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ECONOMICS - Innovative and Economics Research Journal
Journal homepage: www.economicsrs.com

VOLATILITY INTEGRATION AND DYNAMIC CONNECTEDNESS AMONG THE INDIAN STOCK MARKET, GOLD PRICES, OIL PRICES, EXCHANGE RATES AND NATURAL GAS

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Received 10.01.2025. | Sent to review 26.01.2025. | Accepted 14.05.2025.

Original article

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JEL Classification:
G10, G15, Q40, Q41

Doi: 10.2478/eoik-2025-0039

UDK: 339.137:662.767(4-672EU)

ABSTRACT

The main goal of this study is to look at how the Indian stock market benchmark index Nifty 50, the price of gold, the price of crude oil, the USD/INR exchange rate, and natural gas are all dynamically linked to each other. Data is collected on a daily basis from January 01, 2009 to March 31, 2023. We used the DCC GARCH and Diebold & Yilmaz (2012) connectedness frameworks, along with Granger causality, to find the short- and long-term volatility transmissions between the variables. There is no volatility spillover that exists between the Nifty 50 and gold price, the Nifty 50 and crude oil, the Nifty 50 and natural gas, the gold price and exchange rate, the gold and natural gas, the exchange rate and crude oil, and the exchange rate and natural gas in the short run. The DCC GARCH findings indicate that portfolio diversification will benefit investors in the short run in the aforementioned pairs. However, a significant volatility spillover relationship exists in the long run, which eliminates the opportunity for portfolio diversification. Natural gas is self-sufficient, and it is least affected by the volatility of other markets. We found significant dynamic interconnectedness between the Nifty 50, the exchange rate, and the Brent Price. The result of Diebold & Yilmaz connectedness suggests that while making investing decisions, investors should take into account the volatility of the Nifty 50, gold, and exchange rates. The research findings have remarkable relevance to investors and policymakers for risk management, portfolio optimization, and diversification and to better understand the market dynamics. Analysis also provides prominent indicators for policymakers regarding monetary and fiscal policies, considering the impact that exchange rates, gold, and crude oil exert on the stock market.

Keywords: *Volatility Spillover, DCC GARCH, Diebold and Yilmaz, Granger Causality, Gold Price, Crude oil, Exchange Rate*

1. INTRODUCTION

Since 1991, globalization, liberalization, and privatization opened up the Indian market to global trade and allowed international companies to enter the Indian market. Due to this relaxation, the Indian market is now tied to the global economy, and the world has now become a global village. Therefore, an incident that occurs in 'one nation' does not always affect that nation alone; it can have a contagion effect on economies everywhere (Vo & Ellis, 2018). As a result, volatility, complexity, and uncertainty in the global financial environment have increased. Hence, rational investors seek to optimize their risk-adjusted return by diversifying their holdings across a variety of asset classes. A number of portfolio managers diversify their portfolios across equity, oil, and gold to maximize risk-adjusted returns (Jain & Biswal, 2016).

Geopolitical conflicts and trade disputes are reshaping the dynamics of the stock market, gold, crude oil, and exchange rate. Global trade dynamics are rapidly evolving. Crude oil and gold are two major commodities in India's import basket and have a significant effect on the USD/INR exchange rate. Crude oil plays a remarkable role in India's energy requirements, and India is the second largest importer of crude oil and stands in the fifth position in gold imports. They are considered crucial commodities, and their volatility has significant importance in both domestic and international business matters. (Rastogi et al. 2021; Siddiqui & Roy, 2019). Particularly for countries that import gold and oil, such as India, their swings cause the value of the Indian rupee (INR) to depreciate while simultaneously raising the rate of inflation.

The USD/INR exchange rate is majorly influenced by changes in the price of gold and crude oil, which have a substantial effect on the performance of developing countries like India. Crude oil and gold are being an international commodity that are anticipated to have a negative impact on the USD reserves of importing countries, which will change the value of the home currency relative to the USD (Raji, Juzhar, & Jantan, 2014). Furthermore, it has been observed from several studies (Mishra & Dash, 2024; Mastilo et al., 2024; Shafiq, Qureshi & Akbar, 2023; Li et al., 2022; Gharib et al., 2023; Salisu et al., 2023; Yousaf et al., 2022) that volatility in the oil price could lead to significant impact in the stock market. About 85% of India's crude oil requirements are fulfilled by importing. India is a strong, resilient economy, and its growth is outpacing other major economies of the world, which can be seen in robust macroeconomic indicators. The rise in government spending on infrastructure, downward trend of inflation, declining external debt to GDP ratio, rise in foreign exchange reserve (approx. $700 bn), stable capital inflows, and increased number of unicorns indicate that India is on the right trajectory to move ahead on its path to becoming a USD 5 trillion economy. India is on track to surpass Germany and Japan and become the third largest economy by 2029, surpassing the UK as the fifth largest economy.

Earlier studies have explored the behavior of volatility spillover between exchange rates, crude oil, and gold on stock markets, yet there has been no focus on researching the interrelationship between each pair of stock market, crude oil, gold, natural gas, and exchange rate simultaneously. Additionally, this paper adds to the literature on pairwise network connectedness among the stock market, crude oil price, gold price, natural gas, and exchange rate (Rareș Bircea & Kardos, 2024). The authors were unable to locate any study that has comparatively examined and discussed the dynamic interrelationship with natural gas simultaneously.

Modeling price volatility is crucial in present finance and econometrics for potential risk dissemination with the basket of assets (Sahoo, 2024). The primary motivation of this study is to explore volatility spillover and dynamic interconnectedness among the return of the Indian stock market index Nifty 50 (SM), crude oil price (CO), gold price (GP), natural gas (NG), and exchange rate (ER). Understanding volatility is crucial when it comes to financial modeling (Nordstrom, 2021), and modeling stock market volatility is a widely attractive issue in the literature (Gungor & Gungor, 2024). Investors may find it helpful to understand the dynamics of SM, CO, GP, NG, and ER in order to diversify their investment portfolios and appropriately hedge exchange rate risk in order to improve risk-adjusted return. Hence, an empirical examination of the volatility of all the variables mentioned above will be helpful to the policymakers, academicians, regulators, financial analysts, and investors. Considering the lack of combined studies on the volatility spillover and connectedness among SM, CO, GP, NG, and ER, it seems to be a novel and significant area of research.

The study covers the daily log return data of SM, CO, GP, NG, and ER, spanning from 1st January 2009 to 31st March 2023, which constitutes 3329 observations from Bloomberg Terminal in USD terms to maintain the consistency of the data. In order to discover the volatility spillover, connectedness, causality relationship, and dynamic interdependence among the variables, the authors of this paper have used DCC GARCH, Diebold & Yilmaz (2012) connectedness framework, dynamic conditional correlation, and Granger causality test. The following objectives are proposed: (1) To assess the volatility spillover among SM, CO, GP, NG, and ER and (2) to explore the dynamic connectedness relationship among SM, CO, GP, NG, and ER. (3) To identify short- and long-term diversification opportunities for investors. (4) To provide insights into policy implications based on the connectedness of financial markets.

The foremost contribution of this study is that the authors have also considered natural gas (NG) as one of the factors affecting the volatility of the GP, ER, CO, and SM. Energy stocks contribute 11.72% in the Nifty 50. As far as researchers' knowledge, no research has examined all the possible combinations of variables together to ascertain how shifting exchange rates, gold, crude oil, and natural gas prices impact the Indian stock market. In the short run, there is no spillover between SM-GP, SM-OP, SM-NG, GP-ER, GP-NG, ER-OP, and ER-NG. However, evidence of a statistically significant relationship in the long run implies that there is a possibility of time-varying and dynamic asymmetry in the volatility spillover effects between all the variables. Authors find diversification opportunity among SM, ER, GP, COP, and NG; no transmission of information is witnessed in the short run.

