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When the Oil Price Spillover: Examining the Volatility Spillover Effect between Crude Oil Price and Rupee-Dollar Exchange Rates

Akhil Sharma*
School of Commerce and Management Studies, Central University of Himachal Pradesh, Kangra, India
E-mail: akhilsharma@hpcu.ac.in

Abdul Rishad
ICFAI Business School, Hyderabad, India
E-mail: ktdahsir@gmail.com

Vikas Kumar Tyagi
Panipat Institute of Engineering and Technology, Panipat, India
E-mail: vikas.dtyagi.15@gmail.com

Jagdeep Singla
Bhagat Phool Singh Mahila Vishwavidyalaya, Sonipat, India
E-mail: jagdeepsingla@gmail.com

Abstract

This study investigates the long-standing debate between crude oil price variations and currency exchange rate volatility using daily data from July 1, 2009, to January 31, 2024. The GARCH family models were utilized to assess the symmetrical and asymmetrical impacts of oil price changes on exchange rate movements. The results indicate that the Indian Rupee (INR) appears to depreciate in value relative to the US dollar (USD) as oil prices rise. Furthermore, the Engle and Ng (1993) test indicated a significant asymmetric effect in oil-exchange nexus, validating the application of asymmetric GARCH models. The study unveils several insights into the dynamic between oil price shocks and exchange rate volatility. It shows that the effects of positive and negative oil price alterations on exchange rates are dissimilar, displaying different levels of impact based on whether the oil prices are escalating or declining. The study also reveals that oil price shocks have enduring effects on exchange rate movements, not just transient ones. Given these findings, policymakers in India should adopt a proactive approach to manage exchange rate fluctuations by implementing strategies that mitigate the adverse effects of oil price shocks.

Keywords: Currency exchange rate, Oil price fluctuations, Russia-Ukraine war, COVID-19 pandemic, India

JEL classification: F31, Q43, F51, I18, O53

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* Corresponding author.

1. Introduction

The volatility of global oil prices profoundly shapes the economic landscape, with countries like India- importing over 85% of its crude oil—spending USD 232.7 billion in 2022-23 and USD 234.3 billion in 2023-24. Changes in oil prices significantly impact trade balances, inflation, and currency valuation, drawing increasing attention to the nexus between oil prices and exchange rates. In India, fluctuations in oil prices can lead to substantial exchange rate volatility, directly affecting the value of the Indian rupee (INR) against the US dollar (USD). The ongoing conflict between Russia and Ukraine and the COVID-19 pandemic have had far-reaching repercussions on economies worldwide. The COVID-19 pandemic, which originated in China in December 2019 and was declared a global pandemic on March 11, 2020, resulted in approximately seven million deaths worldwide by 2023 (Wise, 2023). During this period, oil prices plummeted to $11.57 per barrel due to reduced economic activity from lockdowns and movement restrictions (Taghizadeh-Hesary, 2020). As the pandemic's effects subsided, the Russia-Ukraine war erupted on February 24, 2022, causing a dramatic rise in oil prices, with Brent crude increasing from $74.17 per barrel in January 2022 to $129.02 per barrel by March 2022 (Adekola et al., 2022). Unexpected fluctuations in crude oil prices significantly impact currency rates, particularly for nations reliant on oil imports and exports. The recent acquisition of discounted Russian oil has provided a crucial buffer for India, allowing the nation to mitigate the adverse effects of rising global oil prices. This strategic shift not only enhances energy security but also stabilizes the rupee by reducing the trade deficit, as cheaper imports can help manage inflationary pressures. Our research explores how fluctuations in oil prices affect the exchange rate in India during global and geopolitical events, highlighting the importance of this sensitivity for economic policy and investment strategies in India.

Since the imposition of the first oil embargo in 1973, there has been a substantial surge in global interest in the issue of oil. Numerous investigations by scholars and policymakers have delved into the patterns of oil prices and their repercussions on macroeconomic indicators. The empirical evidence indicates that fluctuations in oil prices exert a significant impact on both gross domestic product (GDP) and industrial production (Kelikume & Muritala, 2019; Gündüz, Kuzucuoğlu, & Gündüz, 2022) inflation (Sarmah & Bal, 2021; Li & Guo, 2022), and monetary policy (Wen, Min, Zhang, & Yang, 2019). Subsequent research has revealed an inverse correlation between variations in oil prices and prospects for investment (Hamilton, 2003; Wu & Wang, 2021; Bugshan, Bakry, & Li, 2023). Extensive studies have been carried out to explore the relationship between oil prices and stock market performance, as evidenced by works from Huang, Masulis, and Stoll (1996), Sadorsky (2003), Narayan, Narayan, and Sharma (2013), Kumar (2019), and Bashir (2022).

