually led to a reduction in the earnings of a company, and thereby affecting the equity valuation of the company.

Jain and Biswal (2016) examined the dynamic relationship between exchange rate, gold price, crude oil price, and stock price in India using the GARCH, EGARCH, and TGARCH models. The lead-lag linkages between the variables were analyzed by the symmetric and asymmetric non-linear causality tests. The results showed that a decrease in gold and crude oil prices caused a depressing Indian rupee value and stock returns.

Mishra and Debasish (2016) investigated the causal relationship between oil price and exchange rate volatility spillovers in India with daily data from June 2003 to March 2016. The estimated GARCH and EGARCH results highlighted that the Indian currency depreciated against the US dollar for an increase in crude oil price. The response of the exchange rate to positive and negative oil price shocks was found to be similar. The volatility in crude oil price affected the cost of production, leading to a change in the price of the good and its demand, which altered the exchange rate.

Sathyanarayanan et al. (2018) examined the volatility in crude oil price and its impact on the Indian stock market for the period January 1, 2006 to December 31, 2015 using the BSE Sensex and applied the GARCH model. The estimated results showed a significant variation in crude oil prices, which directly influenced stock returns and volatility in Sensex.

Nirmala and Deepthy (2018) modeled the commodity market volatility using data from multi-commodity exchanges from April 1, 2013 to March 31, 2018 by applying the symmetric and asymmetric ARCH and GARCH models. The AIC and SIC criteria were used to identify the best fit models that described volatility in the commodity market. The analysis signaled high persistence of volatility in commodity indices and the presence of leverage effect.

Amudha and Muthukamu (2018) analyzed the volatility and the leverage effect in the Indian equity stock market during April 24, 2003 and September 7, 2015. The study period corresponded to the time when the equity market experienced three bull and three bear phases along with good and bad news of shocks and volatility. The GARCH model was applied to study the volatility, and EGARCH and TGARCH models were used to examine the leverage effect and the negative relationship between asset volatility and asset returns. The study established persistent volatility and volatility clustering. There was an asymmetric reaction of asset returns to news, and the negative shocks had more impact on volatility than the positive shocks of similar magnitude.

Mohanamani et al. (2018) analyzed the dynamic linkage between gold price, oil price, exchange rate, and Indian stock market returns using daily data from January 1, 2003 to December 12, 2017 and applied the VECM method. The study provided evidence that a weakened foreign exchange market led to a rise in the gold price and a fall in oil price, creating high volatility in the BSE index. The cointegration test showed that there existed cointegration between the variables. The VECM results revealed that stock exchange returns were negatively influenced by the exchange rate and oil price volatilities. An increase in oil price gradually paved the way for an increase in exchange rate fluctuation, which in turn impacted the long-term movements of stock prices.

Hussain et al. (2019) examined the relationship between international crude oil price, exchange rate, and stock price in India using daily data for the period January 2010 and October 2018 using the GARCH estimation method. The trace, eigenvalue, and pairwise cointegration tests showed no cointegration of BSE with the crude oil price and exchange rate. The Granger causality test identified that past exchange rate and oil price influenced future BSE returns. There existed two-way volatility spillovers between the exchange rate (US$) and the returns on the BSE stock market and unidirectional volatility spillover from the BSE index to the oil price. Therefore, the equity returns of the BSE were found to be influenced by the volatilities in the exchange rate and crude oil price.

Data and Methodology

This paper used daily data for 14 years from January 2006 – March 2019 on crude oil price, exchange rate, and BSE Sensex in India, consisting of 3,755 observations to evaluate the dynamic relationship and the volatility spillover effect of the individual market over others. The monthly closing values of S&P BSE Sensex data were obtained from the official website of the Bombay Stock Exchange. The crude oil price data were collected from the official websites of the Ministry of Petroleum and Natural Gas, the Government of India, and the Bloomberg database. The data on the exchange rate were derived from the RBI's *Handbook of Statistics*. Crude oil data were measured in the US dollar price per barrel using WTI (West Texas Intermediate) price, and the exchange rate was measured in terms of Indian ₹ against US$.