The findings of the study add a new dimension to the existing literature. As far as the author's knowledge, this is the first study to apply a combination of the daily log return of the SM, CO, GP, NG, and ER from 2009 to 2023. The short-run and long-run spillovers exist only in the case of SM-ER and GP-CO. Transmission of information in the short and long run indicates that no diversification opportunity exists. The result of robustness by Diebold and Yilmaz witnessed the dynamic interconnectedness between the exchange rate and the Nifty 50. Natural gas is self-sufficient, and it is majorly explained by its own variations rather than by the volatility of other markets.

The rest of the paper is structured as follows: the literature review is covered in the next section. Methodology is covered in the third section, and analysis and findings are covered in the fourth. The final portion covers the paper's closing thoughts.

2. REVIEW OF LITERATURE

The rise in the investor knowledge regarding the benefits of diversification of their holdings across multiple asset classes has encouraged researchers to look into the dynamics of crude oil, gold, exchange rates, natural gas, and the stock market. There are numerous studies in the literature that examined the volatility spillover among SM, CO, GP, and ER. The literature exhibits that there are conflicting results concerning the relationship, necessitating investigation. In particular, Ndlovu & Ndlovu (2024) assessed the dynamic linkages among GP, SM, ER and interest rate (IR) in South Africa by applying Vector Autoregression and a Bayesian VAR Model. Data was collected on a monthly basis from June 1995 to December 2022. A positive relationship exists in GP, SM, ER, and IR. However, a hike in IR induces negative relations with GP and SM. Additionally, a positive shock in GP leads to negative consequences in both IR and SM. Morema & Bonga (2020) explored the volatility spillover between CO, GP, and the equity market of South Africa. They found notable volatility spillover between the GP to SM, and CO to SM. Mishra & Dash (2024) investigated the volatility of Asian stock exchanges with crude oil and discovered no short-run volatility spillover from crude oil to the stock markets of Malaysia, Pakistan, South Korea, and Turkey; however, Chinese, Indian, Japanese, and Singaporean stock exchanges exhibit the short-run volatility spillover from CO in the short run. Pata et al. (2024) assessed the causality among stock returns, crude oil and gold prices in Turkey and found time-varying causality running from CO and GP to Turkish stock market returns and crude oil. GP has a greater impact on SM volatility. Cui (2023) investigated the dynamic relationship amongst GP, ER, CO, and Chinese Stock Market Indexes by the DCC GARCH method for the period from March 1, 2000, to August 3, 2022.

The results reveal that GP and CO are conclusively correlated with the Shanghai Stock Exchange and the China Industrial Index, while significant negative correlations were observed between the USD/CNY ER and the two Chinese stock indices. Jia, Dong & An (2023) discussed the causality relationship between crude, gold, and dollar price in the USA and negative causal relationship was identified between gold and the US dollar index. Jimoh, Rana & Tajudeen (2023) assessed the impact of CO and SM on ER in Indonesia and concluded that lower oil price returns lead the Indonesian currency per US dollar to depreciate and stock returns has negative and significant relationship with exchange rates. Valarmathi, Umamaheswari & Lakshmi (2023) analyzed the relationship between gold prices and stock market prices in India and observed no relationship between gold prices and BSE sectoral indices. Arisandhi & Robiyanto (2022) studied the correlation among exchange rates, gold, and stock prices in ASEAN-5 during the pandemic and found a weak correlation between exchange rates and gold prices on the stock market. A negative correlation was seen during the pandemic which infers the ER was a better substitute than gold, which was correlated with SM positively. Jindal (2023) investigated the relationship amongst crude oil, ER and GP for the period from January 1, 2017, to December 31, 2021, and found a significant relationship between ER and CO with the stock market, while other variables like gold have an insignificant relationship with the stock market in the long run. Civcir & Akkoc (2021) evaluated the relationship between GP, SM and CO in Turkish market and noted time-varying co-movement and volatility spillover in the long run. They also spotted that significant volatility spillover from international commodities, and the shocks are quite persistent in the long-run. Kumar, Singh & Kumar (2022) assessed the volatility spillover among prices of CO, NG, ER, GP and SM by applying EGARCH Technique for the period 1997-2019 and found, EX has a highly significant impact on SM and GP volatility. While analyzing interdependencies between assets such as gold, stocks, interest rates and exchanges, Akbar, Iqbal & Noor (2019) concluded that there is no stable pattern of relationship that exists between variables in long term. In a similar study, Singhal, Chaudhary & Biswal (2019) carried out cointegration test to study return and volatility among the above assets in addition to crude oil. It was also noticeable to find that gold prices internationally seem to have a favorable influence on stock values in Mexico while the contrary can be seen in case of oil prices. Further, the impact of oil prices on exchange rates is negative while the impact of gold prices in short term is near to negligible. Jain & Ghosh (2013) investigated whether there is any long-term association and causality in relation to Global oil prices, metal prices and exchange rate. It was categorically found that there is a tangible relationship in long term between gold prices and exchange rates. The granger causality test remarkably highlights that Indian rupee's value affect the oil prices and metal prices. Sujit & Kumar (2011) found out that a weak relationship exists between variables such as oil price, gold price, stock market S&P 500 and exchange rate. Huseynli (2023) looked into the causal relationship between CO and GP and concluded that there is a one-way causality is running from GP to CO, before the pandemic.

The literature review mentioned above determines the uniqueness of the present work. Several studies have investigated the volatility spillover between exchange rates, crude oil prices, and gold prices on stock markets, but no attention is given to studying the interrelationship between each possible pair of SM, CO, GP, NG, and ER simultaneously. Hence, the current study aims to explore the volatility spillover and dynamic connectedness between each pair of SM, CO, GP, NG, and ER. While numerous studies have worked with crude oil and gold, there has not been a lot of research done on the contribution of natural gas in volatility spillovers. This study uniquely incorporates natural gas into the analysis, addressing a significant gap by assessing how it interacts with stock markets and other commodities. Thus, on the basis of the above studies, the following alternate hypotheses are formulated:

H1: Presence of volatility spillover between ER to SM and vice versa.

H2: Presence of volatility spillover effect from CO to SM and vice versa.

H3: Presence of volatility spillover effect from GP to SM and vice versa.

H4: Presence of volatility spillover effect from CO to ER and vice versa.

H5: Presence of volatility spillover effect from GP to ER and vice versa.

3. METHODOLOGY

The study covers the daily return series data of SM, CO, GP, NG, and ER spanning from 1st January 2009 to 31st March 2023, which constitutes 3329 observations from Bloomberg Terminal in USD terms to maintain the consistency of the data. In order to discover the volatility spillover, dynamic connectedness, and causality relationship among the variables, the authors have used the log return on Nifty 50 (SM), Gold Price (GP), USD/INR Exchange Rate (ER), Crude Oil Price (CO), and Natural Gas (NG). The techniques of DCC GARCH and the Diebold & Yilmaz connectedness framework are used for better decision-making. In broad-spectrum, the GARCH (1,1) model is applied to record volatility clustering in the series (Brooks, 2008). The DCC-GARCH model is effective in capturing spillover effects between variables. It can detect how volatility in one market (say, crude oil prices) may affect another market (like the stock market or exchange rates) (Aggarwal et al., 2021; Rastogi and Agarwal, 2020; Rastogi and Athaley, 2019). The DCC-GARCH model is used in the present study because it provides a robust and flexible framework for analyzing time-varying volatility between multiple financial variables. BEKK-GARCH is more complicated and computationally demanding with more parameters. BEKK-GARCH, although appropriate in spillover volatility modeling, can be less sensitive in time-varying correlations modeling compared to DCC-GARCH. BEKK is applied when there are constant correlation structures, which are limiting in attempting to model markets like in this case where correlations are changing over time. The dynamic connectedness scale is constructed using the Diebold & Yilmaz (2009) (2012) connectedness framework (Hussain, Bashir, and Rehaman, 2023), which quantifies how much volatility in one market (e.g., exchange rates) is transmitted to other markets. This will explain how this method was applied to measure connectedness between the Indian stock market, crude oil, gold, natural gas, and exchange rates. This scale captures both total system-wide connectedness (the overall degree of integration between all markets) and pairwise connectedness (how much one specific market affects another).