Since oil agreements are quoted in USD, variations in oil costs can be directly linked to changes in the currency value in comparison to the USD. Following these changes, there's a subsequent impact on the financial sectors as well as the broader economy (Turhan, Sensoy, and Hacihasanoglu, 2014). In general, oil prices are transmitted to the energy-importing country via the fiscal channel and the import channel. Any rise in oil prices is anticipated to result in a significant outflow of dollars from oil buyers to oil sellers. This, in turn, is expected to have a negative impact on the twin deficits (CAD & FD) of the country, ultimately leading to a depreciation of the domestic currency. This phenomenon has been previously discussed in the academic literature by Krugman (1983a, b) and Golub (1983). When the local currency depreciates, it results in higher costs for imported goods. This is typically significant for countries that rely heavily on energy imports, as such goods make up a substantial portion of overall consumer goods. Consequently, when oil prices ascend, it results in heightened inflation and triggers a surge in interest rates due to the adjustments in monetary policy, aligning with Taylor's rule. Following this, there have been extensive endeavours to substantiate empirically the inherent and multifaceted behavior of oil prices and exchange rates. Scholars have studied this relationship using cointegration and causality frameworks, including Zhang et al. (2008), Krichene (2005), Yousefi and Wirjanto (2004), Bénassy-Quéré et al. (2007), Coudert et al. (2008), and Fratzscher, Schneider, and Van Robays (2014), and more recently, by Musa & Maijama'a in 2021, univariate and multivariate GARCH family model such as GARCH, EGARCH, VAR-GARCH, VECM-GARCH, BEKK-GARCH, DCC GARCH, TVP-VAR (see Ghosh, 2011; Huang and Feng, 2007; Aloui, Aïssa, and Nguyen, 2013; Rautava, 2004; Cifarelli and Paladino, 2010; Jebabli, Arouri, and Teulon, 2014) and time-varying relationship (see Castro Rozo and Jiménez-Rodríguez, 2018; Reboredo and Rivera-Castro, 2013) respectively.

The prevalence of flexible exchange regimes during the latter part of the 20th century has prompted scholars to place greater emphasis on examining their influence on the exchange rates (See Table 1). The findings are inconclusive due to the constraints imposed by the data, methodology, time frame, and geographic scope employed in the existing empirical investigations. Several posit that the appreciation of the United States dollar (USD) can be ascribed to fluctuations in oil prices (Chaudhuri and Daniel, 1998; Olomola and Adejumo, 2006; Narayan, Narayan, and Smyth, 2008; Ahmad and Hernandez, 2013; Castro & Jiménez-Rodríguez, 2020). On the other hand, elevated oil prices can have a detrimental impact on exchange rates in nations that import oil since they raise the cost of imports (Kilian et al., 2009; Beckmann & Czudaj, 2013; Bodart et al., 2012). Furthermore, the research is not confined to a single region; it encompasses various areas worldwide. For example, Chen and Chen (2007), Nikbakht (2010), and Siddiqui et al. (2023) have shown a connection between exchange rate movements and prevailing oil prices in G7 and OPEC countries. Additionally, Adeosun, Tabash, and Vo (2022) focused on BRIC nations, while Vrbka, Horák, and Krulický (2022) studied the linkage in China. Through the application of a four-dimensional structural VAR technique, they studied the consequences of oil price variations on the Yuan's exchange rate, concluding that such variations have a marginal impact on the Yuan's appreciation. China's lesser reliance on foreign oil stems from this incident, differing from its trade partners. In 2007, Habib and Kalamova investigated how oil price shifts impacted actual exchange rates in Norway, Saudi Arabia, and Russia, revealing significant economic dynamics. Particularly in Russia, a substantial, persistent relationship between oil values and the Ruble's exchange rate was found. This was not the case for both Norway and Saudi Arabia, where oil prices did not show a similar influence on their respective currencies. In Reboredo's (2012) study, an analysis was conducted on the co-movements of oil exchange among currencies in the European Union (EU). The results indicate a subtle link between rising oil prices and a decline relative to the US dollar, with differentiated causative factors for different currencies. The correlation, however, seems to be stronger for nations that engage in oil exports as opposed to those that engage in oil imports. The Tiwari, Dar, and Bhanja (2013) utilized Wavelet analysis in both the time and frequency domains to break down the series into distinct frequency bands, uncovering causal relationships between the two series. When analyzed at broader time intervals, causality was not evident. however, by narrowing down the time frame, authors discerned a one-way causality stemming from the exchange rate towards oil prices. Later, Uddin, Tiwari, Arouri, and Teulon (2013) employed a wavelet methodology in the time-frequency domain to investigate the oil-exchange relationship in Japan. By analyzing monthly data from June 1983 to May 2013, they identified varying levels of correlation between the two datasets over various periods. A significant correlation has been observed between two sets of cycles with durations shorter than 34 months, namely the short-term and medium-term cycles. Nonetheless, a tenuous relationship was observed in extended monthly cycles, defined as having a time horizon exceeding 34 months.

