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# Spillover Effects in External and Domestic Markets: GARCH Estimation of Crude Oil Price, Exchange Rate, and Stock Price Volatilities

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**Abstract**

Macroeconomic stability is crucial not only for economic growth but also for the living standards and investments in a market economy. The macroeconomic variables like crude oil price, gold price, exchange rate, inflation and stock returns are highly correlated to each other and are highly volatile, and the volatility in one market spills over to other markets. This paper analyses 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 to March 2019 is used in the GARCH estimation of causal effects of volatility spillovers. The GARCH estimates show that the volatility and volatility spillover of one market cause volatility and volatility spillovers in other markets in India. The crude oil price and exchange rate volatility and volatility spillovers cause volatility in BSE Sensex. The volatility in BSE Sensex is highly overdone by internal shocks of the stock market itself.

**Keywords:** Oil Price, Exchange Rate, Stock Market, Volatility, Causal Effect, GARCH Estimation

**JEL Classification:** B23, C22, C58, E44

## Introduction

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 the stable stock market. The stability of these markets is also important for the living standards and investments in the country. India is among the top fast-growing economies in the world, and much of its manufacturing industry depends on crude oil. India is the third biggest crude oil consumer among the countries in the world. Therefore, any volatility in the crude oil price will have a significant effect not only on the cost of production and price of commodities, but also on the cost of living in India. With increasing globalisation and international trade, the exchange rate plays a significant role in economic growth. Any exchange rate volatility not only affects exports, imports, and commodity prices, but also the domestic financial sector, and more importantly, the interest rate and the value of domestic currency, leading to devaluation. The instability of the financial sector and the stock market volatility poses a grave problem to policy planning, as instability leads to uncertainty that may hinder the way towards economic growth. Stock market volatility often leads to booms and crisis, and even to the crash of the stock market. The volatility in these markets often spills over to the other markets and sectors of the economy, affecting both the real and financial sectors of the economy.

Studies on the causal relationships between macro variables show that the volatility in each market causes risk to the other markets. However, the results are varied and show a wide disparity. While some studies claim support for a long-run causality among the macro variables, other studies contradict the same. Most studies generally analyse the causality between the macroeconomic variables; the element of volatility in each variable and its spillover and effect on the other variables is largely studied less. To fill this gap, this study attempts to understand the dynamic causal relationship and the effects of volatility spillovers among three important macroeconomic variables, viz.

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crude oil price, exchange rate, and stock prices, in India. In the empirical analysis, the daily data from January 2006 to March 2019 are used. The causal relationship between the macro variables and the direction of causality is identified by the Johnsen cointegration and Granger causality tests. The effects of volatility spillovers of the individual markets over the other markets are estimated by the GARCH method.

## Review of Literature

Sujit and Rajesh (2011) examine the dynamic relationship between gold price, oil price, exchange rate, and stock returns using periodic data from January 2, 1998, to June 5, 2011, consisting of 3,485 observations. The periodic relationship between these variables is validated by the cointegration and VAR methods. The estimated results identify that the exchange rate has a direct influence on the gold price, stock market index returns, and oil price. However, the influence of the stock market on the exchange rate is somewhat lesser, relative to other variables. The variance decomposition shows that the crude oil price and gold price explain a significant portion of the exchange rate variation. The fluctuation in gold price is largely dependent on gold price itself than on other variables.

Ugurlu (2014) investigates 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 are estimated using the most popular volatility models like GARCH, EGARCH, TARCH, and PARCH models, and the volatility forecast performance of these models are analysed using GED distribution for the return of BET. The paper identifies that ARMA (2,2) model is the best model for investigating a variable by which GARCH models are estimated. The EGARCH (1,2) model provides the best forecasting performance.

Ali et al. (2020) analyse 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 shows a negative association between equity returns, crude oil price, and gold price. The Johansen cointegration test does not reveal any long-run relationship between the stock returns, crude oil price, and gold price. The Granger causality test identifies one-way causation from oil price to stock returns. The GARCH (1,1) estimates show that the exchange rate and gold price volatilities negatively influence the stock market returns in Pakistan.

