IOSR Journal Of Economics And Finance (IOSR-JEF)
E-Issn: 2321-5933,P-Issn: 2321-5925.Volume 14, Issue 4 Ser. IV (July. – August. 2023),Pp 54-64
www.iosrjournals.org

Time-Varying Integration Between the US Stocks and the IndianCommodities: A DCC-GARCH Analysis

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Abstract
This study investigates the volatility spillovers from the US equity market, represented by the S&P 500 index, to the Indian commodity market, proxied by the Nifty Commodity index, using the Dynamic Conditional Correlation (DCC) GARCH model. The daily returns data from September 2011 to July 2023 has been examined. The DCC model estimates provide evidence of significant volatility clustering and persistence in both the indices. The results also indicate the presence of strong dynamic correlations between the two markets, with spillovers transmitted from the S&P 500 to the Nifty Commodity index. The time-varying correlations reveal the evolving integration between the US and the Indian markets. The diagnostic tests validate the DCC-GARCH(1,1) specification for modelling the return co-movement. The findings demonstrate a significant interconnectedness and show that volatility spillovers exist from the developed US equity market to the emerging Indian commodity market. This has important practical implications for international portfolio diversification and risk management.

Keywords:*DCC-GARCH, volatility spillover, dynamic correlation, emerging markets, financial integration*

Date of Submission: 18-08-2023 Date of Acceptance: 28-08-2023

I. Introduction

Financial markets worldwide have become more interconnected due to trade and investment liberalization, deregulation, and rapid technological progress, enabling a faster flow of information and capital across borders (Bekiros, 2014; Diebold & Yilmaz, 2015). This integration allows a greater transmission of returns and volatility across markets, especially during crisis periods (Singh et al., 2019). Emerging markets, in particular, have seen their linkages with mature economies grow substantially since the 1990s as they opened up capital accounts and developed their financial markets (Bekaert et al., 2011).

Prior empirical research shows that theemerging market returns and risks need to be analyzed, accounting for the spillovers from the developed markets (Ng, 2000; Bekiros, 2014). Their dependence has increased so much so that domestic factors alone cannot explain the emerging market dynamics (Diebold & Yilmaz, 2009). The commodity markets in emerging economies are not insulated because their exports and fiscal revenues depend considerably on the global economy (Arezki et al., 2014). Any growth slowdown in major economies quickly transmits to the commodity prices through falling trade and risk appetite (Reboredo, 2012).

Further, India's total commodity exports have grown from $95 billion in 2000 to over $380 billion in 2022, linking it tightly to the global growth dynamics (UN Comtrade, 2022). The S&P GSCI commodity index returns correlation with the S&P 500 stock returns has risen from 0.2 before 2008 to over 0.6 by 2018, indicating financialization (World Bank, 2020). Foreign portfolio flows into Indian equity markets surged from $8 billion in 2006 to over $36 billion in 2021, transmitting overseas volatility (NSDL, 2022)

A growing body of literature has consequently documented the pronounced return co-movement present between the commodity and the stock markets across countries (Buyuksahin& Robe, 2014; Silvennoinen& Thorp, 2013). For example, the correlationbetween crude oil and equity returns jumped during the 2008 crisis, showingthe transmission of volatility shocks across these asset classes (Reboredo&Ugolini, 2016). Peculiarly though, the examination of the return connectedness specifically between the Indian commodity and the global equity markets has been sparse despite India's large footprint in commodity production and exports (Kaur & Dhillon, 2010).

India is the world's fifth largest economy with a deepening integration into the global commodity and financial markets over the past decade. Its equity markets have experienced surging foreign portfolio inflows, amplifying the susceptibility to swings in the global risk appetite (Pattanaik et al., 2003). On the commodity front, India is amongst the top producers of metals, energy, and agricultural goods, with their exports tied considerably to the economic growth worldwide (Kaur & Dhillon, 2010). Understanding the return comovementbetween Indian commodities and international stocks can thus provide important diversification and hedging insights for global investors amidst rising uncertainty.

A key gap in the literature pertains to the application of recent advances in econometric techniques to uncover the time-varying and dynamic nature of return co-movement, going beyond simple correlation analysis which imposes the constancy of relationships. Methodologies like the dynamic conditional correlation (DCC) model allow tracking how connections between markets evolve across time and frequencies (Barunik&Krehlik, 2016). However, these techniques have not been deployed to specifically elucidate the dynamic linkages between Indian commodities and global equities across timescales. This hinders dynamic risk management.

Therefore, the present study proposes to address this empirical gap through a systematic investigation of the comovement and spillover structure between the Indian commodity and the world equity markets using DCC-GARCH. It will provide timely evidence to enable the construction of optimal internationally diversified portfolios. The findings can also aid policymakers manage contagion. Overall, examining the India-global asset return connectedness will reveal critical stylized facts for dynamic risk modeling and financial stability. Section 2 provides a review of the theoretical and empirical literature. Section 3 expounds on the data and methodology. Section 4 presents the empirical findings and discussion. Section 5 concludes the paper.