Table 1 - Summarization of previous studies on the oil price and exchange rate dynamics

Authors	Country /Regions	Sample period	Models used	Findings
Narayan, Narayan, and Prasad (2008)	Fiji	Daily data from 2000-2006	GARCH and EGARCH	Rising oil prices lead to an appreciation of the Fijian Dollar (FJD) against the USD.
Ghosh (2011)	India	Daily data from July 2007, to November, 2008	GARCH and EGARCH	The INR typically weakens in comparison to the USD following an increase in oil prices.
Adeniyi, Omisakin, Olusegun, Yaqub, and Oyinlola (2012)	Nigeria	Daily data between January, 2009, to September, 2010.	GARCH and EGARCH	Rising oil prices tend to strengthen the Naira against the USD. This correlation has been validated through the EGARCH analytical framework, which highlighted that Naira's reaction to oil price fluctuations isn't uniform—there's a discernible variation when oil prices rise compared to when they fall.
Muhammad, Suleiman, and Kouhy (2012)	Nigeria	Daily time series from 01/02/2007 to 12/31/2010.	GARCH and EGARCH	Rising oil prices lead to depreciation of Nigerian Naira (NGN) against the USD.
Salisu and Mobolaji (2013)	Nigeria	Daily time series data from 01/02/2002 to 03/20/2012.	VAR-GARCH	Any increase in oil price volatility would depreciate the Naira against USD.
Aloui, Aïssa and Nguyen (2013)	Five currencies	Monthly data from 2000-2011	Copula GARCH	Rising oil prices are directly linked to the depreciation of the US dollar.
Jiranyakul (2015)	Thailand	Monthly data from July 1997 to December 2013	ARDL and GARCH	The volatility of real oil prices has been observed to have a positive correlation with the volatility of the real exchange rate, thereby potentially exerting a detrimental effect on the trade balance of the nation.
Sebai and Naoui (2015)	Seven nations	Daily time series from 01/04/2000 to 04/17/2014.	'DCC-GARCH'	Prior to the crisis, no clear correlation existed between oil prices and nominal exchange rates, but a reciprocal dependency developed afterward.
Geng, Geu	Fifteen	Monthly data from	VAR and IRF	The spillover effect of VIX

Authors	Country /Regions	Sample period	Models used	Findings
(2022)	countries	May 2007 to February 2020		and oil price influences exchange rates; and diminished long-term impact post Belt and Road Initiative.
Bagchi & Paul (2023).	Seven nations	Daily data from 1/02/2017 to 6/02/2022.	FIGARCH Model	Oil price shocks affect G7 stock returns and currency rates differently, showing long-term effects.

Source: Author's compilation.

Numerous research efforts have focused on the nexus between oil prices and exchange rates in European regions and key oil-exporting nations like Canada, and Saudi-Arabia. However, emerging markets, especially those heavily dependent on oil imports like India, have not received adequate attention. This study endeavours to delve into the research void by focusing on the intricacies associated with a major global oil importer. Grasping the relationship between oil prices and the exchange rate is paramount for India, given that its reliance on foreign oil equates to 84% of its total consumption, making up 40% of the nation's entire import expenditure (Yiew et al., 2019). Additionally, our study encompasses the effects of the COVID-19 pandemic and the geopolitical shifts following the Russian invasion of Ukraine in February 2022, which saw India's imports of discounted Russian oil rise from less than 2% to approximately 36-40% of total imports. This shift is crucial for understanding how these events influence the relationship between oil prices and the Indian rupee (INR) against the US dollar (USD), thereby providing a more comprehensive analysis of the oil-exchange rate nexus. Prior research has addressed certain facets of the matter at hand; however, there remain several inquiries that require resolution. Thus, the current study aims to investigate how oil prices affect India's exchange rate determination. Do positive and negative oil price shocks have a symmetrical impact on exchange rate volatility? How might variations in oil prices influence the formulation of exchange rate policies in India?

To concisely address these queries, examining the oil price-exchange rate relationship through the lens of Bollerslev's symmetric GARCH model (1986) and the extended asymmetric models—EGARCH by Nelson (1991), and GJR-GARCH by Glosten et al. (1993)—is pivotal. These models are instrumental in analyzing volatility spillover and underlying patterns between oil prices and exchange rates.

2. Data, variable construction and methodologies

To gain insights into the dynamic interplay between global crude oil prices and the INR-USD exchange rate, daily data has been utilized, spanning from July 1, 2009, to January 31, 2024. We utilize the INR-USD exchange rate due to crude oil being priced in US dollars, with data sourced from the Reserve Bank of India. To represent nominal oil prices, we use Global Brent Oil Spot Prices, which are also denominated in USD.

It is worthwhile to note that both referenced variables are in nominal form due to the inaccessibility of the daily inflation data. Further, Narayan, Narayan, and Smyth (2008) explicitly mentioned: "investigating the oil price-exchange rate nexus does not require the knowledge of real values." Subsequently, to ensure consistency, the variables are converted into 'natural logarithm' form to mitigate the risk of heteroskedasticity and normality. The returns series of underlined variables obtained via the following computation:

$$rexc_t = log\left(\frac{exc_t}{exc_{t-1}}\right)\ \ldots \quad (1)$$

$$roil_t = log\left(\frac{oil_t}{oil_{t-1}}\right)\ \ldots \quad (2)$$

Where, exc_t and exc_{t-1} is the INR to USD exchange rate and oil_t and oil_{t-1} are crude oil prices. The $rexc_t$ and $roil_t$ are returns of the nominal exchange rate and nominal oil prices, respectively.