In the Indian context, Ghosh (2011) analyses the nexus of the extreme oil price volatility with the exchange rate. The GARCH and EGARCH methods are applied over the period July 2, 2007, to November 28, 2008. The study observes that the Indian currency depreciates with respect to the US dollar, with rising oil price returns. The EGARCH model provides the best assessment of the data compared to the other GARCH models. The estimate of the asymmetric term is negative and significant, showing the existence of asymmetric response in the data. The study also reveals that the negative effect of oil price shocks on exchange volatility is similar in magnitude to the positive effect of oil price volatility. Moreover, the oil price shock leaves a permanent effect on exchange rate volatility in India.

Sahu et al. (2014) investigate 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, and applying the VECM method of estimation. The results show a long-run relationship between crude oil price and stock price, and the changes in the exchange rate have no significant impact on either stock price or oil price. Higher crude oil price leads to a rise in the cost of production, which reduces the earnings of a company, thus affecting the equity valuation of the company.

Jain and Biswal (2016) examine 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 are analysed by the symmetric and asymmetric non-linear causality tests. The results show that a decrease in gold and crude oil prices causes a depressing Indian rupee value and stock returns.

Mishra and Debasish (2017) investigate 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 show that the Indian currency depreciates against the US dollar for an increase in crude oil price. The response of the exchange rate to positive and negative oil price shocks is similar. The volatility in crude oil price affects the cost of production, leading to a change in the price of the good and its demand, which alters the exchange rate.

Sathyanarayanan (2018) examines 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 applying the GARCH model. The estimated results show a significant variation in crude oil prices, which has a direct influence on stock returns and volatility in Sensex.

Mohanamani et al. (2018) analyse the dynamic linkage between gold price, oil price, exchange rate, and stock market returns using daily data from January 1, 2003, to December 12, 2017, and applying the VECM method. The study finds evidence from India that a weakened foreign exchange market leads to a rise in the gold price and a fall in oil price, creating high volatility in the BSE index. The cointegration test shows there exists cointegration between the variables. The VECM results reveal that stock exchange returns are negatively influenced by the exchange rate and oil price volatilities. An increase in oil price gradually paves way for an increase in exchange rate fluctuation, which in turn impacts the long-term movements of stock prices.

Hussain et al. (2019) examine the relationship between international crude oil price, exchange rate, and stock price in India using daily data for the period January 2010 to October 2018, using the GARCH estimation method. The trace, Eigen value, and pairwise cointegration tests show no cointegration of BSE with the crude oil price and exchange rate. The Granger causality test identifies that past exchange rate and oil price influence future BSE returns. There exists two-way volatility spillovers between the exchange rate (USD) and returns on the BSE stock market, and unidirectional volatility spillover from the BSE index to the oil price. The equity returns of the BSE are therefore influenced by volatilities in the exchange rate and crude oil price.

## Data and Methodology

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

The time series data has to be tested for certain properties before using 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 are not computed based on the actual period, but on the previous period. If data series are non-stationary, the regression analysis is a case of spurious regression. The stationarity of the time series is normally tested using the Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP) unit root test. The long-run relationships, i.e. cointegration of the variables, are tested by the Johansen cointegration test. The causality among the variables is tested by the Granger causality test. The extent of the effect of risk of one market on the other market is estimated by the GARCH method.

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

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

Where $-1 < \rho < 1$ and $\varepsilon_t$ is the white noise error term. Subtracting $y_{t-1}$ from equation (1) yields:

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

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

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

The error term is assumed to be serially uncorrelated. In the ADF test, the null hypothesis ($H_0$: unit root is present) against the alternative hypothesis ($H_1$: no presence of unit root), i.e. whether δ = 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 heteroscedasticity in the errors non-parametrically, by modifying the Dickey-Fuller test statistics (Phillips & Perron, 1988). The PP method estimates the non-augmented Dicky-Fuller test equation:

$$\Delta y_t = \delta y_{t-1} + \varepsilon_t \tag{4}$$

Where $\varepsilon_t$ is I(0).