II. Review of Literature

Theoretical Basis of Volatility Transmission

The theoretical basis for examining volatility transmission between commodity and equity markets lies in academic asset pricing models and information transmission mechanisms. According to the storage theory, pioneered by Kaldor (1939), commodity prices are determined by the current and the future demand-supply conditions. Macroeconomic factors affecting aggregate commodity demand or supply can, therefore, impact markets. Equity markets reflect changing expectations about economic growth prospects, which in turn influence commodity demand (Frankel, 2014; Platen &Sidorowicz, 2017). For instance, a bullish stock market outlook may signal stronger anticipated growth and boost the demand for commodities.

Additionally, commodities serve as an inflation hedge given their real asset properties. Inflation expectations play a key role in equity valuations and risk premiums, creating an inflation channel that links the two markets (Akram, 2009). The seminal capital asset pricing model (CAPM) demonstrates how asset return co-movement is determined by correlation with a market portfolio and sensitivity to market risk (Sharpe, 1964; Lintner, 1965). As financial integration deepens, the commodity and the equity markets will likely have a greater overlap in the global market portfolio, inducing a stronger correlation (King & Wadhwani, 1990).

At a granular level, several theoretical channels for the transmission of shocks between commodities and equities have been proposed (Silvennoinen& Thorp, 2013; Diebold & Yilmaz, 2012):

- Portfolio rebalancing: As investors rebalance positions across asset classes, price changes in one market can propagate to another through hedging and diversification.
- Liquidity spillovers: Shocks to equity market liquidity and trading activity can spill over to commodities through common trader participation.
- Risk appetite: Changes in investor risk perceptions due to equity volatility may transmit to commodities through a 'flight to quality'.
- Growth expectations: Stock markets represent changing expectations about economic growth, which impacts commodity demand.
- Inflation hedging: Commodities act as an inflation hedge. Changing inflation views priced into equities affect commodity markets.
- Financialization: The growing participation of financial institutions, high-frequency traders and index investors in commodity derivatives has strengthened linkages with equities (Tang &Xiong, 2012).

Overall, academic research provides a robust theoretical foundation for how information transmission mechanisms and exposure to common macroeconomic and behavioral factors can engender return and volatility spillovers between commodities and equities.

Empirical Evidence on Return and Volatility Spillovers

Earlier empirical studies using correlation analysis had found limited co-movement between the commodity and the equity markets, suggesting potential diversification benefits from blending the asset classes (Erb& Harvey, 2006). However, since the early 2000s, financialization has induced a stronger interconnectedness. Silvennoinen and Thorp (2013) uncover a structural break in commodity-equity correlations after 2008, with over 25% of commodity price variation explained by equity volatility. Applying nonparametric causality tests, Chevallier and Ielpo (2013) demonstrate significant spillovers from oil prices to US equities after 2000 as commodity trading volumes exploded.

For advanced economies, Antonakakis and Kizys (2015) model strong bidirectional volatility transmission between commodities and equities in Europe over 2001-2014 using dynamic conditional correlation models, with intensified spillovers during the 2008 crisis. Examining Asia, Li and Giles (2015) showthat oil price shocks account for up to a third of the Chinese stock return variation over 2000-2011, based on multivariate GARCH estimations. In Japan, as well, commodity and equity volatility spillovers have been pronounced based on BEKK-GARCH analysis (Chang et al., 2013).

Among emerging markets, Mensi et al. (2013) uncover significant two-way volatility connectedness between commodities and equities in BRIC countries over 1990-2011, especially after 2008. Vargas et al. (2013) demonstrate growing co-movement between commodities like soybeans and Latin American equities as the markets liberalized. For India, Jain and Biswal (2016) showthat the correlation between oil prices and equity indices doubled from 0.4 to 0.8 over 2003-2015, highlighting strengthening spillovers.

At a granular level, specific commodities act as a conduit for volatility transmission. Kumar (2017) finds that Indian gold returns explain over 11% of Nifty index variance. Lutz (2015) shows oil price volatility Granger causes US equity returns but not vice versa. Nazlioglu et al. (2013) show significant volatility spillovers from the oil markets to agricultural commodities. So, both at an aggregate market level as well as at individual commodity levels, the empirical literature establishes a strong evidence of return and volatility spillovers between commodities and equities globally.

Justification for using DCC-GARCH models:

The dynamic conditional correlation (DCC) model, introduced by Engle (2002), provides an effective framework for uncovering the time-varying volatility transmission and correlationbetween assets. DCC has emerged as one of the most widely used multivariate GARCH techniques due to its parsimonious structure and its ability to model dynamic correlations (Caporin& McAleer, 2012). Unlike the restrictive constant conditional correlation or the BEKK specifications, the DCC approach provides flexibility to accommodate both volatility clustering within series and evolving cross-market linkages (Creti et al., 2013).

A key advantage of DCC is its efficient two-step estimation procedure which overcomes the curse of dimensionality that large multivariate GARCH models face (Engle, 2002). This allows us to examine higher-dimensional problems with many assets. Silva et al. (2016) demonstrates the superiority of DCC-GARCH over static correlation modeling,which fails to adapt to the structural shifts in relationships over time. The time-variation in correlations andtransmission of shocks that is revealed by DCC, but is missed in simpler models, provides valuable insights into changing market risks to guide dynamic risk management and portfolio decisions (Ho & Zhang, 2012).