The summary statistics of each variable are shown in Table 2. The statistics show that roil is more volatile than rexc as estimated by the standard deviation. The Skewness indicates the returns of both the series are positively skewed, which indicates the return rises more than it drops. Additionally, the variables exhibit a fat-tail distribution as indicated by the kurtosis value surpassing 3. Finally, the JB test refutes the null hypothesis of normality at a 1% level. Based on the above discussion, it can be concluded that all three statistics—Skewness, Kurtosis, and the JB test— reveal that the return series does not follow a normal distribution at the primary level.

Table 2 - Summary statistics of the variables

Particulars	rexc	roil
Mean	0.015853	-0.004727
Median	0.000000	0.009006
Maximum	3.791923	9.896096
Minimum	-3.755964	-8.245202
Std. Dev.	0.481200	1.870279
Skewness	0.079248	0.170073
Kurtosis	10.10133	5.534452
Jarque-Bera	5249.324*	679.5260*

Source: Output from Eviews

Notes: * indicates significant at 1% level respectively.

The assessment of Figure 1 shows that the fluctuations in INR were relatively more stable until mid-2011. During the period from July 2011 to December 2011, INR experienced a significant drop of almost 18 per cent against the USD, making the INR Asian worst-performing currency of the year. Further, in August 2013, the 'Taper Tantrum's' episode adversely impacted the Indian financial markets. The significant withdrawal by FIIs and heightened demand for USD led to a 20% decline in the value of the Rupee during the tapering episode (Basu, Eichengreen, & Gupta, 2014; Basri, 2017). In the last phase of the sample period, i.e., the year 2018, the increasing crude oil prices and the USA-China trade war marked down the INR to its all-time low of 74.45/USD. The INR lost nearly 14 per cent between April to October 2018 against the USD. The Indian Rupee experienced significant depreciation in 2020, exacerbated by the economic disruptions caused by the COVID-19 pandemic. By 2022, it breached the psychological benchmark of ₹80 against the US Dollar, marking a depreciation of approximately 11.5% during the period. This decline positioned the Rupee as Asia's worst-performing currency, largely driven by substantial capital outflows by Foreign Institutional Investors (FIIs). Concurrently, the US Dollar strengthened due to several global factors, including the Russia-Ukraine conflict, concerns over a global economic slowdown, and rising global inflation. These factors contributed to a surge in US bond yields, further supporting the appreciation of the US Dollar.

With regards to oil prices, it can be observed from Figure 1 that there was a period of stability until the conclusion of 2009. Subsequently, there was an increase in oil prices from $78 per barrel in January 2010 to $112 per barrel in June 2011, representing a nearly 44% rise. During the period spanning from June 2011 to September 2014, the fluctuations in Brent crude oil prices exhibited a notable degree of stability, with an average trading value of $109.89 per barrel. During the middle of 2014, the oil industry experienced a highly unstable period characterized by a significant drop in oil prices. The drop represented around a 60% decrease, moving from $114 per barrel in June 2014 to $46 per barrel in January 2015, inducing widespread concern among countries with a significant dependence on oil exports. This substantial collapse is attributed to an amalgamation of inherent factors and geopolitical resolutions. The study by Alquist and Guénette (2014) highlighted the remarkable augmentation in shale oil output seen in the United States and Canada. Furthermore, the diminished worldwide oil demand, highlighted by Hamilton (2015), coupled with the augmented output by Saudi Arabia and its neighbouring Gulf nations, as pointed out by Holodny (2016), also played substantial roles. Finally, investment in renewable energy, as highlighted by Khan (2017), also played a role in this collapse. The decline in global demand and subsequent increase in supply resulted in a reduction in oil prices to $26 per barrel in January 2016. The oil industry faced a significant setback during the COVID-19 pandemic in 2020, experiencing an unprecedented demand shock. By March, oil prices had plunged by 50%, with Brent crude dropping to $43 per barrel. This sharp decline resulted from widespread lockdowns, business closures, and travel restrictions, which drastically reduced oil demand and disrupted the energy market. The Russia-Ukraine war in 2022 had a profound impact on global oil prices, causing sharp increases and heightened volatility. From the onset of the conflict on February 24 to March 8, 2022 crude oil prices surged to their highest levels since July 2008, with WTI reaching $124.98 per barrel and Brent hitting $127.98 per barrel. The situation escalated further in November 2022, as Brent futures rose by 5.8% and WTI futures by 6.3%, underscoring the ongoing instability in the energy market.

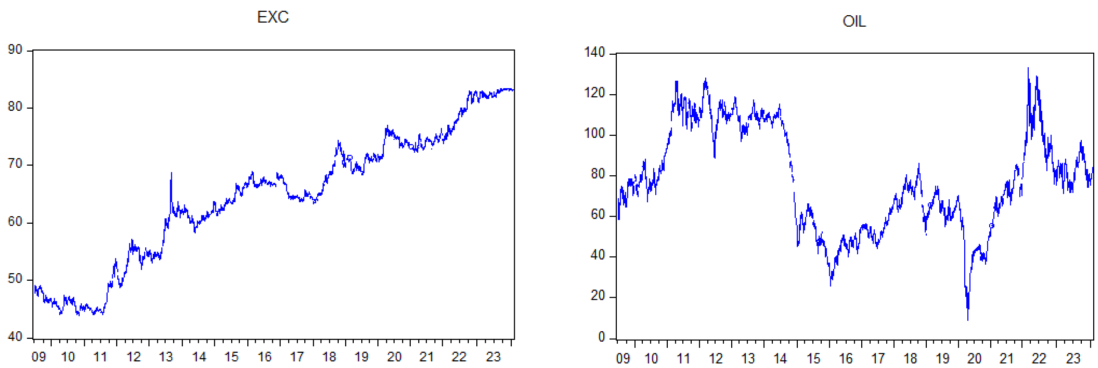

Figure 1- Graphical representation of oil price data and exchange rate series

Further, Figure 2 shows EXC and OIL's QQ plots, indicating that both variables follow identical distributions.

