Volatility Transmissions Across International oil market, commodity futures and stock markets: Empirical evidence from India

Prepared in partial fulfillment of the requirements for the course -

Applied Econometrics (ECON F342)

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Highlights

The highlight of the paper is

- Empirical evidence of strong uni-directional shock and volatility spillovers from the stock market or oil market to the commodities market in India.
- The study also emphasizes the heterogeneous impact of crude oil prices on different commodity sectors, such as nonferrous metals, coal coke, steel ore, energy products, chemical products, grains, oils and fats, and soft commodities.
- The authors use a Vector Autoregression (VAR)(3) and the Generalized Variance Decomposition (GVD) method to analyze the dynamic volatility spillovers between crude oil prices and different commodity sectors.
- The study also explores the implications of these volatility spillovers for investors and policymakers, highlighting the importance of risk management strategies and policy formulation based on the findings.

Abstract

This study investigates the volatility transmissions across international oil markets, commodity futures, and stock markets, focusing on the context of India. The research explores the dynamic relationships among the Indian stock market, global oil prices, and key commodities in India using a trivariate VAR-BEKK-GARCH model. The findings reveal significant unidirectional return spillover effects from the oil market to the Indian stock market, indicating a strong dependence of the Indian stock market on oil prices. The study also identifies significant return interactions between the Indian stock market, global oil market, and major commodities in India. The analysis highlights the absence of return spillovers from the Indian stock market to the oil market, suggesting that the Indian stock market behaves independently from the oil market. Additionally, the study uncovers strong unidirectional return spillovers from the Indian stock market to specific commodity markets in India, such as copper and aluminum. The research emphasizes the importance of understanding these interdependencies for portfolio management and risk mitigation strategies in the Indian financial markets.

JEL Classification

G15; C51: C58: G11; C32

C32 - Multivariate Analysis: Panel Data

C51 - Modeling: Financial Econometrics

C58 - Financial Econometrics: Time Series Models

G11 - Portfolio Analysis: General

G15 - International Financial Markets

Keywords

Volatility transmissions, International oil market, Commodity futures, Stock markets, Empirical evidence, VAR-BEKK-GARCH model, Return spillover effect, Shock spillovers, Portfolio management, Hedge strategies.

Introduction

Financial markets are known for their complex and interconnected nature, where changes in one sector can have a significant impact on other sectors. This phenomenon has far-reaching implications for investors, policymakers, and the broader economic landscape. In this research paper, we delve into the intricate dynamic of volatility spillovers that exist between the international oil market, commodity futures markets, and the Indian stock market, specifically in the Indian context. Our primary objective is to investigate the manner in which fluctuations in one market, such as the rise and fall of oil prices, can impact the inherent stability and potential for price swings in other markets, such as the Indian stock market. To achieve our objective, we conducted a comprehensive review of relevant studies that have explored these interconnected markets. This meticulous examination enabled us to shed light on the complex market interrelationships. Specifically, we analyzed the following: the influence of oil price movements on the volatility of the Indian stock market, the price discovery and volatility transmission between futures and spot markets for Indian commodities, and the impact of macroeconomic factors on the volatility of Indian commodity futures. Our analysis revealed that there is a significant link between the international oil market and the Indian stock market. We found that changes in oil prices have a significant impact on the Indian stock market's volatility, indicating that the oil market acts as a leading indicator of the Indian stock market. Regarding commodities, we found that there is a strong link between futures and spot markets for Indian commodities. Price discovery in the futures market leads to the transmission of volatility to the spot market, indicating the importance of futures markets in determining prices in the commodity market. The findings of our research have several implications for investors, policymakers, and the broader economic landscape. For investors, understanding the complex dynamics at play is crucial for developing informed risk management strategies and making sound investment decisions. Policymakers can use the insights gleaned from this research to formulate effective regulatory policies for financial markets in India, fostering a more stable and predictable economic environment. In conclusion, our comprehensive exploration of volatility transmissions within the Indian financial landscape has shed light on the intricate web of interconnectedness that shapes the present and paves the way for a more informed future.

Literature Review

This research paper delves into the volatility spillovers between the international oil market and stock markets in developing Asian economies, focusing specifically on Karachi, Shanghai, Bombay, and the broader Indian market. The intricate interconnectedness of financial markets necessitates a thorough understanding of these spillovers, as fluctuations in one market can cascade and influence the stability of others. This phenomenon holds significant implications for investors, policymakers, and the broader economic landscape.