By decomposing the covariance matrix into dynamic conditional variances and correlations, DCC parsimoniously models heteroscedasticity in individual series along with flexible correlation dynamics (Belke&Gokus, 2011). This makes it well-suited for investigating interconnectedness and contagion effects between markets. The framework's ability to quantify both the magnitude and the evolution of conditional correlations across periods offers a valuable practical perspective into time-varying risks and integration between assets (Creti et al., 2013).

This review of literature demonstrates the strong motivation for examining return comovement dynamics between the increasingly important Indian commodity markets and the global equity markets. It establishes the relevance of such an examination amidst India's growing financial integration and trade footprint, which has surged overseas investment flows into domestic equities.Empirical evidence of the rising return correlations and volatility spillovers from commodities and US equities all quantitatively justify the examination of the India-US asset connectedness. The gaps in deploying the latest econometric techniques to uncover the time-varying linkages specific to Indian assets are highlighted. The DCC-GARCH framework is justified as an appropriate methodology to address the limitations of static modeling and to uncover the cyclicality ofthe commodity-equity return relationships in order to inform dynamic risk management. The subsequent sections will outline the research methodology, the dataset, and our empirical findings.

III. Data and Methodology

The data used for this study is the daily historical price from 8 September 2011 to 14 July 2023 for both the indices. Due to the variation in holidays between the global market and the Indian market, the data which were missing for either of the variables were dropped from the analysis.

For the preliminary insights, we first report the descriptive statistics, followed by the empirical findings and the discussion of the results.

Methodology

Time-varying volatility models have been popular since the early 1990s in empirical research in finance. The analysis of volatility in the financial market has been widely studied in an ARCH-GARCH framework, pioneered by Engle (1982). This was further developed byBollerslev (1986),Nelson (1991) and others. The most widely used models in this class are the VECH model(Bollerslev, Engle & Wooldridge (1988)) and the BEKK model (Baba, Engle, Kraft and Kroner (1990) and Engle and Kroner (1995)). These models differ in their assumptions and specifications of the variance-covariance matrix but help in modelling time-varying variance and covariance estimates. However, to investigate the spillover effect, the Multivariate GARCH model was put in place as this method explicitly captures the time-varying covariance between two markets. In this paper, we estimate the conditional correlations and the covariance based on the Dynamic Conditional Correlation (DCC) model.

The DCC-GARCH model helps us understand the interdependence in volatility between multiple return series by modelling the conditional covariance matrix as a product of the conditional variances and the correlations (Engle, 2002). The two-step estimation procedure here involves first estimating the series of the univariate GARCH model and then estimating the correlations. The model is written as:

$$y_t = Cx_t + \varepsilon_t$$
$$\varepsilon_t = H_t^{1/2} v_t +$$
$$H_t = D_t^{1/2} R_t D_t^{1/2}$$
$$R_t = diag(Q)_t^{-1/2} Q_t diag(Q_t^{1/2})$$
$$Q_t = (1 - a_m - b_n)R + \lambda_m \, \widetilde{\epsilon_{t-1} \epsilon}_{t-1} + \lambda_n Q_{t-1} \quad (1)$$

Where, y_t is a m x 1 vector of dependent variables.
C is an m x k vector of independent variables,
x_t is a k x 1 vector of independent variables which may contain lags of y_t
$H_t^{\frac{1}{2}}$ is the Cholesky factor of time-varying conditional covariance matrix H_t, v_t is an mx1 vector of normal, independent, and identically distributed observations; D_t is a diagonal matrix of conditional variances,

$$D = \begin{pmatrix} \sigma_{1,t}^2 & 0 & \dots & 0 \\ 0 & \sigma_{2,t}^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{m,t}^2 \end{pmatrix} \quad (2)$$

Where, $\sigma_{i,t}^2 = s_i + \sum_{j=1}^{p_i} \alpha_j \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q_i} \beta_j \varepsilon\sigma_{i,t-j}^2$, i.e., evolving based on the univariate GARCH model for α_j ARCH parameters and β_j GARCH parameters.
R_t is a matrix of conditional quasi-correlations,

$$R_t = \begin{pmatrix} 1 & \rho_{12,t} & \dots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \dots & \rho_{1m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m,t} & \rho_{12,t} & \dots & 1 \end{pmatrix}$$

$\widetilde{\varepsilon_t}$ isa mx1 vector of standardized residuals, $\sqrt{D_t}\varepsilon_t$; and λ_1, λ_2 are the parameters governing the conditional quasicorrelations. a_1 and b_1 are non - negative and satisfy $0 \leq a_1 + b_1 < 1$.

When Q_t is a weak stationary process, the matrix R in (2) is a weighted average of the unconditional covariance matrix of the standardized residuals $\widetilde{\varepsilon_t}$, denoted by $\bar{R}$, and the unconditional mean of Q_t, denoted by $\bar{Q}$. Since, $\bar{R} \neq \bar{Q}$, as shown by Aieli (2009), R is neither an unconditional correlation matrixnor is it the unconditional mean of Q_t. For this reason, the parameters in R are known as quasi-correlations (Aielli, 2009; Engle, 2009).