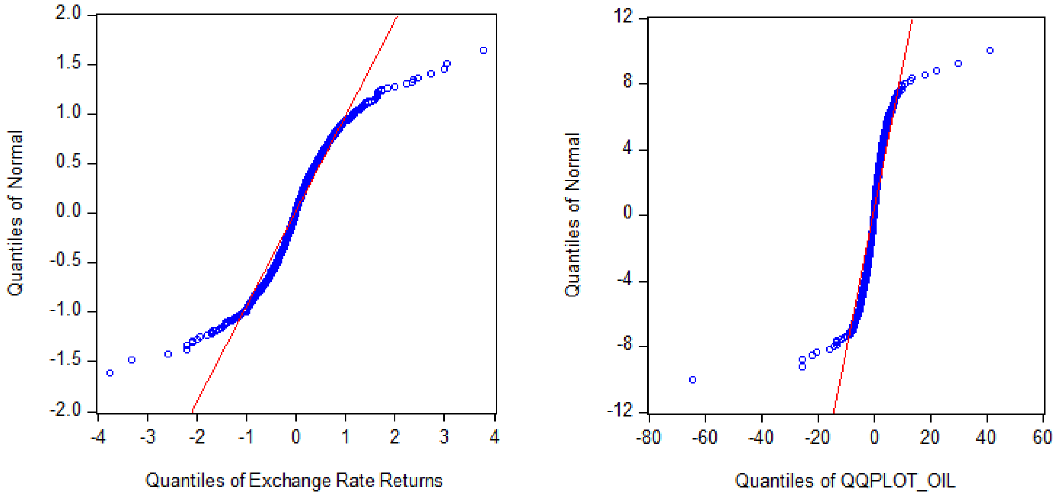

Figure 2 - QQ Plot

The mean equation takes the following specification:

$$rexc_t = \xi + \Psi roil_t + e_t \ldots \tag{3}$$

Further, following Ghosh (2011) and Narayan, Narayan, and Prasad (2008), the study also considers the alternate GARCH-M equation.

$$rexc_t = \xi + \Psi roil_t + \Omega\sigma_t^2 \ldots \tag{4}$$

The mathematical variance expression for both the GARCH (p, q) and GARCH-M (p, q) model is:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} a_i\, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_i\, \sigma_{t-i}^2 \ldots \tag{5}$$

Where the unforeseen squared returns from the prior period represent σ_t^2 is the conditional volatility, and ε_{t-1}^2. ω would be positive always, and α *and* β would be non-negative (>=0). ε_{t-1}^2 derived from a conditional mean equation that could be a simple random walk model, AR (1) model or any other ARMA model. The coefficient α represents how volatility responds to unforeseen returns or disturbances, while the coefficient β illustrates enduring volatility {ω / (1 – α – β)}.

Before moving to asymmetrical GARCH models, one must test for the presence of asymmetry in volatility clustering. For this, Engle and Ng (1993) suggested two sets of observations, i.e., the sign bias test, size bias test. **i) Sign Bias:** To investigate whether the positive and negative returns shock has a different impact on future volatility. **ii) Size Bias:** To investigate the magnitude of the shocks affecting future volatility, i.e., to see whether larger returns are more prominent than smaller return shocks.

The following equation is used to test sign bias and size bias.

$$\mu_t^2 = \varphi_0 + \varphi_1 D_{t-1}^- + \varphi_2 D_{t-1}^- u_{t-1} + \varphi_3 D_{t-1}^+ u_{t-1} + e_t \ldots \tag{6}$$

The test is fit on the residual of the standard GARCH return series u_t. μ_t^2 denotes the squared residual of the return series of the GARCH fitted model, φ_0 is constant, φ_1 is the parameter of the dummy variable D_{t-1}^- that takes the value one if $u_{t-1} < 0$ and zero otherwise. D_{t-1}^+ is

calculated as $1 - D_{t-1}^{-}$ and finally e_t is the residual term. If φ_1 is significant; this means sign bias is present. If φ_2 and φ_3 is found significant; this means size bias is also present.
The specification of the EGARCH model suggested by Nelson (1991) is as follows:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^{p} \theta_i \left|\frac{\mu_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-1}}{\sigma_{t-k}} + \sum_{j=1}^{q} \lambda_j \log(\sigma_{t-j}^2) \ldots \quad (7)$$