Existing Research:

A substantial body of research has explored the complex relationship between oil prices and stock market volatility. Notably, Sarwar, Tiwari, and Tingqiu (2014) employed a bivariate BEKK-GARCH model to analyze volatility spillovers in Karachi, Shanghai, and Bombay from 1997 to 2014. Their findings revealed:

- Bidirectional spillovers in Karachi, indicating a two-way interaction between oil and stock market volatility (Sarwar, Tiwari, & Tingqiu, 2014).
- Unidirectional spillovers in Shanghai, suggesting oil market volatility primarily impacting the stock market (Sarwar, Tiwari, & Tingqiu, 2014).
- Mixed evidence in Bombay, highlighting the need for further investigation (Sarwar, Tiwari, & Tingqiu, 2014).

Further enriching the understanding, Kumar and Maheswaran (2018) examined return and correlation spillovers between crude oil and various Indian industrial sectors. Their findings, utilizing bivariate GARCH and VAR models, emphasized the time-varying nature of these dynamics and offered valuable insights for portfolio construction and risk management in the Indian context (Kumar & Maheswaran, 2018).

Beyond the oil-stock market relationship, other scholars have explored related dimensions of this dynamic. Mahalik, Acharya, and Babu (Year) investigated price discovery and volatility spillovers between futures and spot markets in India (Mahalik, Acharya, & Babu, Year), while Sharma and Shrivastava (2019) examined the long-term linkages between oil prices and macroeconomic indicators in the Indian economy
(Sharma & Shrivastava, 2019). Additionally, Nandy (Pal) and Chattopadhyay (2016) explored the interdependence and volatility spillovers between the Indian stock market and other domestic and international markets (Nandy & Chattopadhyay, 2016), and Sreenu (2020) assessed the impact of crude oil price volatility on Indian stock market returns

(Sreenu, 2020). Finally, Mo, Gupta, Li, and Singh (2018) examined the influence of macroeconomic factors on the volatility of commodity futures in India and India (Mo, Gupta, Li, & Singh, Year).

Research Gaps

While existing research offers valuable insights, gaps remain in our understanding of volatility spillovers, particularly in the context of developing Asian economies. This study aims to contribute to the existing literature by:

1. Building upon the foundational studies mentioned above to offer a nuanced understanding of volatility spillovers between the oil market and Asian stock markets, with a specific focus on the aforementioned economies.

2. Employing sophisticated econometric models and comprehensive analysis to provide a holistic view of these complex dynamics.

3. Contributing knowledge that can be harnessed by investors, policymakers, and academics to navigate the intricate web of relationships within these vital financial markets.

By addressing these gaps, this research aspires to contribute to a more comprehensive understanding of volatility spillovers in the Asian context, ultimately informing informed decision-making and fostering a more stable and predictable financial environment.

Objectives

The objectives of the research paper titled "Volatility transmissions across international oil market, commodity futures and stock markets: Empirical evidence from India" multifaceted and aim to delve into the intricate relationships among the Indian stock market, commodity markets, and global oil markets. The study seeks to employ a sophisticated trivariate VAR-BEKK-GARCH model to analyze the dynamic interactions and volatility transmissions across these markets within the Indian context.

Detailed Objectives:

1. Investigate Volatility Transmissions: The primary goal is to explore how volatility is transmitted across the Indian stock market, commodity markets, and global oil markets. By examining the interconnectedness of these markets, the research aims to uncover the mechanisms through which changes in one market impact the others.

2. Empirical Evidence: The study intends to provide empirical evidence specific to India, shedding light on the unique dynamics of the Indian equity market, commodity markets, and their relationship with global oil markets. By focusing on the Indian context, the research aims to offer insights that are relevant and applicable to the Indian financial landscape.

3. Impact Analysis: Through a comprehensive analysis, the research aims to assess the impact of fluctuations in global oil prices on the Indian stock market and commodity markets. By understanding how volatility is transmitted across these markets, the study seeks to evaluate the implications for investors, policymakers, and market participants in India.

4. Market Interdependencies: By examining the interdependencies among the Indian stock market, commodity markets, and global oil markets, the research aims to uncover potential spillover effects and contagion risks. Understanding these linkages is crucial for risk management and decision-making in the Indian financial markets.

5. Policy Implications: The study aims to provide valuable insights for policymakers and regulators in India by highlighting the interconnected nature of these markets and the implications for market stability and efficiency. By identifying key relationships and transmission channels, the research can inform policy decisions aimed at enhancing market resilience and mitigating systemic risks.

In summary, the research paper seeks to offer a comprehensive analysis of volatility transmissions across the Indian stock market, commodity markets, and global oil markets, providing valuable empirical evidence and insights that are pertinent to understanding the dynamics of the Indian financial landscape.