The correlation process here is driven by two parameters i.e., $a_1 and\ b_1$. It directly models the variance and the covariance but also its flexibility i.e., whether there is short-term or long-term persistence. $a_1\ dcc$ measures the short-run volatility impact, i.e., the persistency of the standardized residuals from the previous period. $b_1\ dcc$ measures the lingering effect of the shock impact on the conditional correlations, which is the persistence of the conditional correlation process. The sum of $a_1\ and\ b_1$, which is less than one, indicates that the conditional correlation in the models is not constant over time.

Granger Causality

After examining the conditional correlations and confirming the interdependence, a causality analysis is done, following thepairwise Granger Causality method, to test whether both the variables exhibit univariate or bivariate dependence. This approach answers whether *x* causes *y*to see how much of the current *y* can be explained by past values of *y*, and to see whether adding lagged values of *x* can improve the explanation. *y* is said to be Granger-caused by *x* if *x* helps predict *y*, or equivalently if the coefficients on the lagged *x*'s are statistically significant. Note that two-way causation is when*x* Granger causes *y* and *y* Granger causes *x*.The following null and alternative hypothesis were considered for testing:
H_0: RNIFTY does not Granger Cause RSAP or

H_0: β1i = 0 for i=1,2,....,q
H_1: RSAP does not Granger Cause RNIFTY or
H_0: β2i = 0 for i=1,2,....,q (X does not Granger cause Y)
The basic Granger causality equation for two series X_t and Y_t is:

$$X_t = \alpha_{10} + \alpha_{11} X_{t-1} + \ldots + \alpha_{1p} X_{t-p} + \beta_{11} Y_{t-1} + \ldots + \beta_{1q} Y_{t-q} + \varepsilon_{1t}$$

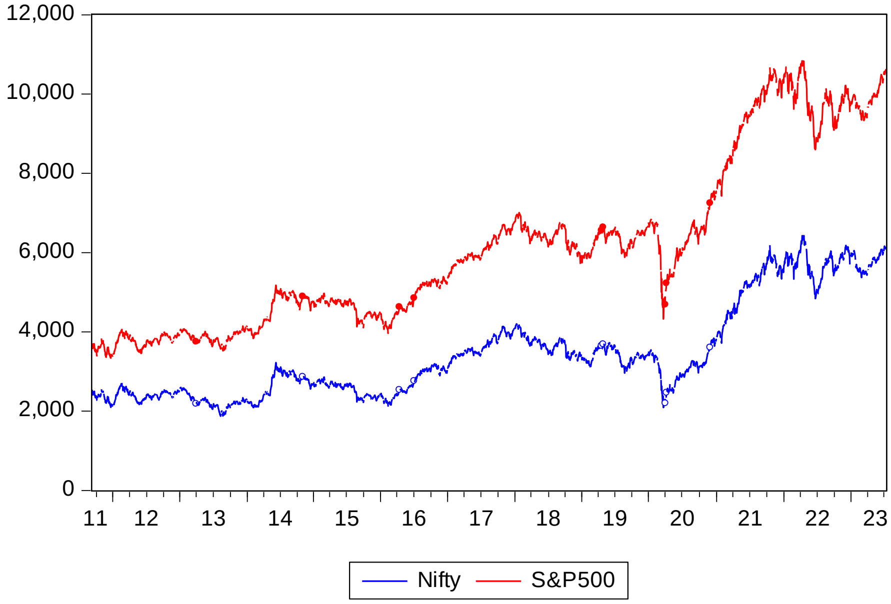
$$Y_t = \alpha_{20} + \alpha_{21} X_{t-1} + \ldots + \alpha_{2p} Y_{t-p} + \beta_{21} X_{t-1} + \ldots + \beta_{2q} X_{t-q} + \varepsilon_{2t}$$

Where:

X_t, Y_t are the time series. p, q are the lag orders. α, β are coefficients that need to be estimated and ε is the error term. The F-test or the chi-square test on the lagged coefficients β determines if the null of no causality can be rejected.