Where the left-hand side equation $\log(\sigma_t^2)$ is the log of the conditional variance. One must

notice how the EGARCH term is different from the GARCH term and includes the log of the variance. The reason is that the parameters are guaranteed to be positive. The ω, θ, γ, and λ are the parameters, respectively. No restriction will be imposed on ω, θ, and γ; however, to attain the stationary λ needs to be positive and less than 1 (Enders, 2014). In equation (7), ω represents the mean of the volatility equation; parameter λ evaluates the persistence in conditional volatility. Larger λ denotes volatility takes a long time to die out unless crises take place in the market (Su, 2010). The parameter γ captures the leverage effect or asymmetrical effect, which is indicated by a negative and statistically significant value of γ. When $\gamma < 0$, conditional variance increases more in response to negative return shocks than to positive ones of the same magnitude. Conversely, if $\gamma > 0$, positive return shocks exhibit greater volatility than negative ones. The model is symmetric if $\gamma = 0$ (Brooks, 2014). The variance equation of the GJR-GARCH (p, q) model can be written as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \theta_i \sigma_{t-i}^2 + \sum_{k=1}^{r} \gamma_k D_{t-k}^{-} \varepsilon_{t-k}^2 + \sum_{i=1}^{q} \lambda_i \varepsilon_{t-i}^2 \ldots \quad (8)$$

Where, D_{t-i}^{-} accounts for a 'dummy variable' that takes the value 1 in case ε_{t-1} is negative and 0 otherwise. A leverage effect is observed when $\gamma > 0$. For ε_t < 0, conditional variance increases more in response to negative shocks than to positive ones of equal size. Conversely, if ε_t > 0, positive shocks are more volatile than negative shocks of the same magnitude (Glosten, Jagannathan, and Runkle, 1993).

The selection of the above models is based on the lowest AIC and SBC criteria. Further, to determine which model is best for predicting volatility, the study employed Day and Lewis (1993) and Duffie, Gray, and Hoang (1999) framework to evaluate 'Whether asymmetrical volatility models perform better than symmetric volatility models?' through the lowest MSE, RMSE and MAE.

3. Empirical results

3.1. Test for heteroskedasticity

Before proceeding with the evaluation of volatility models, it is crucial to ensure that the preliminary conditions of these models are met. These conditions pertain to the existence of volatility clustering and heteroscedasticity within the residuals. Figure 3 presents a time series plot of oil price returns and exchange rate returns, highlighting evidence of volatility clustering in the residuals. Notably, significant clusters are observed in exchange rate returns during 2011–2013, 2018, and 2020, and in oil price returns during 2014–2016 and 2020. This volatility clustering indicates that periods of larger returns tend to be followed by larger returns, while smaller returns are followed by smaller returns.

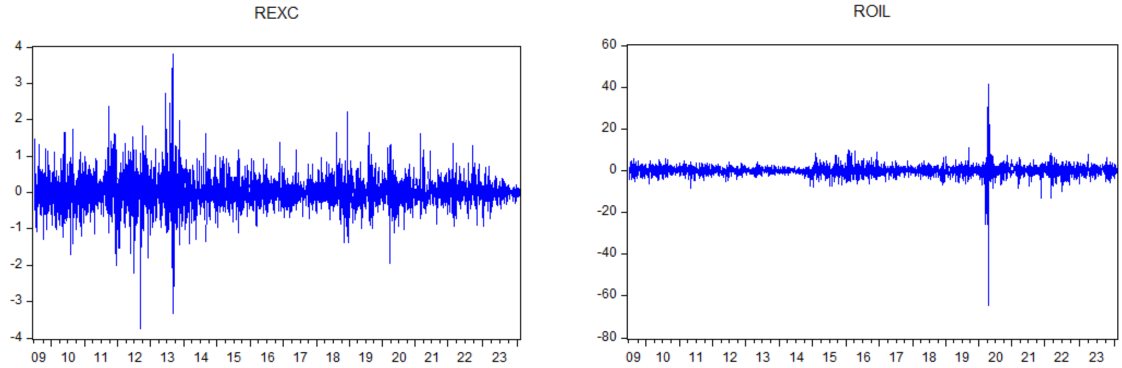

Figure 3 - Time series plot of exchange rate and oil price (Return Series)

3.2. Stationary test

The investigation utilized the conventional "Augmented Dickey-Fuller (ADF)" and "Phillips-Perron (PP)" tests at both levels and 1st differences to assess the potential presence of a unit root. These tests are applied to scrutinize the null hypothesis, which posits that there is no unit root, against the alternative hypothesis that suggests the existence of a unit root. The research comprises three distinct models, the first of which solely incorporates the intercept, the second of which incorporates both the intercept and trend and the final model omits both the intercept and trend. Table 3 presents the outcomes of the ADF and PP tests, indicating that both series exhibit stationarity at the level, irrespective of the selected model. Therefore, additional differencing is unnecessary.

Table 3 - Stationarity results

	ADF			PP		
	Intercept	Intercept & Trend	None	Intercept	Intercept & Trend	None
rexc	-46.343***	-46.337***	-46.262***	-61.878***	-61.870***	-61.809***
roil	-14.973***	-14.971***	-14.975***	-61.166***	-61.157***	-61.174***

Source: Output from Eviews.
Notes: *** indicates significant at 1 per cent level.