3. 1. GARCH MODEL

One of the unique contributions in financial econometrics was done by Engle (1982) for devising of stochastic approach of autoregressive conditional heteroscedasticity (ARCH) for measuring conditional mean and variance. Later, Bollerslev (1986) developed advanced ARCH model in the form GARCH known as generalized autoregressive conditional heteroscedasticity.

The GARCH-models has been proven successful, when it comes to analyzing volatility for an asset (Nordstrom, 2021; Essien et al., 2024). It is a well-known phenomenon that dynamic volatility spread across interconnected assets and markets (Soni, Nandan & Chatnani, 2023). The present study employs the DCC-GARCH model developed by Engle & Sheppard (2001) to ascertain spillover among SM, BOP, GP, NG and ER.

3. 2. TIME –VARYING CONDITIONAL CORRELATION MODEL

It was proposed by Eagle (2002) and is also known as the dynamic conditional correlation (DCC-GARCH) model. It is a non-linear combination of univariate GARCH models and can be formulated as follows:

$$H_t = D_t R_t D_t \tag{1}$$

Where the conditional standard deviation matrix can be expressed as

$$D_t = Diag(h_{11t}^{\frac{1}{2}}, \ldots.., h_{NNt}^{\frac{1}{2}}) \tag{2}$$

Or in matrix form

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 & \ldots & 0 \\ 0 & \sqrt{h_{22t}} & \ldots & \ldots \\ \ldots & \ldots & \ldots & 0 \\ 0 & \ldots & 0 & \sqrt{h_{NNt}} \end{bmatrix} \tag{3}$$

Each element h_{iit} can be expressed in a univariate GARCH form as follows

$$h_{it} = \alpha_{i0} + \sum_{q=1}^{Q} \alpha_{iq} + \epsilon_{\{i,t-q\}}^{2} + \sum_{p=1}^{p} B_{ip} h_{i,t-p} \tag{4}$$

The univariate GARCH model can take different orders and the simple first order GARCH (1,1) model is usually used.

The Matrix Rt represents the correlation matrix of standard errors u_t and the conditional correlation matrix R_t takes the form of a symmetric matrix as follows

$$\begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \ldots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \ldots & \rho_{2n,t} \\ \rho_{13,t} & \rho_{13,t} & 1 & \ldots & \ldots \\ \ldots & \ldots & \ldots & 1 & \rho_{n-1,n,t} \\ \rho_{1n,t} & \rho_{2n,t} & \ldots & \rho_{n-1,n,t} & 1 \end{bmatrix}$$

Two fundamental requirements need to be met in order to create the conditional correlation matrix Rt:

1. Since the covariance matrix Ht is positive definite, Rt also needs to be positive definite.
2. The conditional correlation matrix Rt's members must all be less than or equal to 1.

To verify that the two conditions are satisfied in the conditional correlation matrix, it can be split as:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5}$$

Where

$Q_t = q_{itj}$ represents an N X N symmetric positive definite matrix and expressed as

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1}$$

Where,

$\overline{Q} = cov(u_t u_t) = E(u_t u_t)$ is an N X N unconditional covariance matrix (u_t unconditional covariance matrix)

Where $u_t = \frac{\epsilon_{it}}{\sqrt{h_{iit}}}$ represents the standard error where α, β represent nonnegative parameter scalars so that $\alpha + \beta < 1$ to ensure that the covariance is positive.

$Q_t^{*-1} = Diag(q_{11t}^{\frac{1}{2}}, \ldots.., q_{NNt}^{\frac{1}{2}})$ also represents a diagonal matrix with the square root elements of the main diagonal of the matrix Q_t.

Source: (Alshenawy & Abdo, 2023)

3. 3. GRANGER-CAUSALITY TEST

The Granger Causality Test is developed by C.W.J Granger in 1969. Granger Causality test is helpful to determine whether one time series is helpful in predicting other time series (Hussein & Osman, 2024), the following bivariate regression model can be used to ascertain:

Equation for X Granger-causes Y

$$Y_t = \alpha 0 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{j=1}^{p} \beta_j Y_{t-j} + \mathcal{E}_{1t} \tag{6}$$

Where,

Y_t = value of the dependent variable
X_{t-i} = lagged (previous) values of X independent variable
Y_{t-j} = lagged values of Y (own lags).
α_i and β_j = Coefficients of X_{t-i} and Y_{t-j}
$\mathcal{E}_{it}$ = error term
p = maximum number of lags

Equation for Y Granger-causes X

$$X_t = \text{h}0 + \sum_{i=1}^{p} \lambda_i X_{t-i} + \sum_{j=1}^{p} \delta_j Y_{t-j} + \Theta_{2t} \tag{7}$$

Where,

X_t = value of the dependent variable
Y_{t-i} = lagged (previous) values of Y independent variable
X_{t-j} = lagged values of X (own lags).
λ_i and δ_j = Coefficients of X_{t-i} and Y_{t-j}
θ_{2t} = error term
p = maximum number of lags

3. 4. DYNAMIC CONNECTEDNESS APPROACH

Using the Vector Impulse Response Function (VIRF) function which measures how the shock or innovation in one variable (e.g. ER) impacts the other variable (e.g. SM) which is helpful in calculating the Generalized Forecast Error Variance Decomposition (GFEVD) to understand the contribution of each variable to the forecast error of another variable. The decomposition provides the "shares" or contributions of each variable to the forecast error variance of the target variable.

To facilitate comparisons, these decompositions (shares) are then normalized for making the results more interpretable and comparable. This ensures that the combined influence of all variables sums to 100% for each forecast error variance decomposition, making it easier to compare across variables (i) and periods. The calculation is conducted as follows:

$$\phi_{ji,t}^{g}(J) = \frac{\sum_{t=1,}^{J-1} \tilde{\Psi}_{i,j,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \tilde{\Psi}_{i,j,t}^{2,g}} \tag{8}$$

where $\sum_{j=1}^{N} \tilde{\phi}_{i,j,t}^{g}(J) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}_{i,j,t}^{g}(J) = N$

Total connectedness index (TCI) is calculated as

$$\text{TCI}_t^{g} = \frac{\sum(_{i,j=1,,i\neq j}^{N}) \tilde{\phi}_{ij,t}^{g}(J)}{N} \tag{9}$$

The spillovers variable i communicates to variables j, which are known as total directional connected TO others and are calculated as

$$TO = \text{C}_{i\to j,t}^{g}(J) = \frac{\sum(_{i,j=1,,i\neq j}^{N}) \tilde{\phi}_{ji,t}^{g}(J)}{\sum_{j=1}^{N} \tilde{\phi}_{ji,t}^{g}(J)} \tag{10}$$

While the spillovers variable i receives from the variables j which are described as total directional connectedness FROM others are evaluated as:

$$FROM = C^{g}_{i\leftarrow j,t}(J) = \frac{\Sigma(^{N}_{j=1,,i\neq j})\tilde{\Phi}^{g}_{ij,t}\ (J)}{\Sigma^{N}_{i=1}\tilde{\Phi}^{g}_{ij,t}\ (J)} \quad (11)$$

The net total directional connectedness explain as the impact variable i has on the analysed network:

$$NET = C^{g}_{i,t} = C^{g}_{i\rightarrow j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \quad (12)$$

If any variable i is a net transmitter of innovation or shocks it indicate NET of variable i is positive, or that network is being driven by variable i. Conversely, any variable i is a net receiver of innovation or shocks implies NET of variable i is negative and is driven by the network. At last, the pairwise directional connectedness (Net) (NPDC) between variable i and variable *j* is evaluated as follows:

$$NPDC_{ij}(J) = \tilde{\Phi}^{g}_{ij,t}\ (J) - \tilde{\Phi}^{g}_{ji,t}\ (J) \quad (13)$$

Positive value of DC_{ij} suggest that variable *i* dominates variable *j* and negative value implies that variable *i* is dominated by variable *j*

4. EMPIRICAL RESULTS

The result is divided into four sections. First section deals with the Descriptive Statistics, followed by and Granger Causality test and finally DCC GARCH model. The movement of SM, ER, GP, CO and NG from the period January 01, 2009 to March 31, 2023 are shown below. To begin, authors have made an effort to comprehend the return series' features and properties, as well as its visual representation. The return series' measures of central tendency such as Median, Mean, Kurtosis, Skewness and Standard Deviation and more are shown in Table I below.