The time-series data have to be tested for specific properties before using it for analysis. First, the series should be stationary, i.e., the mean and variance are to be constant over time, and the covariance between two time periods should not be computed based on the actual period but based on the previous period. If data series are non-stationary, then regression analysis is a case of spurious regression. The stationarity of the time series was tested by the Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP) unit root test. The long-run relationships, i.e., cointegration of the variables were tested by the Johansen cointegration test. Further, the causality among the variables was tested by the Granger causality test. Lastly, the extent of the effect of risk of one market on the other market was estimated by the GARCH method.

➯ **Augmented Dicky-Fuller (ADF) Unit Root Test :** Consider a simple AR(1) process:

$$y_t = \rho y_{t-1} + \varepsilon_t \qquad (1)$$

where, $-1 < \rho < 1$ and ε_t is the white noise error term. Subtracting y_{t-1} yields:

$$\Delta y_t = \delta y_{t-1} + \varepsilon_t \qquad (2)$$

where, $\delta = (\rho - 1)$. If $\delta = 0$, then $\rho = 1$ and the series is non-stationary. Adding the lagged values of y yields:

$$\Delta y_t = \beta_1 + \beta_2 t + \delta y_{t-1} + \sum^{p}_{i=1} \alpha_i \Delta y_{t-i} + \varepsilon_t \qquad (3)$$

The error term is assumed to be serially uncorrelated. In the ADF test, the null hypothesis is H_0: unit root is present against the alternative hypothesis is H_1: no presence of unit root, i.e., whether $\delta = 0$ is tested. The unit root test is carried out with both intercept and trend value of each variable, and the optimum lag length is selected using some information criteria.

➯ **Phillips – Perron (PP) Unit Root Test :** The PP test corrects for any serial correlation and heteroskedasticity in the errors non-parametrically by modifying the Dickey-Fuller test statistics (Phillips and Perron, 1988). The PP method estimates the non-augmented Dicky-Fuller test equation:

$$\Delta y_t = \delta y_{t-1} + \varepsilon_t \qquad (4)$$

where, ε_t is $I(0)$.

➯ **Johansen Cointegration Test :** Consider a VAR of order p:

$$y_t = \alpha y_{t-1} + \ldots + \alpha_p y_{t-p} + \beta x_t + \varepsilon_t \qquad (5)$$

In terms of differencing:

$$\Delta y_t = \pi y_{t-1} + \sum^{p-2}_{i=1} \tau \Delta y_{t-i} + \beta x_t + \varepsilon_t \qquad (6)$$

where, $\pi = \sum^{p}_{i=1} \alpha_i - I$ and $\tau = -\sum^{p}_{j-i+1} \alpha_j$. If π, the coefficient matrix, has reduced rank $r < k$, there exists kxr matrices α and β, each with rank r such that $\pi = \alpha\beta'$ and $\beta' yt$ is $I(0)$. Then r is the number of cointegrating relations (cointegrating rank), and each column of β is the cointegrating vector. The π matrix is estimated as an unrestricted VAR and the restrictions implied by the reduced rank of π are to be tested statistically for rejection or acceptance.

➯ **Granger Causality Test :** The Granger causality assumes that the future cannot cause the past. If event x occurs after event y, then x cannot Granger cause y. A variable x is said to Granger cause another variable y if the past value of x helps predict the current level of y. The causality may also run the other way. If y also causes x, then it is not clear which variable influences which variable, and the information on one will not help predict the other. The causal relationship may be none, unidirectional, or bidirectional. Unlikely, that information on x will help predict y. The Granger causality test estimates pairs of regression on the lagged values of both variables:

$$y_t = \beta_1 + \sum^{p}_{i=1} \beta_{1i} x_{t-i} + \sum^{p}_{j=1} \beta_{1p+j}\ y_{t-j} + \varepsilon_{1t} \qquad (7)$$

$$x_t = \beta_2 + \sum^{p}_{i=1} \beta_{2i} x_{t-i} + \sum^{p}_{j=1} \beta_{2p+j}\ y_{t-j} + \varepsilon_{2t} \qquad (8)$$

where, p is the number of lags that adequately models the dynamic structure, and the errors are white noise. The null hypothesis, which is, x does not Granger cause y, is rejected if the parameters $\beta_{1\,p+j}$ are jointly significant. Unidirectional causality from x to y exists if the estimated coefficients on the lagged x are statistically different from 0, and the set of estimated coefficients on lagged y are not statistically different from 0. Unidirectional causality from y to x exists if the set of lagged x coefficients is not statistically different from 0 and the set of lagged y coefficients are statistically different from 0. Bilateral causality is suggested when the set of x and y coefficients are statistically significantly different from 0 in both regressions. There is no causal relationship if the sets of x and y coefficients are not statistically significant in both the regressions.