IV. Empirical Findings and Discussion

Descriptive Statistics

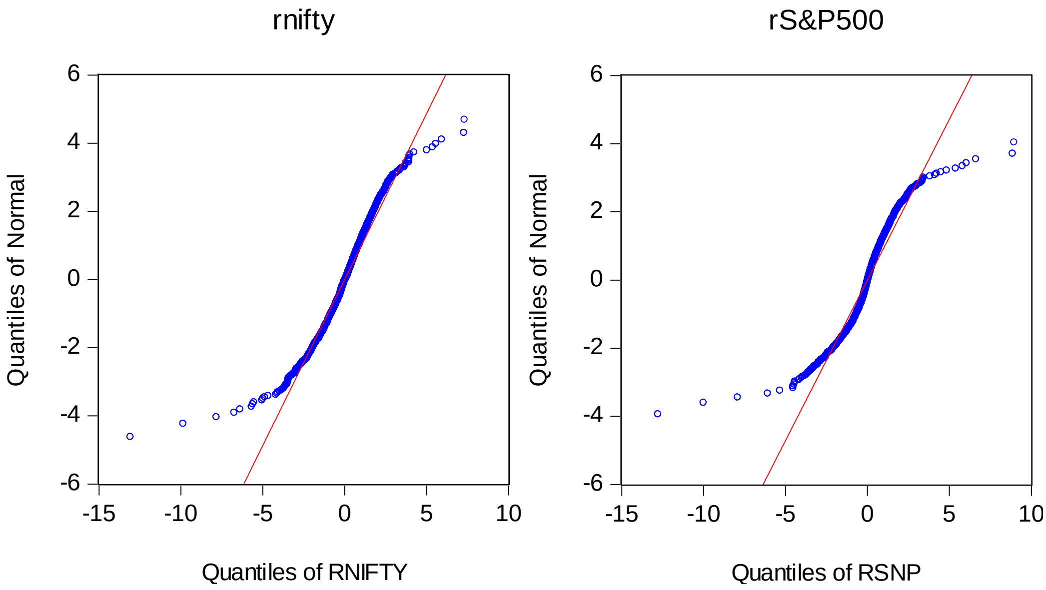


The returns for both the indices are calculated as the differences of the logarithmic daily prices of the indexes, [$\ln(P_t) - \ln(P_{t-1})$], where P is an index price. The period of observation is from 8th Sep 2011 to 14th July 2023. The days of no trading on any of the observed stock markets were left out. The total number of observations amounts to 2837 days. Table 1 presents some descriptive statistics of the data. The mean returns for both the Nifty and the S&P 500 indices are close to zero, indicating that they are centered around zero overall. The median returns are slightly positive, suggesting that more daily returns are positive than negative. The maximum and minimum show the presence of extreme returns: both positive and negative outliers. This indicates fat tails in the distribution. The standard deviations of around 1% are typical for daily stock index returns, indicating moderate volatility. Both the indices are negatively skewed, implying that the left tail is longer with more extreme negative returns compared to positive. High kurtosis values that exceed 3 show that the return distributions have fat tails and are leptokurtic compared to a normal distribution. The Jarque-Bera test statistics are highly significant, rejecting the null hypothesis of normality. The return distributions deviate from a normal distribution. In summary, the presence of extreme returns, high kurtosis, skewness, and non-normality indicate that the returns exhibit time-varying volatility clustering, fat tails and asymmetry, which are typically associated with financial time series data. This motivates the use of GARCH-type models like DCC that can capture these stylized facts.

Table 1Descriptive Statistics

	RNIFTY	RSNP
Mean	0.031284	0.047066
Median	0.083438	0.064327
Maximum	7.327245	8.968316
Minimum	-13.06602	-12.76521
Std. Dev.	1.302676	1.116277

Skewness	-0.740807	-0.739527
Kurtosis	10.03194	17.49889
Jarque-Bera	6102.520	25099.25
Probability	0.000000	0.000000
Observations	2836	2836



Before estimating a DCC(1,1)-GARCH(1,1) model, the series have to be filtered to assure a zero expected (mean) value of the time series. To check the series stationarity, the Augmented Dickey-Fuller test and the Phillips Perron tests are used. Both the tests show that the p-value is higher than 0.05, which leads to the acceptance of the null hypothesis of non-stationary series. To make the series stationary, the difference of natural logarithms is estimated. The difference of natural logarithmshasa unit root test p-value of 0.01, which leads to the rejection of the null hypothesis of non-stationary series. On the basis of the stationarity tests, we conclude that the time-series of indices returns are stationary. Therefore, to satisfy the basic assumption of the DCC-GARCH model, the return index is used in place of the price series.

Table 2. Unit Root Tests

(ADF)			(PP)	
At Level				
	RNIFTY	RSNP	RNIFTY	RSNP
With Constant	-15.20***	-15.0618***	-52.56***	-59.32***
With Constant & Trend	-15.2225***	-15.0729***	-52.56***	-59.31***
Without Constant & Trend	-15.1649***	-14.8067***	-52.57***	-59.32***
Notes: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1%. and (no) Not Significant				
*MacKinnon (1996) one-sided p-values.				