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

$$y_t = \alpha\, y_{t-1} + \cdots + \alpha_p\, y_{t-p} + \beta x_t + \varepsilon_t \tag{5}$$

In terms of differencing:

$$\Delta y_t = \pi y_{t-1} + \sum_{i=1}^{p-2} \tau \Delta y_{t-i} + \beta x_t + \varepsilon_t \tag{6}$$

Where $\pi = \sum_{i=1}^{p} \alpha_i - I$ and $\tau = -\sum_{j-i+1}^{p} \alpha_j$. If $\pi$, the coefficient matrix, has reduced rank, r < k, there exist kxr matrices $\alpha$ and $\beta$ each with rank r such that $\pi = \alpha\beta'$ and $\beta' y_t$ is I(0). Then, r is the number of cointegrating relations (cointegrating rank) and each column of is the cointegrating vector. The $\pi$ matrix is estimated as an unrestricted VAR and the restrictions implied by the reduced rank of 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. It is unlikely that information on x will help predict y. The Granger causality test estimates pairs of regression on the lagged values of both variables:

$$y_t = \beta_1 + \sum_{i=1}^{p} \beta_{1i}\, x_{t-i} + \sum_{j=1}^{p} \beta_{1p+j}\, y_{t-j} + \varepsilon_{1t} \tag{7}$$

$$x_t = \beta_2 + \sum_{i=1}^{p} \beta_{2i}\, x_{t-i} + \sum_{j=1}^{p} \beta_{2p+j}\, y_{t-j} + \varepsilon_{2t} \tag{8}$$

Where p is the number of lags that adequately models the dynamic structure and the errors are white noise. The null hypothesis that x does not Granger cause y is rejected if the parameters $\beta_{1p+j}$ 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 are 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 regressions.

## ARCH and GARCH Models of Volatility

Generally, the time-varying serial correlation or volatility and conditional heteroscedasticity or volatility clustering in the time series are modelled 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:

$$y_t = \bar{y} + e_t \tag{9}$$

Where $e_t$ is iid with mean zero. The volatility clustering or conditional heteroscedasticity can be expressed as:

$$e_t^2 = \gamma_0 + \gamma_1 e_{t-1}^2 + \cdots + \gamma_p e_{t-p}^2 + u_t \tag{10}$$

Where $u_t$ is a zero-mean white noise process. This expression is the autoregressive conditional heteroscedasticity (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: $H_0: \gamma_1 = \gamma_2 = \cdots = \gamma_p = 0$. The test statistic follows the chi-square distribution.

If the p-value is smaller than the five per cent 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, $\sigma^2$. To control the lags within the reasonable limits in ARCH (q), Bollerslev (1986) suggests a more parsimonious and generalised ARCH or GARCH (p,q) model:

$$\sigma_t^2 = \sum_{i=1}^{p} \gamma_i\, e_{t-i}^2 + \sum_{j=1}^{q} \theta_j\, \sigma_{t-j}^2 \tag{11}$$

Where $\gamma_i, \theta_j > 0$ and $(\gamma_i + \theta_j < 1)$. In the GARCH (p,q) specification, the conditional variance $\sigma_t^2$ 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 captures the persistence of volatility in the series. The sum of ARCH and GARCH coefficients specify 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, there exists an infinite order of moving averages of the form:

$$y_t = \mu + \sum_{i=1}^{\infty} \theta_i e_{t-1} \qquad \theta_0 = 1, \sum_{i=1}^{\infty} \theta_i^2 < \infty \quad (12)$$

The mean-reverting model is thus specified as:

$$(e_t^2 - \bar{\sigma}^2) = (\mu + \theta_1)(e_{t-1}^2 - \bar{\sigma}^2) + (v_t - \theta_1 v_{t-1}) \quad (13)$$

Where $\bar{\sigma}^2 = \frac{\mu}{(1-\gamma_1-\theta_1)}$ is the unconditional long-run volatility level and $v_t = e_t^2 - \sigma_t^2$.

*Impulse Response Function:* The speed of mean reversion is given by the magnitude of ($y_1 + \theta_1$). In the case of the most fitting model, the rate of mean-reverting time ($y_1 + \theta_1$) is very close to one. The average time it takes for $|e_t^2 - \bar{\sigma}^2$ to decrease by one-half, i.e. 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 $\theta_i$, the decay rate, i.e. the lag at which the IRF reaches ½.