➯ **ARCH and GARCH Models of Volatility :** Generally, the time-varying serial correlation or volatility and conditional heteroskedasticity or volatility clustering in the time series are modeled as a simple autoregressive (AR) process. In the absence of autocorrelation, the stationary time series y_t can be expressed in terms of its mean and the white noise error:

$$y_t = \bar{y} + e_t \qquad (9)$$

where, e_t is iid with mean zero. The volatility clustering or conditional heteroskedasticity can be expressed as:

$$e^2_t = \gamma_0 + \gamma_1 e^2_{t-1} + ... + \gamma_p e^2_{t-p} + u_t \quad (10)$$

where, u_t is a zero-mean white noise process. This expression is the autoregressive conditional heteroskedasticity (ARCH) model (Engle, 1982). Since an ARCH model can be written in terms of squared residuals, a simple Lagrange Multiplier (LM) test can be used to test for the presence of ARCH effects in the residuals: $H_0: \gamma_1 = \gamma_2 = ... = \gamma_p = 0$. The test statistic follows the chi-square distribution.

If the p-value is smaller than the 5% significance level, the null hypothesis that there are no ARCH effects is to be rejected. The time series shows volatility clustering or persistent residuals. Then, the previous history, usually long periods, is to be used to estimate the time-varying volatility, σ_2. To control the lags within the reasonable limits in ARCH (q), Bollerslev (1986) suggested a more parsimonious and generalized ARCH or GARCH (p,q) model:

$$\sigma^2_t = \sum^p_{i=1} \gamma_i e^2_{t-i} + \sum^q_{j=1} \theta_j \sigma^2_{t-j} \quad (11)$$

where, γ_i , $\theta_j > 0$ and $(\gamma_i + \theta_j < 1)$. In the GARCH ($p$, q) specification, the conditional variance σ^2_t is thus a linear combination of the squared residuals in the past p periods and the conditional variance in the previous q periods.

➯ **Mean Reversion :** The GARCH coefficients of a stationary GARCH model capture the persistence of volatility in the series. The sum of ARCH and GARCH coefficients specifies the rate at which the volatility mean reverts to its long-run level. The half-life of the volatility shock measures the average number of time periods for the volatility to revert to its long-run level, and its moving average is used to forecast the series of volatility. In a covariance stationary time series y_t, there exists an infinite order of moving averages of the form:

$$y_t = \mu + \sum^\infty_{i=1} \theta_i e_{t-1} \text{ and } \theta_0 = 1, \sum^\infty_{i=1} \theta^2_i < \infty \quad (12)$$

The mean-reverting model is thus specified as:

$$(e^2_t - \overline{\sigma}^2) = (\mu + \theta_1)(e^2_{t-1} - \overline{\sigma}^2) + (v_t - \theta_1 v_{t-1}) \quad (13)$$

where, $\overline{\sigma}^2 = \dfrac{\mu}{(1 - \gamma_1 - \theta_1)}$ is the unconditional long-run volatility level and $v_t = e^2_t - \sigma^2_t$.

➯ **Impulse Response Function :** The speed of mean reversion is given by the magnitude of $(\gamma_1 + \theta_1)$. In the case of the most fitting model, the rate of mean-reverting time $(\gamma_1 + \theta_1)$ is very close to one. The average time it takes for $|e^2_t - \overline{\sigma}^2|$ to decrease by one-half, that is, the half-life of a volatility shock, is given by:

$$L_{half} = \ln \left(\frac{1}{2}\right) / ln(\gamma_1 + \theta_1) \quad (14)$$

The Impulse Response Function (IRF) plots θ_i, the decay rate, that is, the lag at which the IRF reaches ½.