SM, ER, GP, CO have given the positive returns except for NG in the given time period. Natural Gas has given the negative return during the same period. NG is highly risky because its standard deviation is high as compared to others SM, ER, GP and CO. The value of kurtosis and skewness signify that returns do not follow normal distribution. Only Gold Price displays a negatively skewed distribution and rest indicator follow the positive skewed distributions.

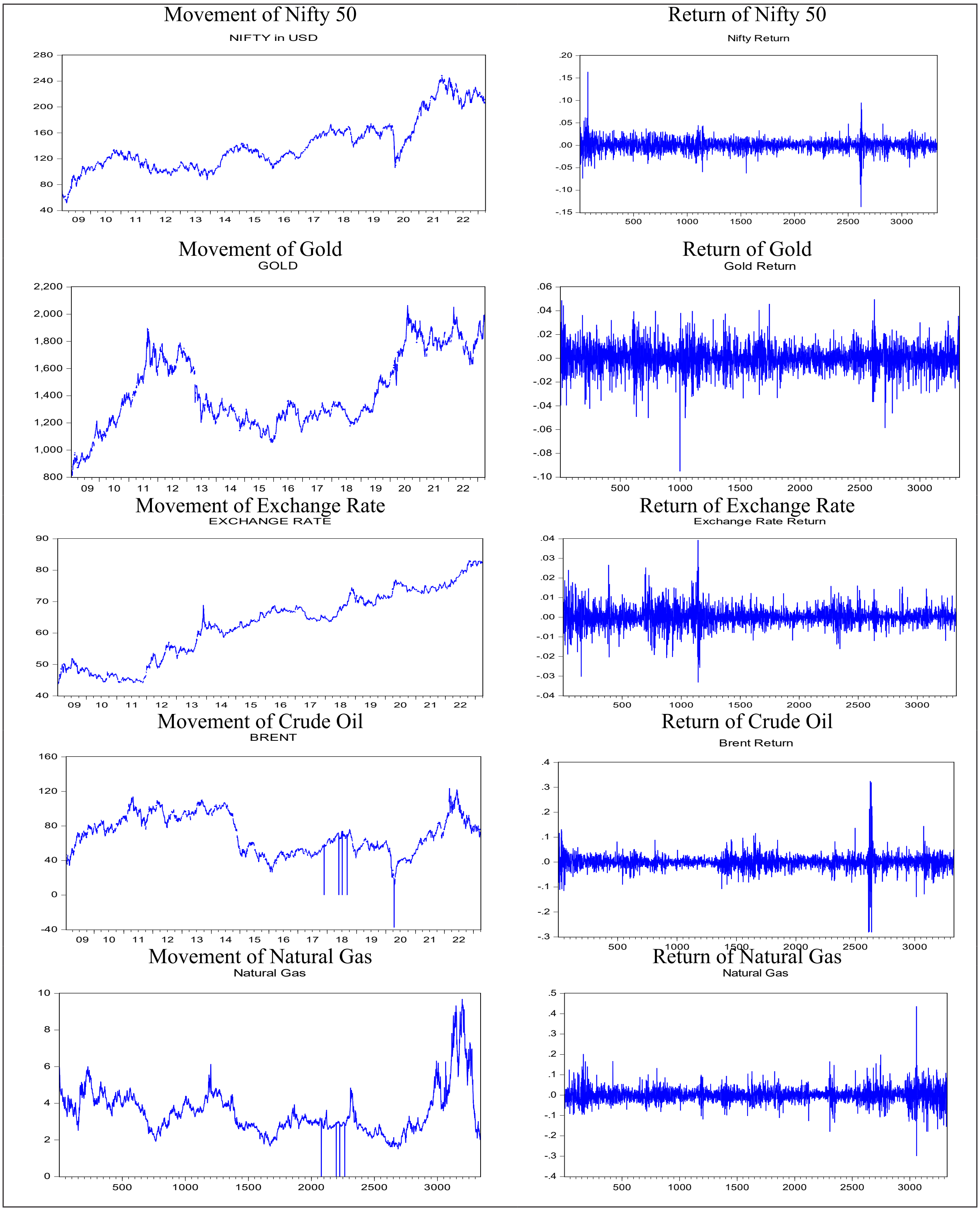
Table 1. Descriptive Statistics

	Log Return ER	Log Return GP	Log Return SM	Log Return CO	Log Return NG
Mean	0.000186	0.000251	0.000350	0.000347	-0.000250
Median	0	0.000553	0.000586	0.001044	-0.000334
Maximum	0.039328	0.049666	0.163651	0.324825	0.435521
Minimum	-0.332281	-0.9512069	-0.1374738	-0.2822061	-0.300480
Std. Dev.	0.004742	0.010462	0.013236	0.028335	0.036721
Skewness	0.270117	-0.429506	0.042007	0.342703	0.472328
Kurtosis	9.286561	7.563163	17.20168	27.20690	12.90651
Jarque-Bera	5522.829*	2940.491*	27639.58*	80760.22*	13684.48*
p value	0.0000	0.0000	0.000000	0.00000	0.000000
ARCH LM Test (p value)	0.0000	0.0000	0.0000	0.0000	0.0000
ADF Test (p value)	0.0001	0.0000	0.0002	0.0004	0.0001
Total Observations	3329	3329	3329	3329	3329

Source: Author's own Analysis, LR indicates log return, * indicates significance at 5%

SM, GP, ER, NG and CO have a Kurtosis score greater than three indicates a leptokurtic distribution, which means the series could have extremely high or extremely low returns (Yadav, Sharma & Bhardwaj, 2022). Jarque Bera test also supported the fact that all returns do not follow normal distribution. The authors have also confirmed the presence of the ARCH effect in all the daily series and found all the series are fit for DCC-GARCH estimation (Rastogi, Kanoujiya & Doifode, 2024). The ADF test (Dickey & Fuller, 1979) has also applied to confirm the stationarity of the series. All the return series were stationary. Figure I shows the movement of SM, GP, ER, NG, CO with their respective log returns. Volatility clustering is observed in all the return series under study. This verify that the residual or error term is conditional heteroscedastic and that the GARCH and ARCH models can adequately be applied to capture its characteristics (Kumar, Singh & Kumar, 2022). All the variables show fluctuating return patterns.

Figure 1. Plots of daily movement of SM, GP, ER, CO, NG and Respective Returns



Source: Figure Created from compiled data using R software

4. 1. GRANGER-CAUSALITY TEST

In Table II, the result shows, there is uni-directional relationship exists between GP – SM, ER – SM, CO- SM, NG - SM, GP – NG, GP – CO and ER -CO. The Hypotheses H01², H02², H03², H04¹, H04², H06¹, H07¹ and H08¹ are rejected. In the context of Nifty 50 and GP, there is a one-way causal link where GP influences Nifty 50, but SM does not influence GP with a lag of 2. Thereby Hypothesis H01² is rejected. Similarly, a uni-directional causal relationship is eminent in SM- ER implying that ER causes Nifty 50, this finding is consistent with the findings of (Kumar, 2019; Sheikh et al., 2020; Moraliyska 2023). Hence hypothesis H02² is rejected. Similar relationship was found between GP – NG and GP – CO. GP causes NG and CO but NG and CO do not cause GP which confirm the rejection of H06¹ and H07¹ Hypotheses.