3.3 Ordinary Least Square (OLS) estimation

Likewise, in Narayan, Narayan, and Smyth (2008), we first run the mean equation (specified as equation 3) with OLS regression. The intuition behind this step is that one can examine whether OLS regression should be considered our preferred model or not. The findings presented in the second column of Table 4 show that there is a negative and statistically substantial coefficient related to the oil price. A 10% increase in oil prices may cause a 0.19% depreciation of the Indian Rupee against the US Dollar. The study also computed Q-statistics and ARCH-LM statistics to access for auto-correlation in the residuals. In all three cases, i.e., six lags, 24 lags, and 36 lags, we found that OLS regression suffered from the ARCH effect and serial correlation problem as the p-value approaches zero or almost zero. Therefore, OLS regression is no longer reliable as the model suffers from the ARCH effect.

3.4. GARCH (1,1) and GARCH-M (1,1) results

The third and fourth columns of Table 4 report the results of the GARCH (1,1) and GARCH-M (1,1) models based on the lowest SBC criteria. The mean equation of GARCH (1,1) indicates the negative and statistically significant effect of the oil price on the exchange rate. Precisely, a 10 per cent increase in oil price returns will depreciate the INR vis-à-vis USD by 0.11 per cent. The GARCH-M (1,1) results are consistent with the GARCH (1,1) model, except for the statistically insignificant variance term in the GARCH-M (1,1) model. This implies that the volatility of the exchange rate does not affect the exchange rate itself. Turning to the equation for variance, the research determined that the coefficients of both ARCH and GARCH terms hold significance at the 1 per cent level. The volatility persistence term is $\lambda_1 = 0.94$, approaches to 1 signify that the oil price fluctuations have a permanent effect on exchange rate volatility. Finally, to check whether the model suffered from serial correlation or ARCH effect, the study employed residual-based diagnostic tests such as Ljung-Box Q-Statistics and ARCH-LM effect, which are reported in Table 4. Both the Q-statistics and ARCH-LM test signify that the model does not suffer from any autocorrelation problem and ARCH effect.

Table 4 - Estimation Results of OLS, GARCH (1,1), GARCH (1,1)-M, EGARCH (1,1), GJR-GARCH (1,1)

Parameters	OLS	GARCH (1,1)	GARCH (1,1)-M	EGARCH (1,1)	GJR-GARCH (1,1)
Mean Equation					
C	0.015**	0.002	0.007	0.005	0.004
ϑ	-0.019*	-0.011*	-0.011*	-0.011*	-0.011*
δ (GARCH)			-0.048		-
AR(1)		-0.065*	-0.065*	-0.062*	-0.062*
AR(2)		-0.040*	-0.041*	-0.039*	-0.039*
AR(3)		-0.001	-0.002	-0.003	-0.002
Variance Equation					
Ω		0.000	0.000	-0.083*	0.000
Θ		0.051*	0.051*	0.099*	0.057*
γ_1		-	-	0.036*	-0.033*
λ_1		0.940*	0.940*	0.965*	0.959*
Diagnostic Tests					
Q-Statistics (6)	38.315*	16.852*	17.328*	14.450**	15.203*
Q-Statistics (24)	56.979*	33.692**	34.275**	33.699**	33.299***
Q-Statistics (36)	91.058*	47.538	47.809	48.232	46.774***
ARCH-LM (6)	36.406*	13.626***	13.740**	18.246**	15.665**
ARCH-LM (24)	53.071*	25.444	25.619	31.438	27.702
ARCH-LM (36)	81.179*	38.708	39.214	46.191	41.844

Source: Output from Eviews.
Notes: *,**,*** represents significant at 1%, 5 % and 10 percent respectively.

3.5. Engle and Ng's (1993) results

Table 5 displays the outcomes of the test by Engle and Ng (1993). The results confirm the presence of asymmetry in volatility clustering, justifying the use of asymmetric GARCH models. The sign bias term (ϑ_1 = -0.052233, p = 0.0072) is negative and statistically significant, indicating that past negative shocks reduce volatility rather than increase it. The coefficient for negative size bias (ϑ_2 = −0.310837, p = 0.0000) suggests that larger negative shocks decrease volatility, whereas the positive size bias coefficient (ϑ_3 =0.548464, p = 0.0000) shows that larger positive shocks significantly increase volatility. The joint test statistics, including the F-statistic (11.335, p = 0.000) confirm that the variables collectively contribute to explaining volatility asymmetry. These findings highlight an atypical volatility response where negative shocks dampen volatility rather than amplify it. Given the strong evidence of asymmetric effects, the use of models such as EGARCH and GJR-GARCH, is necessary for capturing the volatility dynamics more accurately.

Table 5 - Engle and Ng's results

Variable	Coefficient	Std Error	t-Statistics	Prob.
ϑ_0	0.040302	0.019480	2.068909	0.0386
ϑ_1	-0.052233	0.027451	3.102766	0.0072
ϑ_2	-0.310837	0.045764	-6.792143	0.0000
ϑ_3	0.548464	0.041507	13.21387	0.0000

Engle and Ng Joint Test Statistics

Test Statistics	Value	Df	Prob.
F-Statistics	11.335	(3, 2489)	0.000
Chi-Square	34.007	3	0.000

Source: Output from Eviews.