Empirical Analysis and Results

The descriptive statistics of the variables used to study the causal relationship between oil price, exchange rate, and BSE Sensex in India are presented in Table 1. The BSE Sensex and oil price are positively skewed and leptokurtic, while the exchange rate is negatively skewed and leptokurtic. The Jarque-Bera statistic, measuring the difference of skewness and kurtosis of series from the normal distribution, shows that there exists normality.

Table 1. *Descriptive Statistics of the Variables*

Description	Crude Oil Price	Exchange Rate	BSE Sensex
Mean	0.002	0.012	0.037
Median	0.091	0.000	0.112
Maximum	19.21	4.020	14.618
Minimum	–31.196	–9.168	–13.557
Standard deviation	2.378	0.508	1.309
Skewness	–0.503	–1.503	–0.545
Kurtosis	16.263	40.121	15.856
Jarque–Bera statistic	27674.62	216952.8	26034.99
Probability	0.000	0.000	0.000
Sum	–7.886	45.913	139.282
Sum sq. dev.	21228.48	968.936	6432.524
Observations		3754	

Figure 1. *Trends in Daily Crude Oil Price, Exchange Rate, and BSE Sensex at Levels*

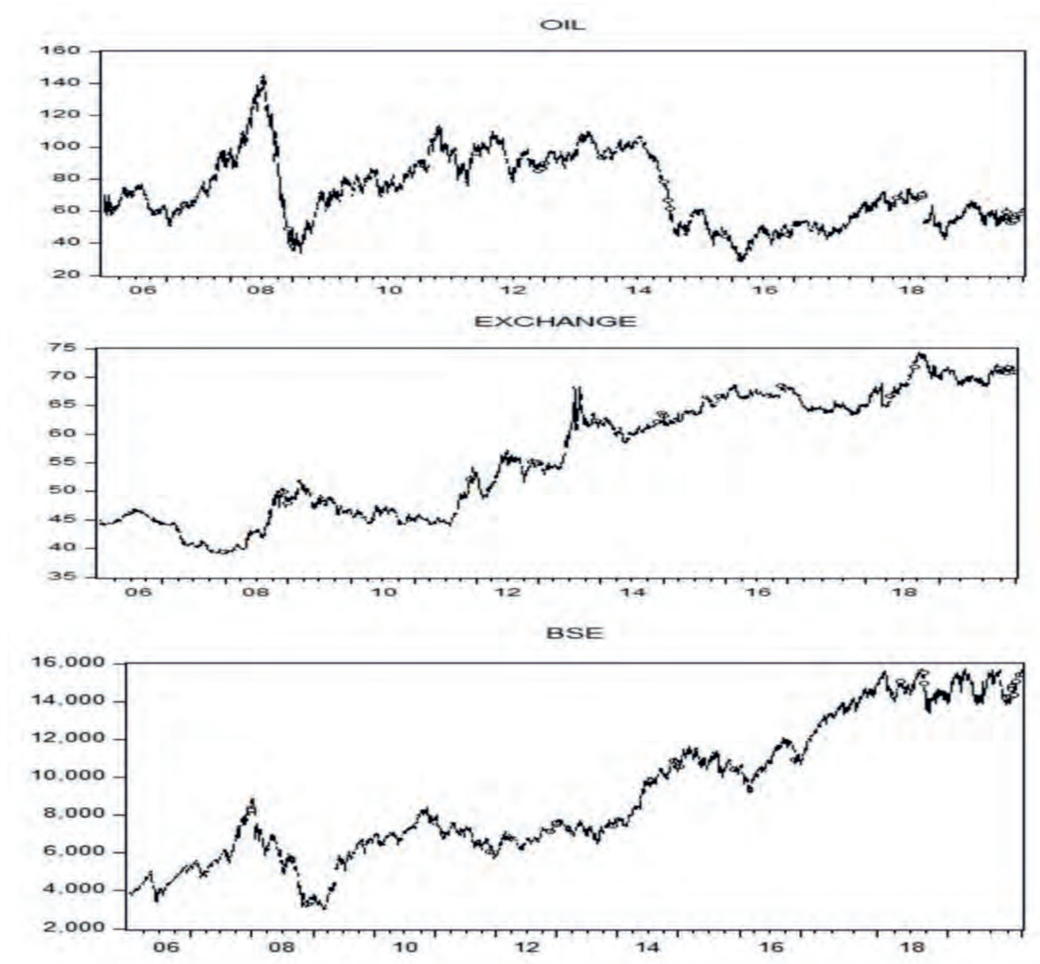

Figure 1 presents the trends in the series of daily oil price, exchange rate, and Sensex. All the graphs show a high range of fluctuations, implying that the means vary over the period, and therefore, all the series