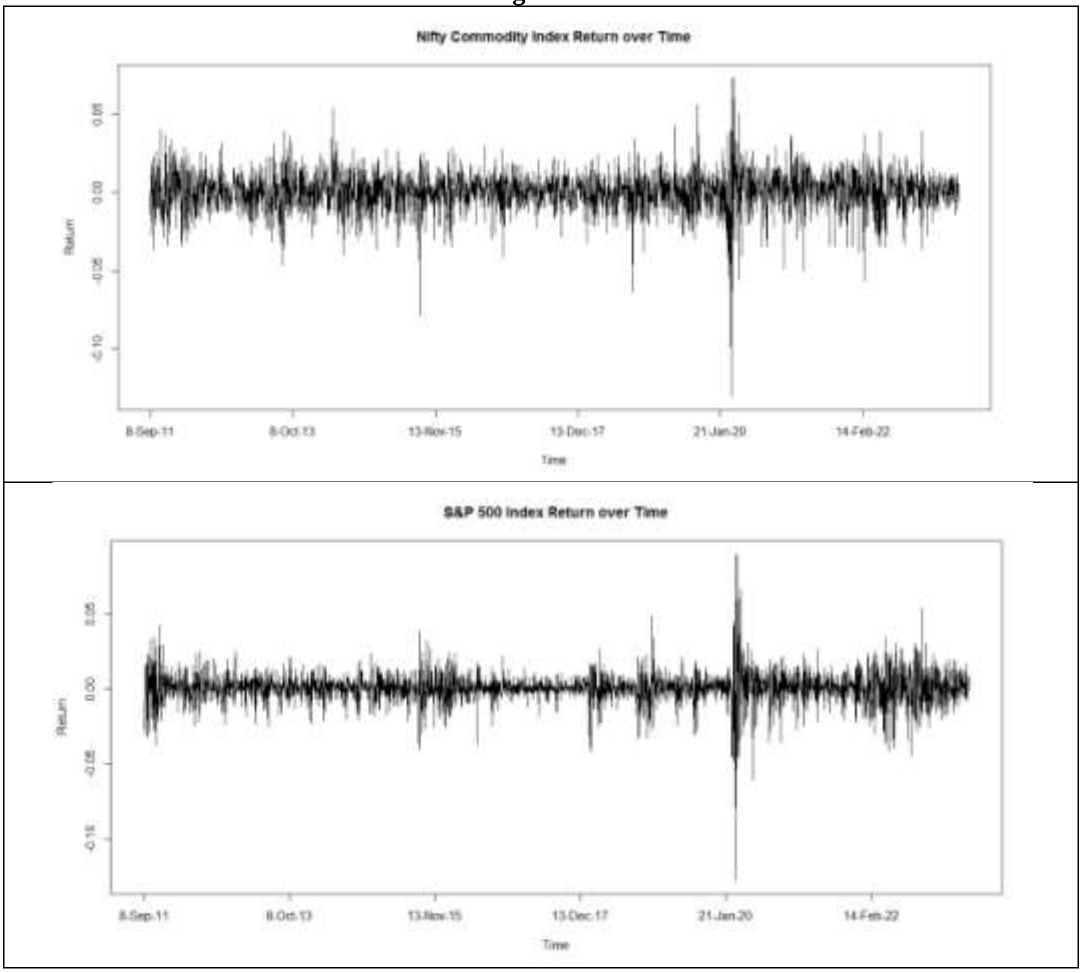
The ARCH-LM test is an important diagnostic check to avoidmisspecification and to ensure that GARCH is suitable before estimation (Tsay, 2005). The presence of ARCH (autoregressive conditional heteroskedasticity) effects, which manifest as volatility clustering in time series, needs to be formally tested before specifying a GARCH or DCC-GARCH model. The ARCH-LM (Lagrange multiplier) test examines the null hypothesis of no ARCH effects against the alternative that ARCH effects are present (Engle, 1982). For the Nifty and the S&P return series, the ARCH-LM test shows that p-values are significant at 1% level, thus, strongly rejecting the null of no ARCH. This implies that the returns exhibit time-varying volatility clustering that is typical in financial series, validating the use of GARCH-type models that can capture this. The presence of significant ARCH effects also provides useful insights into the return dynamics. Volatility clustering indicates that periods of high/low volatility are autocorrelated and are likely to be followed by similar volatility regimes. This has implications for risk management and forecasting. Table 3. Summarizes the results from the ARCH LM test.

Table 3. ARCH LM-test

Null hypothesis: no ARCH effects			
	Chi square	df	P Value
Return of NIFTY Index	536.34	12	2.20E-16
Return of SAP Index	1128.4	12	2.20E-16

Figure 1. depicts the daily returns for the NIFTY commodity Index and the S&P 500 Index with respect to time, which shows a similarity in the index price return. Both the indices have shown maximum variability in return where observation count is between 2000-2100.

Figure 1:



Here, the model fits a multivariate normal distribution to the Nifty and the S&P 500 return series. A DCC(1,1) specification is used with 1 lag for the volatility and correlation dynamics. For Nifty, the ARCH (α) and GARCH (β) coefficients are significant, indicating volatility clustering and persistence. β is close to 1, showing high persistence. The S&P also shows volatility clustering but a relatively lower persistence based on the coefficient values. The DCC parameters capture the correlation dynamics. dccb1 is highly significant, indicating varying correlations. dccb1 is close to 1, whichshows high persistence in correlations. dcca1 is insignificant. The information criteria values are all negative, indicating that the DCC model provides useful information gain over a simple model. In summary, the results indicate the presence of volatility clustering and time-varying correlations. The DCC(1,1) model suitably captures these dynamics based on significant parameter estimates and model fit metrics.

For the DCC-GARCH (1,1), a1 for S&P, a1 and b1 for Nifty, and joint b1 from the DCC-GARCH model are significant at 1% significant level. It can, therefore, be concluded that the DCC-GARCH (1,1) accurately captures both the univariate ARCH and GARCH structures of the time series as well as the interaction between the different assets. Furthermore, from the DCC-GARCH (1,1) in Table 4, it can be seen that all the individual GARCH series fulfill the criteria that $a + b < 1$. The DCC parameters also follow the same criteria. It can be seen that the joint parameter, a1+b1, has value of 0.9970, which is lesser than 1. The individual parameters are all larger than zero,and at the same time, the sum is less than 1, which ensures positive unconditional variance.

dcca1 provides the contribution of the realized correlation matrix from the last period while dccb1 provides the contribution of a long-run correlation matrix that is due to all the previous periods. Since dccb1 (p value=0.00) is significant at 1% significance level while dcca1 (p value=0.232) is not significant, we can conclude from our model that the S&P 500 Index has a long-term spillover effect on the NIFTY Commodity Index.