Table 2. Granger Causality Test

S. No.	Countries	Hypotheses No.	Null Hypotheses	lags	*F*-Statistic	Null Hypotheses Decision
H01	SM- GP	H01¹	SM does not Cause GP in Granger Sense	2	0.66172	A
		H01²	GP does not Cause SM in Granger Sense	2	7.54753*	R
H02	SM- ER	H02¹	SM does not Cause ER in Granger Sense	2	0.02868	A
		H02²	ER does not Cause SM in Granger Sense	1	7.28102*	R
H03	SM- CO	H03¹	SM does not Cause CO in Granger Sense	1	1.5565	A
		H03²	CO does not Cause SM in Granger Sense	3	2.62725*	R
H04	SM – NG	H04¹	SM does not Cause NG in Granger Sense	1	0.02908	A
		H04²	NG does not Cause SM in Granger Sense	1	0.64019	A
H05	GP– ER	H05¹	GP does not ER in Granger Sense	1	0.52978	A
		H05²	ER does not Cause SM in Granger Sense	1	0.26646	A
H06	GP – NG	H06¹	GP does not Cause NG in Granger Sense	1	0.72168	A
		H06²	NG does not Cause GP in Granger Sense	2	0.43349	A
H07	GP – CO	H07¹	GP does not Cause CO in Granger Sense	2	3.033563	R
		H07²	COP does not Cause Gold Price in Granger Sense	2	1.04003	A
H08	ER- CO	H08¹	ER does not Cause CO in Granger Sense	1	5.05478*	R
		H08²	CO does not Cause ER in Granger Sense	1	0.18378	A
H09	ER- NG	H09¹	ER does not Cause NG in Granger Sense	1	0.94848	A
		H09²	NG does not Cause ER in Granger Sense	1	0.04845	A

* reveals significant at 5 %, ** reveals significant at 10%, R indicates rejected, A indicates Accepted.

Source: Author's own Analysis using R software

4. 2. DCC-GARCH MODEL

The DCC-GARCH model is important because it comprise time-varying correlation between two financial series and volatility dynamics. The table III shows the value of α1, β1, α2, β2, θ1, θ2 coefficients for each possible pair. The α1 and α2 measure the short-term volatility impact due to new shocks in the system and β1 and β2signifies the persistence of long-term volatility whereas θ1 and θ2 represents the correlations dynamics between different assets class. The values of α indicates the coefficient of GARCH evaluated using the past squared residual and β values denotes the coefficient of GARCH that is helpful in predicting the volatility based on conditional variance of previous days. As shown in Table III, α and β values of all the variables SM, GP, CO, ER, and NG signifies that significant persistence of volatility and can be forecasted with the residual and historical volatility. DCC α and DCCβ are called as spillover parameters are represented as θ1 and θ2 in this paper (Yadav, Sharma & Bhardwaj (2022)). The short-term analysis helps investors identify immediate diversification opportunities, while the long-term analysis provides insights into more persistent market linkages. This dual focus offers a complete picture of market dynamics, which is important for both tactical and strategic decision-making.

The analysis of DCC-GARCH results demonstrate that the coefficients of DCC α (sum of estimates) represented as θ1 for all pairs of SM, ER, CO, GP and NG are discovered positive, suggesting the existence of a steady level of volatility spillover among the SM, ER, CO, GP and NG. However, the p-values for DCC α between SM- GP, SM- CO, SM – NG, GP – ER, GP – NG, ER - CO and ER - NG not statistically significant, meaning that there may be no relevant relationship and that the observed spillover is just the result of chance (Sainath et al. 2023) and in the short run there is no spill over between SM- GP, SM- CO, SM – NG, GP – ER, GP – NG, ER - CO. The findings contradict those of Mishra & Dash (2024), Shabbir et al. (2019), Singhal & Ghosh (2016) who demonstrate that there is short-term spillover from the oil to the Indian stock market. The possible reasons might be the difference in time periods and market conditions.

Furthermore, the p-values for DCC β are found to be highly statistically significant suggests that there may be a chance of time varying and asymmetry in the pairwise volatility spillover effects among all the variables meaning thereby they are interconnected in the long run. It implies that reduce diversification benefits prevail for SM, ER, GP, CO and NG. Hence, we accept our research hypothesis H1, H2, H3, H4 and H5 that persistence of volatility spillover between ER to SM, CO to SM, GP to SM, CO to ER and GP to ER in the long run and this finding is in line with the previous studies conducted by (Rastogi, Kanoujiya & Doifode (2024); Salem et al., 2024; Hussain, Bashir & Rehman (2023); Tripathy & Mishra (2023); Umar et al., 2022; Morema & Bonga (2020)).

Additionally, the value of (α+β) signifies the persistence of volatility and in every case this sum is close to 1. The fact that β>α, suggesting that the previous shocks had a greater influence on the current variances (Hung, 2020).

When long term volatility persist regulators easily come up with plans and implement a strong monetary policy to address it, However, in the short term, this is not the case since policymakers lack the time to respond to such volatility (Yadav et el. 2021). We find immediate diversification opportunity amongst SM, ER, GP, CO and NG as there is no transfer of information is noticed in the short run. This finding is in line with the (Morema & Bonga 2020). The short run and long run spillover exist only in the case of SM- ER and GP – CO which indicates movement of information in the short run and long run both hence no diversification opportunity exist.

To summarize, there is consistent level of volatility spillover between the all pairs of SM, ER, CO, GP and NG, are witnessed; statistically significant βdcc estimates demonstrate that the long-term volatility spillover effects may exhibit some asymmetry.

Table 3. The Estimates of Bivariate DCC-GARCH between Nifty 50 with Gold Price, Exchange Rate, NG and CO

	α_1	β_1	$\alpha_{2,}$	$\beta_{2,}$	θ_1 (DCC α)	θ_2 (DCC β)	Log-Likelihood	Observation
SM- GP	0.076482* (0.0001)	0.909645* (0.0000)	0.059326* (0.0002)	0.918369* (0.0000)	0.002775 (0.305982)	0.994177* (0.0000)	20809.03	3329
SM- ER	0.072092* (0.0376)	0.911025* (0.0000)	0.076482* (0.0000)	0.909645* (0.0000)	0.029503* (0.0000)	0.955058* (0.0000)	24022.65	3329
SM- CO	0.076482* (0.0001)	0.909645* (0.0000)	0.132576* (0.02300)	0.852621* (0.0000)	0.005800 (0.105688)	0.989584* (0.0000)	18175.3	3329
SM – NG	0.076923* (0.0001)	0.909234* (0.0000)	0.086130** (0.0.0000)	0.910836* (0.0000)	0.0000 (0.9998)	0.924646* (0.000396)	16863.81	3321
GP – ER	0.059326* (0.0002)	0.918369* (0.0002)	0.76140** (0.060176)	0.906749* (0.00010)	0.00000 (0.150000)	0.912219* (0.00000)	24227.27	3329
GP – NG	0.057683 * (0.00000)	0.920629* (0.00000)	0.86130* (0.00000)	0.910836* (0.00000)	0.000738 (0.801320)	0.986525* (0.00000)	17372.84	3321
GP – CO	0.059326* (0.0002)	0.918369* (0.0002)	0.138576* (0.02395)	0.852621* (0.00000)	0.035432* (0.00025)	0.932918* (0.00000)	18711.95	3329
ER – CO	0.075149 (0.107163)	0.909187* (0.00000)	0.132576* (0.023754)	0.852621* (0.00000)	0.00000 (0.99942)	0.924145* (0.00000)	21543096	3329
ER - NG	0.73279** (0.083953)	0.910492* (0.00000)	0.86130* (0.00000)	0.910836* (0.00000)	0.008713 (0.249445)	0.900235* (0.00000)	20277.16	3321
CO -NG	0.075544* (0.0000)	0.911450* (0.0000)	0.134002* (0.00194)	0.850335* (0.0000)	0.001490 (0.34934)	0.997090 (0.0000)	16865.21	3321

Source: Author's own Analysis using R software

The authors Mandatory Model fitting criteria are given as:

i) β_1 and β_2 must be significant

ii) $\alpha_{1,}$ $\alpha_{2,}$ β_1, $\beta_{2,}$ θ_1 and θ_2 must be a positive value

iii) $\alpha_1 + \beta_1 \;<= 1$ and $\alpha_2 + \beta_2$ must be $<= 1$

iv) $\theta_1 + \theta_2$ < or = 1

* and ** denotes the significance level at 5% and 10% respectively.