3.6. EGARCH (1,1) results

The outcomes from the EGARCH (1,1) estimation are presented in the fifth column of Table 4. Firstly, the mean equation of EGARCH (1,1) reveals a negative and statistically significant impact of oil price fluctuations on the volatility of the exchange rate. To put it accurately, a 10% rise in oil prices will lead to a 0.11% devaluation of the INR compared to the USD, a result that aligns well with the GARCH (1,1) model. Second, in the variance equation, both the ARCH and GARCH coefficients are statistically significant at a 1 per cent level of significance, signifying the persistence of volatility. Third, the asymmetric term gamma (γ_1) is significant at a 1 per cent level, meaning that oil price fluctuation has an asymmetrical impact on exchange rate volatility. Further, the positive coefficient of γ_1 signifies that positive oil price shocks (good news) result in higher exchange rate fluctuations relative to negative shocks (bad news). Finally, the residual-based diagnostic test confirms that the model is free from autocorrelation and ARCH effects.

3.7. GJR-GARCH (1,1) results

This research additionally incorporates the GJR-GARCH (1,1) model to validate the asymmetrical and positive impact of fluctuations in oil prices on the volatility of exchange rates. The result of the same is reported in the last column of Table 4. The primary equation of the GJR-GARCH (1,1) model demonstrates that changes in oil prices have a considerable and negative effect on the instability of exchange rates, according to statistical significance. A 10 per cent rise in oil price returns would depreciate the INR against the USD by 0.11 per cent. Second, in the variance equation, both the ARCH and the GARCH coefficients are significant at 1 per cent, indicating the persistence of volatility. Third, the asymmetric term gamma (γ_1) is statistically significant at a 1 per cent level, meaning that oil price shock has an asymmetrical impact on exchange rate volatility. Additionally, the negative sign of γ_1 implying that favourable news leads to greater fluctuations in exchange rates compared to unfavourable news. Finally, the diagnostic test based on residuals appears to be impeccable since the model is devoid of autocorrelation issues and does not exhibit any ARCH effects.

Along with the model diagnostic tests, the researcher examined the model accuracy by forecasting the volatility derived from each model. The best-predicting model was based on the lowest value of three parameters, i.e., RMSE, MSE and MAE, and the result of the same is stated in Table 6 corresponding to the models applied. As illustrated in Table 6, the predicting error of the EGARCH (1,1) model derived from the heavy-tailed distribution is the lowest among all models and is thus considered the best predicting model. This simply means that asymmetrical models can better forecast the INR-USD exchange rate than the symmetrical models, i.e., AR (5)-GARCH (1,1).

Table 6: Forecasting accuracy of the models

Model	MSE	RMSE	MAE
AR(3)-GARCH (1,1)	0.159312	0.39421	0.28524
AR(3)-EGARCH (1,1)	0.158110	0.39314	0.27982
AR(3)-GJR-GARCH (1,1)	0.159218	0.39402	0.28516

Source: Output from Eviews.

4. Conclusion and policy recommendations

This article seeks to enhance the comprehension of volatility and spillover effects of the relationship between crude oil prices and exchange rates. The research applied symmetric volatility models such as ARCH, GARCH (1,1), GARCH-M (1,1), as well as asymmetric models including Engle and Ng (1993), EGARCH (1,1), and GJR-GARCH (1,1). In GARCH (1,1) and GARCH-M (1,1) models, the total of coefficients associated with ARCH and GARCH terms in the variance equation approximates one. This suggests that there is a notable presence of continuing volatility, which can be attributed to the series exhibiting a low degree of mean reversion. The study additionally uncovered an unbalanced association between variations in oil prices and exchange rate volatility, where rises in oil values have a more pronounced influence on currency values compared to declines in prices. The EGARCH model's predictability was remarkably high, as demonstrated by its distinctly low forecasting error relative to other models, especially in cases of heavy-tailed distributions. As a result, it can be considered the most suitable model for predicting the movement of oil prices with exchange rates. The analysis indicates that the significance of shocks lies in their magnitude and direction. Based on the investigation, past negative shocks reduce volatility, while larger positive shocks significantly increase it. Policymakers should incorporate this insight into their decision-making when formulating exchange rate policies to mitigate volatility risks effectively.

Additionally, there are numerous pathways available for more inquiry and possible refinement relating to the merits of this research. This study examines the nominal exchange rates between the Rupee and the US Dollar to assess how oil price fluctuations impact the exchange rate. Future research should consider Effective Exchange Rates (nominal or real) for a broader understanding of crude oil price effects on various currencies and investigate structural breaks to capture the time-varying features of these variables. This will help researchers understand the magnitude of transmission during economic shocks. Additionally, our study focuses only on the direct relationship between oil prices and exchange rates. However, it is worth mentioning that there are other theoretical channels, such as the monetary channel or the net foreign assets channel, that could potentially play a role in this relationship. While these channels fall outside the purview of our present study, they offer valuable paths for prospective exploration and research.

Conflict of Interest

The authors declare no conflict of interest.

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