are not stationary. The crude oil price exhibited an extraordinarily high price in 2008, and the volatility was quite high over time. After a certain fall, the exchange rate kept rising, thus, showing dynamic volatile clustering. The stock market was highly volatile, that is, it kept rising and falling dynamically. Figure 2 shows the first differenced series are stationary.

Table 2 presents the result of the ADF and PP tests on the unit root of the variables. At levels, the *p*-values of all the variables exceeded the 0.05 critical level implying that the series are non-stationary at levels. At first difference, all the data series are stationary.

Figure 2. ***Stationarity of Daily Crude Oil Price, Exchange Rate, and BSE Sensex at First Difference***

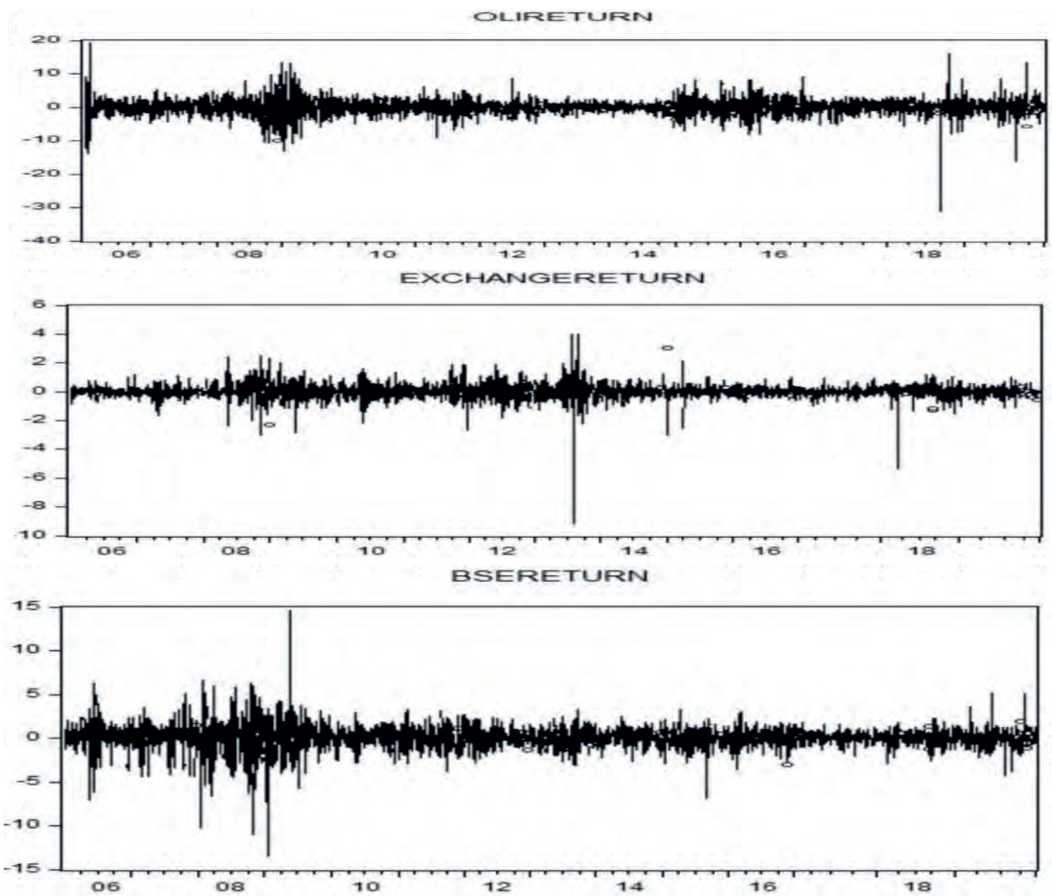

Table 2. ***ADF and PP Unit Root Test at First Difference***

Variable	0.05 Critical Value	ADF test		Phillips–Perron test	
		t - statistic	*p*-value	*t* - statistic	*p*-value
Crude oil price	–2.862	–66.712	0.000	–66.923	0.000
Exchange rate	–2.862	–61.246	0.000	–61.246	0.000
BSE Sensex	–2.862	–55.373	0.000	–55.343	0.000

Table 3 presents the Johansen cointegration test's trace and maximum Eigenvalue statistics. The test statistics indicate the presence of cointegration among the variables.