Some potential reasons for these findings can be the presence of new information flows and the fact that macroeconomic events create volatility clusters in stock returns. Market volatility gets amplified through leveraged positions and trading activity of investors. Periods of high or low volatility perpetuate due to the cascading effects of the initial shocks. Further, central bank announcements and policy changes may have induced volatility clusters especially during the episodes of financial crises. The high persistence can be due to structural factors like market microstructure and persistence-inducing trading patterns. In the case of time-varying correlations, evolving macro-financial links between India and the US markets cause dynamic correlations. Over the time, different policy and growth drivers have led to shifting correlations. The ongoing financial integration and globalization, with consistent bilateral trade and investment flows,mayhave induced persistent interdependence.

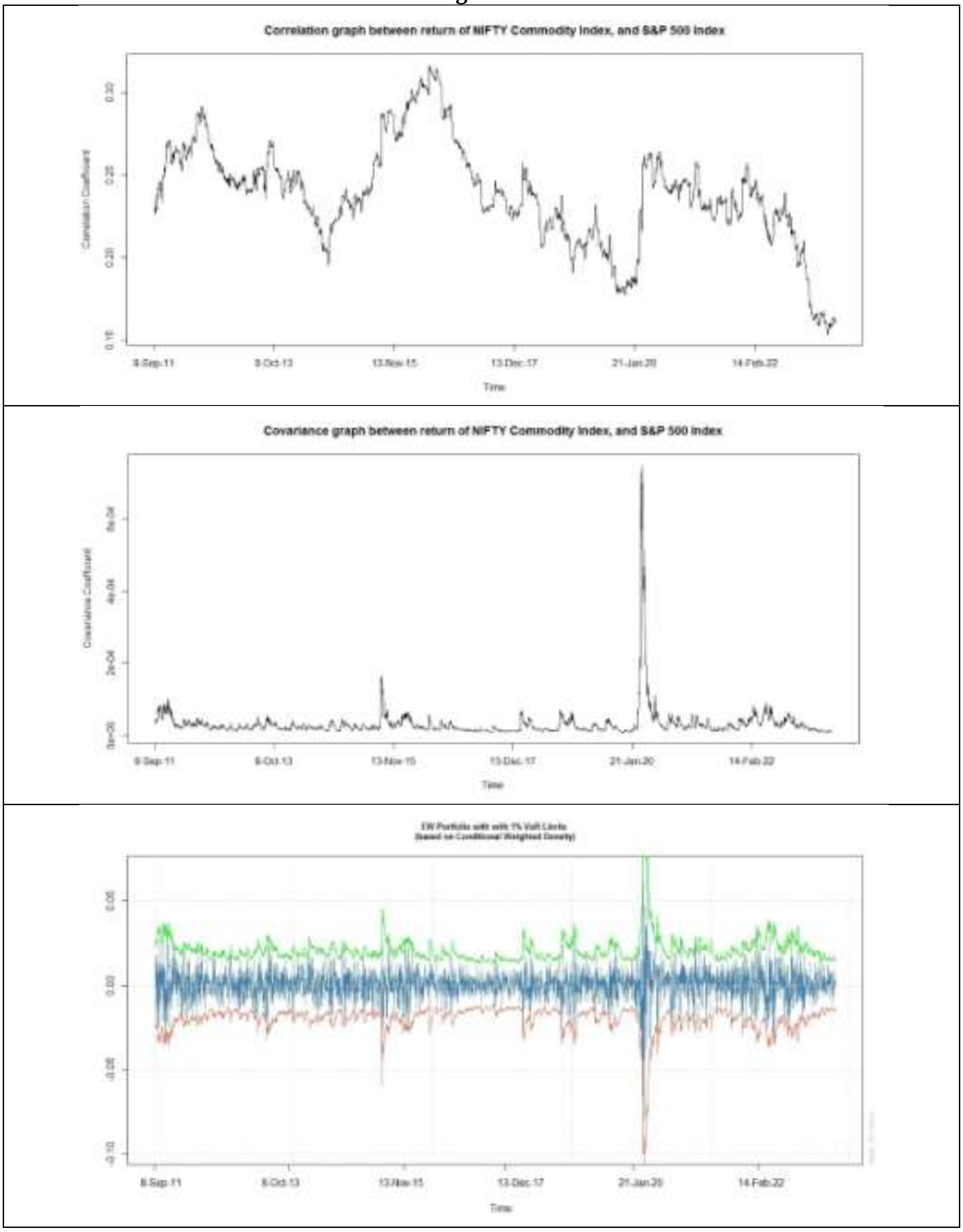
Table 4. Estimated DCC-GARCH

Optimal parameters	Estimate	Std. Error	t value	Pr(>|t|)
[Return of S&P].mu	0.0008	0.00048	0.7127	0.08677
[Return of S&P].omega	0.000004	0.00003	0.1260	0.8997
[Return of S&P].alpha1	0.17743	0.103045	0.7218	0.0850***
[Return of S&P].beta1	0.79248	0.248861	0.1844	0.00145***
[Return of NIFTY].mu	0.00051	0.000224	0.2776	0.0227
[Return of NIFTY].omega	0.00001	0.000001	0.8678	0.0001
[Return of NIFTY].alpha1	0.07287	0.005345	0.6330	0.0000***
[Return of NIFTY].beta1	0.89451	0.00977	0.5551	0.0000***
[Joint]dcca1	0.002405	0.002012	0.1954	0.2319
[Joint]dccb1	0.99531	0.00626	0.0162	0.0000***
Information Criteria				
Akaike	-12.661			
Bayes	-12.638			
Shibata	-12.661			
Hannan-Quinn	-12.652			