## Empirical Analysis

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 statistics, measuring the difference of skewness and kurtosis of series from the normal distribution, show that there exists normality.

**Table 1: Descriptive Statistics of 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 | | |

Fig. 1 presents the trends in the series of daily oil price, exchange rate, and Sensex. All the graphs show a high range of fluctuations, meaning that the mean values are varying over the period and therefore, all the series are not stationary at levels. The crude oil price exhibits an extraordinarily high price in 2008 and the volatility is quite high over time. After a certain fall, the exchange rate keeps rising, showing dynamic volatile clustering. The stock market is highly volatile, rising and falling dynamically. Fig. 2 shows that the first differenced series is stationary.

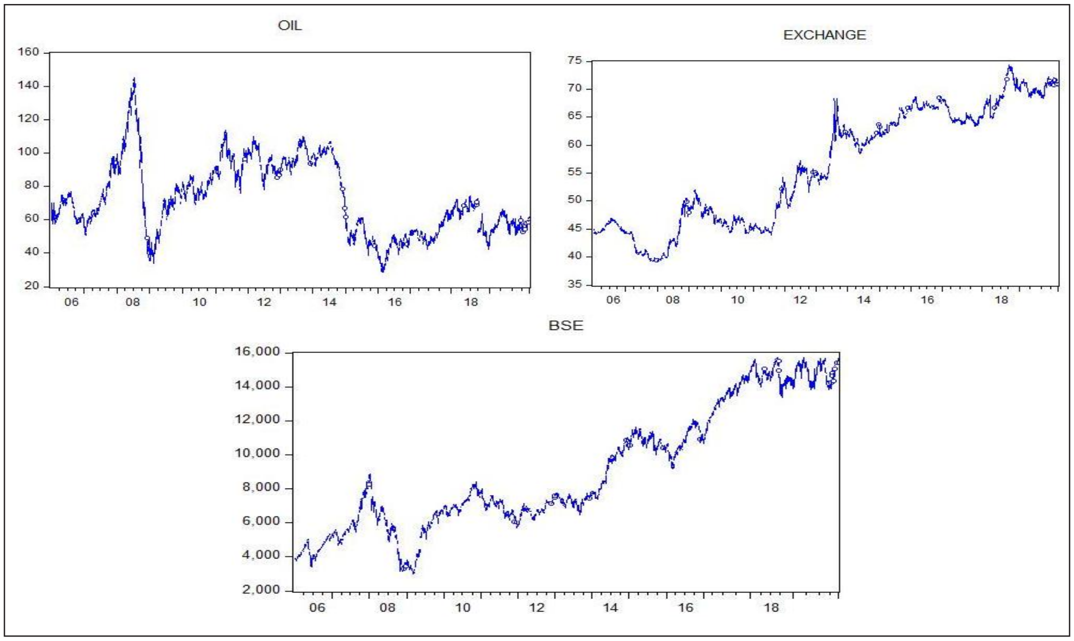


**Fig. 1: Trend in Daily Crude Oil Price, Exchange Rate, and BSE Sensex at Levels**

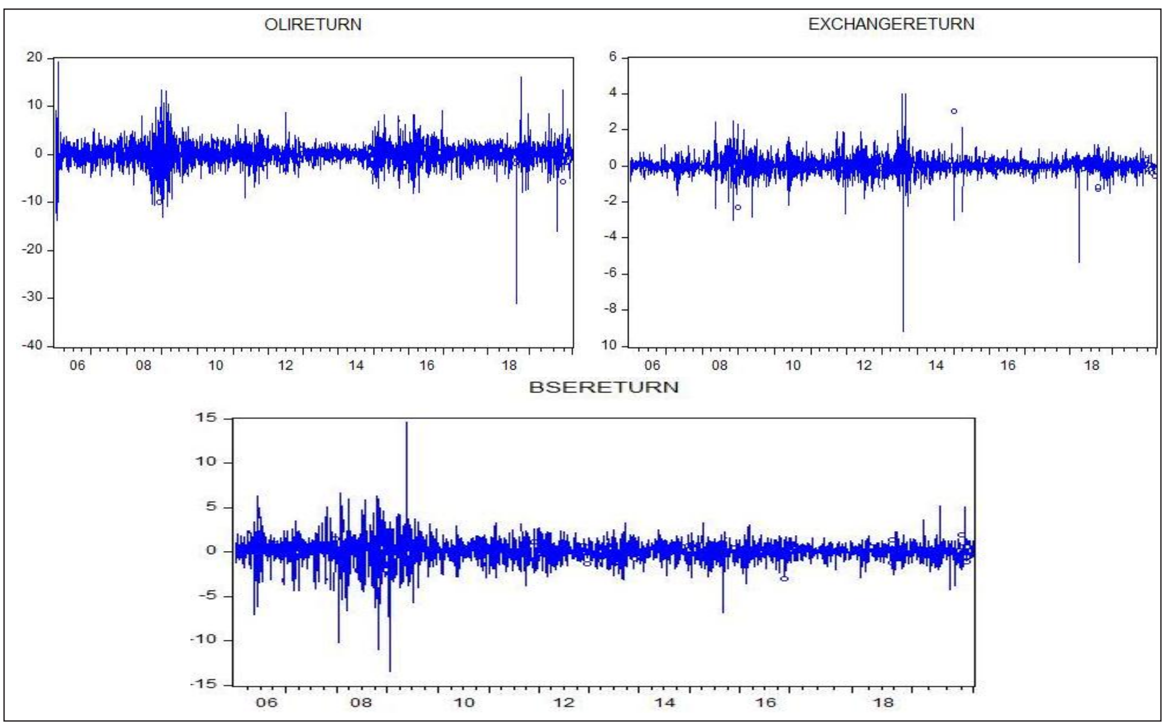


**Fig. 2: Stationarity of Daily Crude Oil Price, Exchange Rate, and BSE Sensex at First Difference**

*Unit Root Test:* Table 2 presents the results of the ADF and PP tests on the unit root of the variables. At levels, the p-values of all the variables exceed the 0.05 critical level, implying that the series is non-stationary at levels. At first difference, all the data series are stationary.

**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 |

*Johansen Cointegration Test:* Table 3 presents the trace and maximum Eigen value statistics of the Johansen cointegration test. The test statistics indicate the presence of cointegration among the variables.

**Table 3: Johansen Cointegration Test**

| *Hypothesised 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 |

*Granger Causality Test:* 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, with the causality running from crude oil price to BSE Sensex. The causal relation between crude oil price and the exchange rate is unidirectional, with crude oil price affecting the exchange rate.

**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 |

*Optimal Lag Length:* In the estimation of the GARCH model, the appropriate lag length that can be used for ARCH effect estimation is to be chosen using the VAR equation. In Table 5, the AIC criterion identifies seven lags as the optimal lag length for estimation.

**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 |

Note: *Significant at 5% level.

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

$$\textit{BSE sensex} = 0.043 - 0.452\ \textit{Exchange rate} + 0.0422\ \textit{Crude oil price} \quad (15)$$