Data

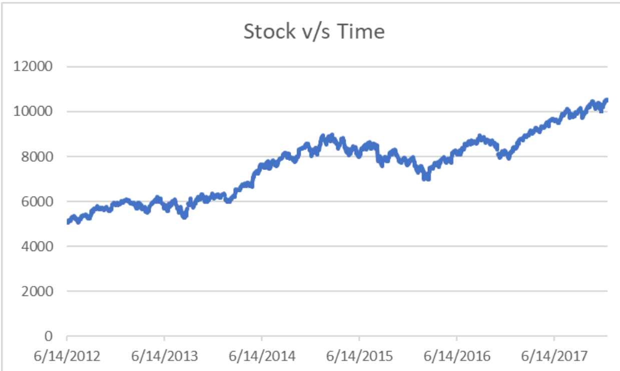
Introduction

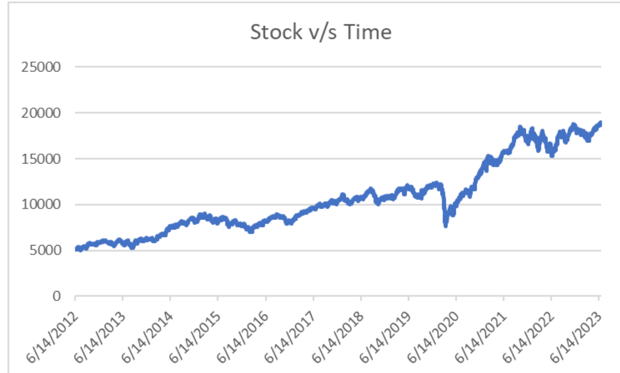
In this research, we examine the relationships between the stock market, the global oil market, and various commodity markets using a comprehensive trivariate VAR-BEKK-GARCH model. We select daily data on the Nifty50 index, Brent oil prices, and commodity futures over an extended period to represent the Indian stock market, global oil dynamics, and the broader commodity spectrum. We begin by conducting preliminary analyses, including stationarity tests, to ensure the reliability and suitability of our data for time-series modeling. We then use cointegration tests to examine the long-term relationships among these markets and gain insights into any persistent interdependencies. Our analytical lens, the VAR model, helps us to inspect return spillovers, which capture the linear interplays across the markets. We also use the BEKK-GARCH model to analyze the complex web of volatility spillovers, which offer insights into conditional variances and covariances. This dual analysis helps us to understand the directionality and magnitude of market interactions and sheds light on the implications for portfolio management and hedging strategies. Our study provides valuable insights into the interconnectedness of major financial markets and contributes to the existing literature.

The following graphs constitute the relations between oil,stock and commodities versus time based on the data that was gathered for the purpose of research from various sources.

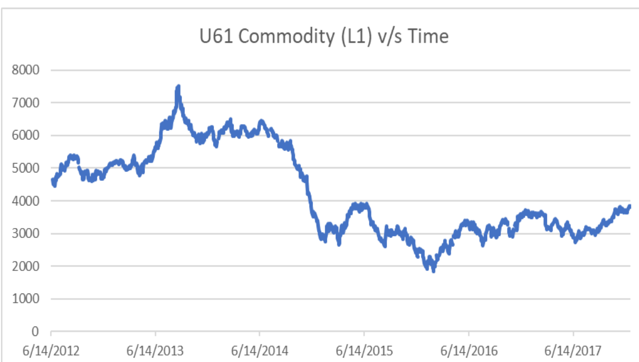
Bloomberg Notation	Commodity Name
U61	Crude oil
Y01	Copper
U52	Gold
Jl1	Silver
O91	Aluminum
T21	Wheat

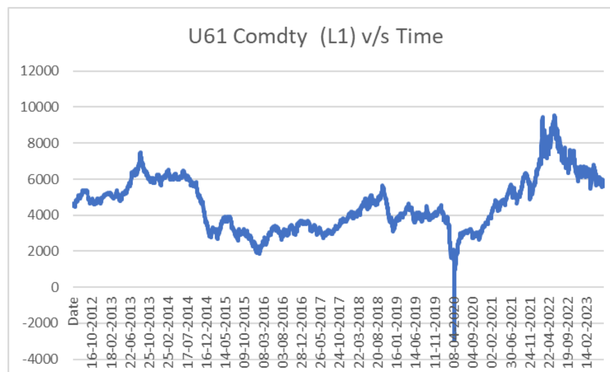
Graph 1 & 2: Stock v/s Time ((For the Year 2012-2017(left) and 2012-2023(right) respectively)