Table 4 presents the Granger causality test results in the direction of the long-run causal relationship between the variables. There exists a bidirectional causal relationship between exchange rate and BSE Sensex. The causality between crude oil price and BSE returns is unidirectional, i.e., the causality running from crude oil price to BSE Sensex. Moreover, the causal relation between crude oil price and the exchange rate is unidirectional, i.e., crude oil price affecting the exchange rate.

In the estimation of the GARCH model, the appropriate lag length that can be used for ARCH effect estimation was chosen using the VAR equation. The AIC criterion, in Table 5, identifies seven lags as the optimal lag length for estimation.

To check for the ARCH effect in the residuals, a regression equation is estimated as:

$$BSE\ sensex = 0.043 - 0.452\ Exchange\ rate + 0.0422\ crude\ oil\ Price \quad (15)$$

Using residual diagnostics, the presence of autocorrelation in the model is evaluated. Figure 3 presents the residual graph of volatility clustering to understand the presence of the ARCH effect. The residuals are fluctuating, showing heteroskedasticity, implying that volatility in one variable causes volatility in other variables.

Table 3. ***Johansen Cointegration Test***

Hypothesized No. of CE(s)	Eigen Value	Trace Statistic	0.05 Critical Value	Prob.	Max. Eigen Value Statistic	0.05 Critical Value	Prob.
None*	0.307	3539.088	29.797	0.0001	1378.295	21.132	0.0001
At most 1*	0.001	10.793	15.495	0.389	11.087	14.264	0.661
At most 2*	0.0006	0.27056	3.841	0.361	0.706	3.841	0.322

Table 4. ***Pairwise Granger Causality Test***

Null hypothesis	*F*-Statistic	*p*-value	Causality
Exchange rate does not Granger cause BSE Sensex	0.07052	0.0002	Yes
BSE Sensex does not Granger cause exchange rate	51.6654	3.00E-12	Yes
Crude oil price does not Granger cause BSE Sensex	4.17015	0.0008	Yes
BSE Sensex does not Granger cause crude oil price	1.73991	0.3267	No
Crude oil price does not Granger cause exchange rate	1.0167	0.0248	Yes
Exchange rate does not Granger cause crude oil price	1.65075	0.0719	No

Table 5. ***VAR Optimal Lag Length***

Determinant residual covariance (*df* adjusted)	2.318
Determinant residual covariance	2.305
Log-likelihood	–17538.32
Akaike information criterion (at lag 2)	9.332*
Schwarz criterion (at lag 2)	9.395
Number of coefficients	21

Figure 3. ***Actual and Fitted Residuals***

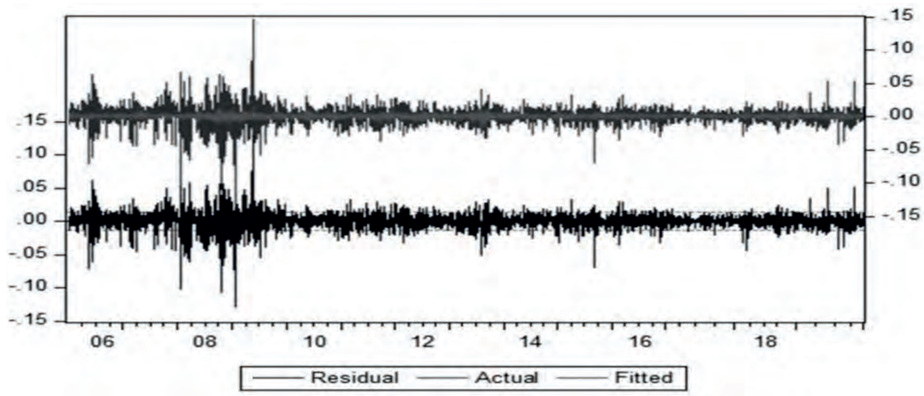

Table 6. ***Heteroscedasticity Test of ARCH Effect***

Variable	Coefficient	*t*-statistic	Prob.
Constant	0.952	9.185	0.000
Residual(–1)^2	0.106	6.524	0.000
Residual(–2)^2	0.124	7.623	0.000
R-square	0.251	Durbin – Watson statistic	2.014
F-value	67.044	Prob. *F*	0.000