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

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

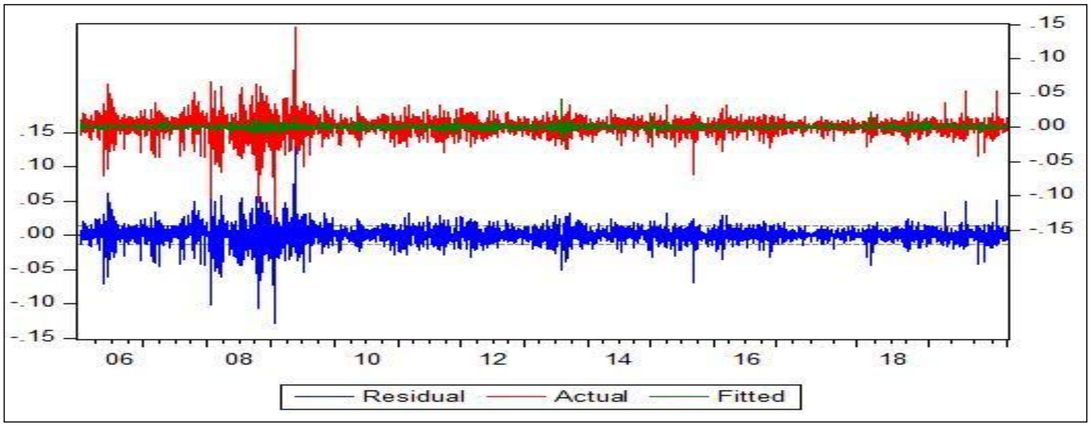


**Fig. 3: Actual and Fitted Residuals**

**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 |

Table 7 shows that the p-values of the correlogram Q-statistics on all the lags are statistically significant, showing the presence of autocorrelation. The autocorrelation in the squared residuals is also statistically significant, satisfying the condition of ARCH estimation.

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

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

As there exists an ARCH effect, the GARCH model is estimated with lags. The correlogram squared residuals and ARCH LM test are 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 direct effect on the BSE Sensex. An increase in crude oil price leads to about a two per cent 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.

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

| *Variable* | *GARCH(1,1) Model* | | *Variance Equation* | | |
|---|---|---|---|---|---|
| | *Coefficient* | *Z-Statistic* | *Variable* | *Coefficient* | *Z-Statistic* |
| Exchange rate | −0.280 (0.019) | 5.526 [0.00] | Residual$(-1)^2$ | 0.121 (0.007) | 16.038 (0.00) |
| Crude oil price | 0.020 (0.006) | −14.460 [0.00] | GARCH(−1) | 0.872 (0.007) | 119.789 (0.00) |
| Constant | 0.0008 (0.0001) | 3.137 [0.002] | Constant | 2.24E−06 (2.68E−07) | 8.345 |
| 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 in brackets.

After adjusting for the GARCH effect, residual statistics and heteroscedasticity tests to confirm the volatility spillover effects, reported in Table 9, show no presence of heteroscedasticity autocorrelation, as the respective p-values are greater than 0.05 significance level, thus rejecting the null hypotheses. Therefore, the risk factor involved in the exchange rate and crude oil price affects the domestic stock market and volatility in stock prices.

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

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th>Lag</th><th>AC</th><th>PAC</th><th>Q-Statistic</th><th>Prob.</th></tr>
<tr><td>| |</td><td>| |</td><td>1</td><td>0.009</td><td>0.009</td><td>0.3170</td><td>0.573</td></tr>
<tr><td>| |</td><td>| |</td><td>2</td><td>−0.015</td><td>−0.015</td><td>1.1570</td><td>0.561</td></tr>
<tr><td>| |</td><td>| |</td><td>3</td><td>0.009</td><td>0.009</td><td>1.4556</td><td>0.693</td></tr>
<tr><td>| |</td><td>| |</td><td>4</td><td>−0.004</td><td>−0.004</td><td>1.5042</td><td>0.826</td></tr>
<tr><td>| |</td><td>| |</td><td>5</td><td>−0.011</td><td>−0.010</td><td>1.9408</td><td>0.857</td></tr>
<tr><td>| |</td><td>| |</td><td>6</td><td>0.001</td><td>0.001</td><td>1.9482</td><td>0.924</td></tr>
<tr><td>| |</td><td>| |</td><td>7</td><td>−0.013</td><td>−0.013</td><td>2.5400</td><td>0.924</td></tr>
<tr><td>| |</td><td>| |</td><td>8</td><td>−0.015</td><td>−0.014</td><td>3.3739</td><td>0.909</td></tr>
<tr><td>| |</td><td>| |</td><td>9</td><td>−0.014</td><td>−0.014</td><td>4.1205</td><td>0.903</td></tr>
<tr><td>| |</td><td>| |</td><td>10</td><td>−0.025</td><td>−0.025</td><td>6.4435</td><td>0.777</td></tr>
</table>

## Conclusion

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 the BSE Sensex using daily data for 14 years, from January 2006 to 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 are applied. The Johansen cointegration test is used to understand the long-run association between the crude oil price, exchange rate, and stock prices. The Granger causality tests show bidirectional causality between exchange rate and BSE Sensex, and 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 price and exchange rate.

The volatility in BSE Sensex is also highly overdone by internal shocks of the stock market itself. Overall, 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.

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