4. 3. NETWORK CONNECTEDNESS

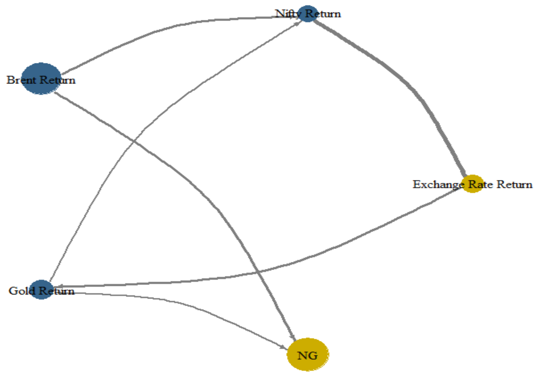
Diebold & Yilmaz (2009) connectedness method is employed to analyze the interconnectedness among SM, CO, GP, NG and ER. This connectedness method is one of the most popular methods to study connectedness (Sawarn & Dash, 2023). Table IV presents the static return connectedness across all markets and total system-wide (systemic risks) is 58.81%. A high pairwise connectedness between two markets can highlight the strong ties between the two markets (Boakye et al. 2023). The high measure indicates high connectedness among the assets and implies low diversification opportunities among SM, CO, GP, NG and ER. The table's column shows the amount of spillover it receives from other assets or markets. Out of all the assets, the nifty return's volatility may be explained by its own shocks to the extent that it is 81.11%, the least among all series, and is most impacted by external shocks. Exchange rates have the largest spillover impact on Nifty (13.47), followed by Gold (1.35) and Natural Gas (0.92).

Table 4. Network Connectedness: Spillover

	GP Return	CO Return	ER Return	NG Return	SM Return	Received
GP Return	92.11	4.68	0.97	0.89	1.35	7.89
CO Return	4.66	89.32	0.67	2.2	3.16	10.68
ER Return	0.7	0.68	84.17	0.98	13.47	15.83
NG Return	1.08	2.46	1.05	94.49	0.92	5.51
SM Return	1.55	3.39	13.1	0.85	81.11	18.89
Transmitted	7.99	11.22	15.78	4.91	18.89	58.81
NET	0.1	0.54	-0.05	-0.6	0.01	14.7

Source: Author's own Analysis using R software

Figure 2. Pairwise Network Connectedness among SM, CO, GP, NG and ER



Source: Figure Created from compiled data using R software

The thicker line in Figure II illustrates the significant dynamic interconnectedness between the exchange rate and the Nifty 50. It is witnessed that 13.1% of the spillover from the Exchange Rate goes to the Nifty 50, whereas 13.47% goes to the Exchange Rate from the Nifty 50. Further, Natural gas and gold are self-sufficient by nature, and their volatility did not spread to other markets. This gives a significant indicator that they are more vulnerable to its own shocks 92.11% and 94.49%, in that order.

5. CONCLUSION

The present study is designed to assess the volatility integration among the Indian stock market Nifty 50, prices of gold, oil prices, exchange rates, and natural gas. The techniques of DCC GARCH, Diebold & Yilmaz (2012) connectedness framework have been used to detect the volatility spillover and connectedness among the variables described above. The daily data is collected during the time frame January 01, 2009 to March 31, 2023 from the Bloomberg database. DCC-GARCH models are used to assess the volatility communication between the set of variables. The central research question focused on understanding how volatility spillovers between these key financial assets affect market dynamics, diversification opportunities, and investment strategies for both investors and policymakers. The significant short-term volatility transmission is observed from ER to SM and CO to GP. This means volatility in ER significantly impacts the SM as well as the volatility of CO impacting the GP, thereby no portfolio diversification opportunity exists. There is no significant short-run spillover witnessed between SM-GP, SM-CO, SM-NG, GP-ER, GP-NG, and ER-CO; thereby, a portfolio diversification opportunity exists in the short run. However, there exists a time-varying volatility spillover between all the markets SM-GP, SM-CO, SM-NG, GP-ER, GP-NG, ER-CO, and CO-NG, meaning thereby they are interconnected in the long run. It implies that reduced diversification benefits prevail for SM, ER, GP, CO, and NG, and investors should exercise caution when making investments in these markets. The result of the Granger Causality Test infers that unidirectional relationships exist between SM to GP, SM to ER, SM to CO, GP to CO, and ER to CO.

The short-run and long-run spillovers exist only in the case of SM-ER and GP-CO, indicating that the transfer of information is possible in the short run and long run, hence no diversification opportunity exists. The strong connectedness among the stock market—exchange rate, crude oil—natural gas, and stock market—crude oil verifies that low diversification opportunities exist among the above pair of variables. The result of Diebold & Yilmaz connectedness suggests that while making investing decisions, investors should take into account the volatility of the Nifty 50, gold, and exchange rates.

The findings provide an explicit answer to the research question by confirming the existence of high long-run volatility spillovers among Nifty 50, exchange rates, and crude oil, indicating high market dependence. Such long-run dependences restrict diversification possibilities since a change in one asset will have an effect on others. This holds more especially for institutional investors using strategic asset allocation since such long-run volatility relations have to be accounted for while formulating risk management.

Alternatively, the study confirms the short-run reality of volatility whereby no significant spillovers were observed among some asset pairs, i.e., Nifty 50 and gold, or natural gas and exchange rates. This confirms the reality that, in the short run, investors, and retail investors in general, are still capable of enjoying diversification opportunities through the formulation of portfolios that take advantage of these relatively uncorrelated assets. Such opportunities are useful in guiding tactical portfolio decisions on the basis of short-run market realities.

This study provides new evidence by incorporating natural gas, a necessary but less researched commodity by previous research. Incorporating natural gas provides new evidence of interlinkage between the energy commodities and the stock market. In contrast to the majority of the previous studies on each of the pairs of assets, this study systematically examines all pairwise interactions of the stock market, exchange rates, crude oil, gold, and natural gas. This study fills knowledge gaps of the entire network of the spillover volatilities. This study also identifies short- and long-run spillover effects, which are beneficial to short-run traders and long-run investors. This study contributes to the literature by identifying which pairs of assets are diversification opportunities in the short run and which are long-run interconnections.

6. MANAGERIAL IMPLICATIONS

Investors can use the findings to diversify their portfolios effectively. It is a well-established phenomenon that portfolio risk reduces with low or negatively correlated assets. Analysts can forecast markets by observing changes in these correlations. For example, the high correlation between crude oil and gold suggests a shift in market sentiment. By arresting the dynamic nature of the above correlations, it offers valuable insights for different market participants and policymakers in making more informed decisions. Short-run results suggest that there is little spillover between asset classes like the stock market and gold or between natural gas and exchange rates. This information can therefore be exploited by retail investors who are more risk-averse in order to diversify their portfolios in the short term by investing in uncorrelated assets. For example, an investment in Indian equities along with investments in gold or natural gas might offer better short-run risk-adjusted returns. Institutional investors can hedge risks using high-powered tools such as futures and options, but the retail investor has to rely on diversification of different asset classes. Both types of investors will need to realize that there are short-term diversification opportunities that exist, especially if the volatility transmission between assets is low, so they can take advantage of them through investment in less correlated assets like gold and natural gas.

The research findings have important implications for investors, speculators, and policymakers for risk management, portfolio optimization, and diversification and to better understand the market dynamics. Analysis also provides prominent signals for policymakers regarding monetary and fiscal policies, considering the impact that ER, GP, and BP exert on the stock market.