Notes: Significance at 1 percent "***" , 5 percent "**" , 10 percent "*"

Figure 2 shows that there are strong conditional correlations between the returns of the NIFTY commodity index and the S&P 500 index, indicating that the relationship between the Indian commodity market and the international stock market returns is temporarily variable. This is may be because the Indian commodity market has grown more independent of the global stock markets due to the Indian commodity market's robust macroeconomic conditions. This is seen by the pattern of falling correlation between it and those markets throughout the course of the observation period.

Figure 2:



Granger Causality

The Granger causality test results in the table 5 below confirm a significant bidirectional causality between the Nifty (RNIFTY) and the S&P 500 (RSAP) returns. For the first null hypothesis that "RNIFTY does not Granger cause RSAP", the low p-value of 0.0032 leads to the rejection of this null. This means that the Nifty returns do Granger cause or help predict the S&P 500 returns. There is causality from Nifty to S&P 500. For the second nullhypothesis that "RSAP does not Granger cause RNIFTY", the extremely low p-value again leads to the rejection of the null. This implies the S&P 500 returns Granger cause the Nifty returns. There is causality from S&P 500 to Nifty. Each return series provides information to help forecast the other, indicating interconnectedness and spillovers in both the directions between the Indian and the US equity markets.

Null Hypothesis:	**Lag(s)**	**F-Statistic**	**Prob.**	**Decision**
RNIFTY does not Granger CauseRSAP	1	8.71318	0.0032	Reject***

RSAP does not Granger Cause RNIFTY	162.576	0.0000	Reject***

These linkages can be attributed to the increasing financial and macroeconomic integration between India and the US, which allows news and shocks to rapidly transmit across markets, creating return predictability. Further, common exposure to global factors like oil and commodity cycles generates spillovers. Institutional investors who allocate capital across both markets inducecorrelated trading patterns. The contagion effects during crises and the structural factors like time zone lags also contribute. Overall, the deepening linkages and the exposure to common variables in an increasingly interdependent world underlie the bidirectional return predictability between the Indian and the US equity markets.

Policy Suggestions

The time-varying correlations between the Indian and the US markets point to the need for dynamic and adaptive risk management strategies by investors because such linkages evolve. Static hedging may be suboptimal. Regulators should account for greater interconnectedness and spillover effects when crafting policies related to international capital flows and financial stability. Policymakers should factor the transmission of overseas shocks into domestic policymaking, like the monetary and the fiscal policies. Global coordination may be warranted to manage contagion.

Portfolio managers should frequently rebalance and diversify across markets with changing correlations to optimize risk-adjusted returns. Dynamically weighted investing can improve performance. Regulators could implement trading halts or limits during crisis episodes to curb panic-induced contagion effects, which impair predictability. Macroprudential policies on bank leverage and credit growth monitoring can mitigate volatility transmission from the US financial shocks. Central banks should account for the US developments in setting policies for inflation, growth and liquidity management given. It is imperative to educate and guide retail investors aboutthe risks of chasing global trends without accounting for transient relationships and spillovers.

V. Conclusion:

This study investigated volatility transmission and time-varying correlations between the Indian commodity market, represented by the NIFTY index, and the US equity market proxied by the S&P 500, using the DCC-GARCH methodology proposed by Engle (2002). The presence of volatility clustering and ARCH effects validated the use of GARCH-type models like DCC that can capture heteroscedasticity in financial time-series (Bollerslev, 1986).

The DCC model estimates revealed significant volatility persistence in both the Nifty and the S&P 500 returns, which is evidenced by the high GARCH coefficients that are close to one, consistent with the findings in prior emerging market studies (Aloui et al., 2011). The DCC dynamic correlations were also highly persistent but declined over the sample period, indicating the presence of strong but time-varying interdependence across markets (Hassan & Malik, 2007).

The model diagnostics and information criteria indicated that DCC(1,1) suitably captured the return dynamics. The results align with Kuper and Lestano (2016) who also established linkages between emerging commodity and global equity markets using multivariate GARCH. However, the time-varying correlations provide greater insights than static modeling.

Overall, the DCC-GARCH analysis established a significant interconnectedness between the Indian commodity and the US equity markets but also demonstrated that these linkages evolve over time. The model provided a robust framework to uncover the transient cross-market return relationships. Volatilities of stock indices returns were more influenced by long-term correlation rather than by past return variation. Conditional correlations between the NIFTY Commodity Index and the global S&P 500 stock indices returns in the observed period were highly volatile and showed a declining trend over the period due to more resilientmacroeconomic conditions of the Indian economy. The findings have important implications for international portfolio diversification and risk management under uncertainty.

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