The heteroscedasticity test result, presented in Table 6, shows significant *p*-values, thereby rejecting the null hypothesis of homoscedasticity. The heteroscedasticity test with four lags rejects the null hypothesis of no ARCH effect.

Table 7 shows that the *p*-values of the correlogram *Q*-statistics on all the lags are statistically significant,

Table 7. ***Correlogram of Residuals and Squared Residuals***

Auto-Correlation	Partial Correlation	Lag	Residuals				Squared Residuals			
			AC	PAC	*Q*-stat.	Prob.	AC	PAC	*Q*-stat.	Prob.
|* |	|* |	1	0.074	0.074	20.813	0.000	0.156	0.156	91.603	0.000
| |	| |	2	–0.013	–0.019	21.461	0.000	0.173	0.152	203.43	0.000
| |	| |	3	–0.030	–0.028	24.870	0.000	0.146	0.104	283.48	0.000
| |	| |	4	–0.009	–0.005	25.171	0.000	0.152	0.101	370.62	0.000
| |	| |	5	–0.011	–0.011	25.650	0.000	0.129	0.067	433.03	0.000
| |	| |	6	–0.027	–0.026	28.371	0.000	0.113	0.046	480.66	0.000
| |	| |	7	–0.019	–0.016	29.735	0.000	0.121	0.057	536.03	0.000
| |	| |	8	0.039	0.040	35.330	0.000	0.095	0.027	570.06	0.000
| |	| |	9	0.052	0.044	45.422	0.000	0.115	0.051	619.99	0.000
| |	| |	10	0.025	0.018	47.788	0.000	0.085	0.018	647.35	0.000

Table 8. ***GARCH (1,1) Estimates of BSE Sensex***

GARCH (1,1) model			Variance Equation		
Variable	**Coefficient**	***z*-statistic**	**Variable**	**Coefficient**	***z*-statistic**
Exchange rate	–0.280	5.526	Residual(–1)^2	0.121	16.038
	(0.019)	[0.00]		(0.007)	[0.00]
Crude oil price	0.020	–14.460	GARCH(–1)	0.872	119.789
	(0.006)	[0.00]		(0.007)	[0.00]
Constant	0.0008	3.137	Constant	2.24E–06	8.345
	(0.0001)	[0.002]		(2.68E–07)	
F-statistic		0.317	*R*-square		0.030
Prob.*F*		0.574	Adjusted *R*-square		0.025
R-square		0.317	Log-likelihood		11773.17
Durbin–Watson statistic		2.001	Durbin–Watson statistic		1.826

Note. Standard errors in parentheses. Probability values are in brackets.

Table 9. ***Correlogram of Squared Residuals after GARCH (1,1) Estimation***

Autocorrelation	Partial correlation	Lag	AC	PAC	*Q*-statistic	Prob.
| |	| |	1	0.009	0.009	0.3170	0.573
| |	| |	2	–0.015	–0.015	1.1570	0.561
| |	| |	3	0.009	0.009	1.4556	0.693
| |	| |	4	–0.004	–0.004	1.5042	0.826
| |	| |	5	–0.011	–0.010	1.9408	0.857
| |	| |	6	0.001	0.001	1.9482	0.924
| |	| |	7	–0.013	–0.013	2.5400	0.924
| |	| |	8	–0.015	–0.014	3.3739	0.909
| |	| |	9	–0.014	–0.014	4.1205	0.903
| |	| |	10	–0.025	–0.025	6.4435	0.777

highlighting the presence of autocorrelation. The autocorrelation in the squared residuals is also statistically significant, thus, satisfying the condition of ARCH estimation.