7. FUTURE SCOPE OF RESEARCH

The researchers may also explore a different variable, such as inflation, interest rates, bond yield, etc. They might also think about doing research for an extended period not covered in this study.

High-frequency trading data captures the trades and quotes at millisecond intervals. Hence, the utilization of high-frequency trading data might increase the knowledge regarding volatility spillovers and asset class connectedness. With high-frequency data, it is possible to illustrate more granularity about price dynamics. This may be beneficial in analyzing the intraday spillovers of volatility in the Indian stock market, crude oil, gold, and exchange rates. The HFT data will allow the researchers to analyze the way shocks are transmitted through the assets. Neural networks, and deep learning methods in particular, are very potent tools for financial market volatility forecasting and modeling. This can be done more effectively by recurrent neural networks or long short-term memory networks, especially in cases where time series data reflects temporal dependencies and would be helpful for predicting spillovers in volatility between asset classes over time.

REFERENCES

Aggarwal, V., Doifode, A., & Tiwary, M. K. (2021). Volatility spillover impact of FII and MF net equity flows on the Indian sectoral stock indices: Recent evidence using BEKK-GARCH. *International Journal of Indian Culture*, 22(3), 350–363. https://doi.org/10.1504/IJICBM.2021.114084

Akbar, M., Iqbal, F., & Noor, F. (2019). Bayesian analysis of dynamic linkages among gold price, stock prices, exchange rate and interest rate in Pakistan. *Resources Policy,* 62, 154-164. https://doi.org/10.1016/j.resourpol.2019.03.003

Akkoc, U., & Civcir, I. (2019). Dynamic linkages between strategic commodities and stock market in Turkey: Evidence from SVAR-DCC-GARCH model. *Resources Policy,* 62, 231-239. https://doi.org/10.1016/j.resourpol.2019.03.017

Alshenawy, F. Y., & Abdo, D. A. (2023). Using multivariate dynamic conditional correlation GARCH model to analyze financial market data. *Journal of Business Research,* 45(4), 34-64. https://doi.org/10.21608/zcom.2023.213791.1258

Arisandhi, V. D., & Robiyanto, R. (2022). Exchange rate, gold price, and stock price correlation in ASEAN-5: Evidence from the Covid-19 era. *Journal Manajemen Dan Kewirausahaan,* 24(1), 22-32. https://doi.org/10.9744/jmk.24.1.22-32

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review,* 45(2), 217-229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

Boakye, R. O., Mensah, L., Kang, S., & Osei, K. (2024). Connectedness across commodities, stocks, exchange rates and bonds markets in Africa: The Covid-19 pandemic case. *International Journal of Emerging Markets*. https://doi.org/10.1108/IJOEM-03-2023-0411

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics,* 31(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Brooks, C. (2008). Introductory econometrics for finance. *Cambridge University Press*. https://doi.org/10.1017/CBO9780511841644

Cui, J. (2023). The relationship between the gold price, crude oil price, exchange rate and Chinese stock market indexes. *Highlights in Business, Economics and Management,* 10, 180-188. https://doi.org/10.54097/hbem.v10i.8037

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association,* 74(366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal,* 119(534), 158-171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society,* 50(4), 987-1007. https://doi.org/10.2307/1912773

Engle, R., & Granger, C. (1991). Long-run economic relationships: Readings in cointegration. *Oxford University Press*. https://econpapers.repec.org/bookchap/oxpobooks/9780198283393.htm

Engle, R. F., & Sheppard, K. (2001). Theoretical and empirical properties of dynamic conditional correlation multivariate GARCH. MIMEO, UCSD. https://pages.stern.nyu.edu/~rengle/Dcc-Sheppard.pdf

Essien, N. A., Umah, C. A., Amarachi, I. A. U., & Samson, T. K. (2024). Modeling Retail Price Volatility of Selected Food Items in Cross River State, Nigeria Using GARCH Models. *Acadlore Transactions on Applied Mathematics and Statistics,* 2(2), 94-103. https://doi.org/10.56578/atams020204

Gharib, M. R., Jamali, N., Chamanabad, S. N., & Goharimanesh, M. (2023). Examining the Role of Empowerment Criteria on Employee Performance: A Quantitative Analysis in the Oil Industry. *Journal of Engineering Management and Systems Engineering,* 2(2), 96-107. https://doi.org/10.56578/jemse020201

Güngör, A., & Güngör, M. S. (2024). The nexus between economic policy uncertainty and stock market volatility in the CEE-3 countries. *The South East European Journal of Economics and Business,* 19(2), 60-81. https://doi.org/10.2478/jeb-2024-0016

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438. https://doi.org/10.2307/1912791

Hung, N. T. (2020). Analysis of the time-frequency connectedness between gold prices, oil prices and Hungarian financial markets. *International Journal of Energy Economics and Policy*, 10(4), 51-59. https://doi.org/10.32479/ijeep.9230

Huseynli, N. (2023). Analyzing the relationship between oil prices and gold prices before and after Covid-19. *International Journal of Energy Economics and Policy,* 13(2), 373-378. https://doi.org/10.32479/ijeep.13820

Hussein, A. M. & Osman, B. M. (2024). The Impact of Rapid Urbanization on Poverty Levels in the Context of Climate Change: Empirical Evidence from Somalia. *Challenges in Sustainability,* 12(4), 281-291. https://doi.org/10.56578/cis120404

Hussain, M., Bashir, U., & Rehman, R. U. (2024). Exchange rate and stock prices volatility connectedness and spillover during pandemic induced-crises: Evidence from BRICS countries. *Asia-Pacific Financial Markets*, 31(1), 183-203. https://doi.org/10.1007/s10690-023-09411-0

Jain, A., & Biswal, P. C. (2016). Dynamic linkages among oil price, gold price, exchange rate, and stock market in India. *Resources Policy,* 49, 179-185. https://doi.org/10.1016/j.resourpol.2016.06.001

Jain, A., & Ghosh, S. (2013). Dynamics of global oil prices, exchange rate and precious metal prices in India. *Resources Policy,* 38(1), 88-93. https://doi.org/10.1016/j.resourpol.2012.10.001

Jia, Y., Dong, Z., & An, H. (2023). Study of the modal evolution of the causal relationship between crude oil, gold, and dollar price series. *International Journal of Energy Research,* 2023(1), 01-15. https://doi.org/10.1155/2023/7947434

Jimoh, O. R., Rana, M. A., & Tajudeen, T. O. (2023). Modelling the impact of crude oil prices and stock price index on Indonesia's exchange rates. *Studies in Business and Economics,* 18(3), 244-260. https://doi.org/10.2478/sbe-2023-0057

Jindal, N. (2023). Oil prices, silver, gold and exchange rate relationship with stock market returns in Indian bourse with ARDL model. *Thailand and the World Economy,* 41(2), 123-136. https://so05.tci-thaijo.org/index.php/TER/article/view/265419

Kumar, S., Kumar, A., & Singh, G. (2023). Gold, crude oil, bitcoin and Indian stock market: Recent confirmation from nonlinear ARDL analysis. *Journal of Economic Studies,* 50(4), 734-751. https://doi.org/10.1108/JES-01-2022-0007

Kumar, S., Singh, G., & Kumar, A. (2022). Volatility spillover among prices of crude oil, natural gas, exchange rate, gold, and stock market: Fresh evidence from exponential generalized autoregressive conditional heteroskedastic model analysis. *Journal of Public Affairs,* 22(4), e2594. https://doi.org/10.1002/pa.2594

Li, D., Hong, Y., Wang, L., Xu, P., & Pan, Z. (2022). Extreme risk transmission among bitcoin and crude oil markets. *Resources Policy,* 77, 102761. https://doi.org/10.1016/j.resourpol.2022.102761

Mastilo, Z., Štilić, A., Gligović, D., & Puška, A. (2024). Assessing the banking sector of Bosnia and Herzegovina: An analysis of financial indicators through the MEREC and MARCOS methods. *Journal of Central Banking Theory and Practice*, 13(1), 167–197. https://doi.org/10.2478/jcbtp-2024-0008

Mishra, A., & Dash, A. K. (2024). Return volatility of Asian stock exchanges: A DCC GARCH analysis with reference to bitcoin and global crude oil price movement. *Journal of Chinese Economic and Foreign Trade Studies,* 17(1), 29-48. https://doi.org/10.1108/JCEFTS-01-2024-0009

Moraliyska, M. (2023). Measuring the Justness of the European Green Transition. *Collection of papers new economy,* 1, 30-41. https://doi.org/10.61432/CPNE0101030m

Morema, K., & Bonga-Bonga, L. (2020). The impact of oil and gold price fluctuations on the South African equity market: Volatility spillovers and financial policy implications. *Resources Policy*, 68,101740. https://doi.org/10.1016/j.resourpol.2020.101740

Nordström, C. (2021). DCC-GARCH estimation. https://www.diva-portal.org/smash/get/diva2:1800505/FULLTEXT01.pdf

Ndlovu, T., & Ndlovu, N. M. (2024). The dynamic linkages among gold prices, stock prices, the exchange rate and interest rate in South Africa. *Journal of Economics and Financial Analysis,* 8(1), 35-56. https://ojs.tripaledu.com/jefa/article/view/89

Pata, U. K., Usman, O., Olasehinde-Williams, G., & Ozkan, O. (2024). Stock returns, crude oil and gold prices in Turkey: Evidence from rolling window-based nonparametric quantile causality test. *Asia-Pacific Financial Markets, 779-797*. https://doi.org/10.1007/s10690-023-09430-x

Rareș Bircea, M., & Kardos, M. (2024). Emigration and Its Impact on the Sending Country. Social and Economic Effects for Romania. *Collection of papers new economy,* 2, 79-96. https://doi.org/10.61432/CPNE0201079r

Rastogi, S., & Agarwal, A. (2020). Volatility spillover effect in Spot, futures and option markets. Test Engineering and Management, 83(3), 10114–10127. http://www.testmagzine.biz/index.php/testmagzine/article/view/9025/6880

Rastogi, S., & Athaley, C. (2019). Volatility integration in spot, futures and options markets: A regulatory perspective. Journal of Risk and Financial Management, 12(2), 1–15. https://doi.org/10.3390/jrfm12020098

Rastogi, S., Kanoujiya, J., & Doifode, A. (2024). Volatility integration of crude oil, gold, and interest rates on the exchange rate: DCC GARCH and BEKK GARCH applications. Cogent Business & Management, 11(1), 2289700. https://doi.org/10.1080/23311975.2023.2289700

Rastogi, S., Doifode, A., Kanoujiya, J., & Singh, S. P. (2023). Volatility integration of gold and crude oil prices with the interest rates in India. *South Asian Journal of Business Studies,* 12(3), 444-461. https://doi.org/10.1108/SAJBS-02-2021-0074

Raji, J. O., Jusoh, J., & Jantan, M. D. (2014). Real money supply, price and fiscal deficit in Nigeria: Evidence from multivariate Granger causality tests. *Journal of Economic Cooperation and Development,* 35(4), 85-112. https://jecd.sesric.org/pdf.php?file=ART13072401-2.pdf

Sahoo, S. (2024). Harmony in diversity: Exploring connectedness and portfolio strategies among crude oil, gold, traditional and sustainable index. *Resources Policy*, 97,105281. https://doi.org/10.1016/j.resourpol.2024.105281

Sainath, A. R., Gnanendra, M., Mohanasundaram, T., James, L., & Misra, S. (2023). Dynamic connectedness and volatility spillover effects of Indian stock market with international stock markets: An empirical investigation using DCC GARCH. *Scientific Papers of the University of Pardubice Series D, Faculty of Economics and Administration,* 31(1). https://doi.org/10.46585/sp31011691

Salisu, A. A., Ndako, U. B., & Vo, X. V. (2023). Oil price and the bitcoin market. *Resources Policy,* 82, 103437. https://doi.org/10.1016/j.resourpol.2023.103437

Shabbir, A., Kousar, S., & Batool, S. A. (2019). Impact of gold and oil prices on the stock market in Pakistan. *Journal of Economics, Finance and Administrative Science,* 25(50), 279-294. https://doi.org/10.1108/JEFAS-04-2019-0053

Shafiq, S., Qureshi, S. S., & Akbar, M. (2023). Dynamic relationship of volatility of returns across different markets: Evidence from selected next 11 countries. *Journal of Economic and Administrative Sciences*. https://doi.org/10.1108/JEAS-09-2022-0216

Siddiqui, S., & Roy, P. (2019). Predicting volatility and dynamic relation between stock market, exchange rate, and select commodities. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis,* 67(6), 1597–1611. https://doi.org/10.11118/actaun201967061597

Singhal, S., Choudhary, S., & Biswal, P. C. (2019). Return and volatility linkages among international crude oil price, gold price, exchange rate, and stock markets: Evidence from Mexico. *Resources Policy,* 60, 255–261. https://doi.org/10.1016/j.resourpol.2019.01.004

Soni, R. K., Nandan, T., & Chatnani, N. N. (2023). Dynamic association of economic policy uncertainty with oil, stock, and gold: A wavelet-based approach. *Journal of Economic Studies,* 50(7), 1501–1525. https://doi.org/10.1108/JES-05-2022-0267

Sujit, K. S., & Kumar, B. R. (2011). Study on dynamic relationship among gold price, oil price, exchange rate, and stock market returns. *International Journal of Applied Business and Economic Research,* 9(2), 145–165. https://www.econbiz.de/Record/international-journal-of-applied-business-and-economic-research/10003764890

Tripathy, N., & Mishra, S. (2023). Dynamic Spillovers Between Crude Oil Price and Gold Price: Empirical Evidence. *International Journal of Business & Economics*, 22(1). https://ijbe.fcu.edu.tw/past_issues/NO.22-1/pdf/vol.22-1-1

Umar, Z., Aziz , M. I.A, Zaremba, A., & Tran, D. K. (2023). Modelling dynamic connectedness between oil price shocks and exchange rates in ASEAN+ 3 economies. Applied Economics, 55(23), 2676-2693. https://doi.org/10.1080/00036846.2022.2104801

Valarmathi, A., Umamaheswari, S., & Lakshmi, M. R. (2023). A study on dynamic relationship between gold price and stock market price in India. *Journal of Survey in Fisheries Sciences,* 10(3), 6529–6539. https://sifisheriessciences.com/journal/index.php/journal/article/view/2176

Vo, X. V., & Ellis, C. (2018). International financial integration: Stock return linkages and volatility transmission between Vietnam and advanced countries. *Emerging Markets Review,* 36, 19–27. https://doi.org/10.1016/j.ememar.2018.03.007

Yadav, M. P., Sharma, S., & Bhardwaj, I. (2023). Volatility spillover between Chinese stock market and selected emerging economies: A dynamic conditional correlation and portfolio optimization perspective. *Asia-Pacific Financial Markets,* 30(2), 427–444. https://doi.org/10.1007/s10690-022-09381-9

Yadav, N., Tandon, P., Tripathi, R., & Shastri, R. K. (2021). A dynamic relationship between crude oil price and Indian equity market: An empirical study with special reference to Indian benchmark index Sensex. *Benchmarking: An International Journal,* 28(2), 582–599. https://doi.org/10.1108/BIJ-06-2020-0306

Yousaf, I., Beljid, M., Chaibi, A., & Ajlouni, A. T. (2022). Do volatility spillover and hedging among GCC stock markets and global factors vary from normal to turbulent periods? Evidence from the global financial crisis and Covid-19 pandemic crisis. *Pacific-Basin Finance Journal,* 73, 1–45. https://doi.org/10.1016/j.pacfin.2022.101764