As an ARCH effect existed, the GARCH model was estimated with lags. The correlogram squared residuals and ARCH LM test were performed to check for volatility spillover from one market to another. The GARCH (1,1) estimates, presented in Table 8, show that the crude oil price has a significant and direct effect on the BSE Sensex. An increase in crude oil price leads to an approximate 2% increase in the stock price. The estimated effect of the exchange rate on the stock market is significantly negative, showing that there is an inverse relationship between the exchange rate and Sensex. In the variance equation, both ARCH and GARCH terms are statistically significant, implying that the volatility in BSE Sensex is also influenced by its own shocks.

Further, residual statistics and heteroscedasticity were tested to confirm the volatility spillover effect. The findings, reported in Table 9, show no presence of heteroscedasticity and autocorrelation as the respective *p*-values are greater than the 0.05 significance level, thereby refuting the null hypotheses. Thus, the risk factor involved in the exchange rate and crude oil price affects the domestic stock market and volatility in stock prices.

Conclusion and Policy Implications

Macroeconomic factors like crude oil price, exchange rate, gold price, inflation, and stock returns play a vital role in the economic growth of a country. As these variables are highly related to each other and are highly volatile, the volatility in one market spills over to other markets. This paper examines the dynamic causal relationship between crude oil price, exchange rate, and BSE Sensex using daily data for 14 years from January 2006 – March 2019 for India consisting of 3,755 observations and applying the GARCH estimation method to understand the volatility effects of one market on the other markets in India. The Augmented Dickey – Fuller and Philips – Perron unit root tests of stationarity were applied. Moreover, the Johansen cointegration test was used to understand the long-run association between the crude oil price, exchange rate, and stock prices. The Granger causality test results show bidirectional causality between exchange rate and BSE Sensex, unidirectional causality from crude oil price to BSE Sensex and exchange rate in the long-run. The volatility effects of crude oil price and exchange rate on the stock market show that the BSE Sensex is influenced by the fluctuations in crude oil prices and exchange rates. The volatility in BSE Sensex is also highly overdone by internal shocks of the stock market itself. In conclusion, the stock market swings are highly affected by its own shocks as well as by the volatility in other macroeconomic variables like oil price and exchange rate. Thus, the volatility and volatility spillover of one market cause volatility and volatility spillovers in other markets in India.

This paper has shown, comprehensively, the nature of the relationship among the movement of crude oil price, exchange rate, and asset prices in India. The empirical results of this paper show that the demand-side and supply-side shocks of the crude oil price and the co-movement of the volatilities in macro variables have important implications for policymakers, investors, risk managers, asset allocation strategies, and macroeconomic modeling of the economy. Given the critical role of the financial sector in the economy and its proximity to all the markets, regulating international financial investments, such as foreign direct investment and foreign institutional investments, should be the top priority of policymakers in order to secure stability in national markets. Investors and fund managers, too, should diversify their portfolios for effective risk management and shock hedging. This calls for effective monetary policy and regulatory mechanisms that should be forward-looking to control volatility in macro variables. There is also a need for well-designed and market-friendly adjustment mechanisms to control volatility spillovers from one market to another.

Limitations of the Study and Scope for Future Research

The paper has considered only a few macroeconomic variables in the empirical analysis. More macro variables, including gold price, energy price, international stock prices, inflation, and interest rate, can be incorporated. Logically, the paper used only the conventional time series analysis and applied the GARCH method of estimation. Further research shall focus on more broad dynamic stochastic general equilibrium modeling, and more comprehensive multivariate and factor GARCH methods like EGARCH, IGARCH, NGARCH, PGARCH, and TGARCH models and regime-switching stochastic volatility processes to allow for a parsimonious representation of time-varying variances and covariances and account for both observed and unobserved heterogeneity in variables. Further research can also consider the potential structural breaks in the variables due to friction, including regulatory constraints and exogenous factors that might contribute to varying rates of adjustment.

Author's Contribution

T. Lakshmanasamy, the sole author of this paper, singularly conceived, designed, developed, prepared, and wrote the whole paper.

Conflict of Interest

The author certifies that he has no affiliation with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgement

The author received no financial support for the research, authorship, and/or for the publication of this article.

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