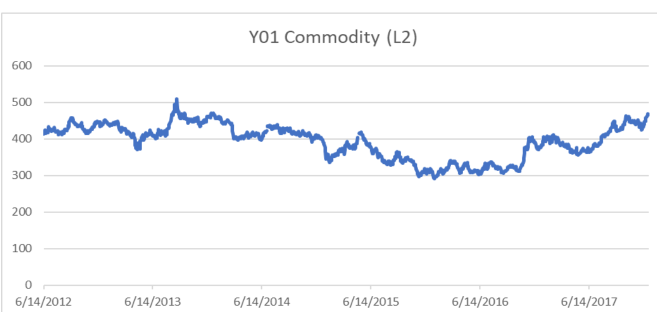


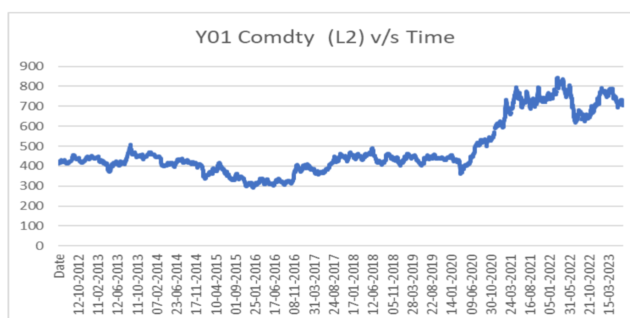
Graph 3 & 4: Crude Oil v/s Time ((For the Year 2012-2017(left) and 2012-2023(right) respectively)



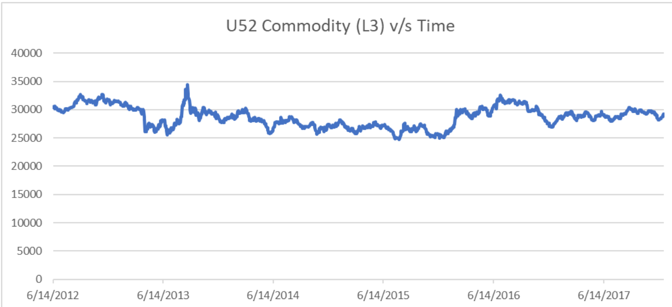


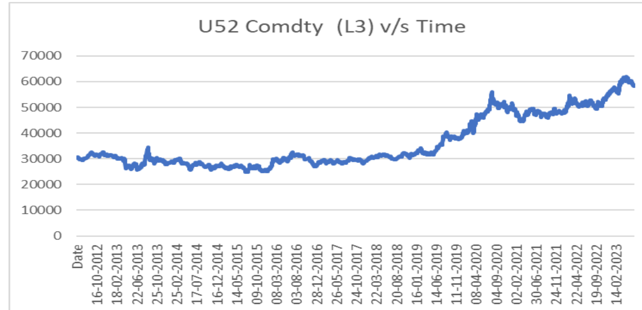
Graph 5 & 6: Copper Prices v/s Time ((For the Year 2012-2017(left) and 2012-2023(right) respectively)



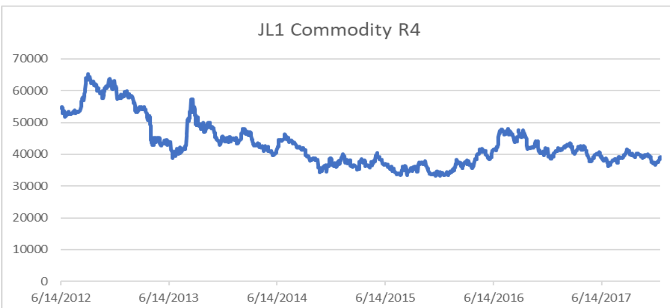


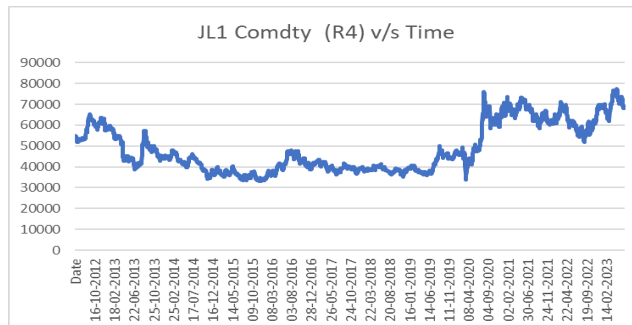
Graph 7 & 8: Gold Prices v/s Time ((For the Year 2012-2017(left) and 2012-2023(right) respectively)



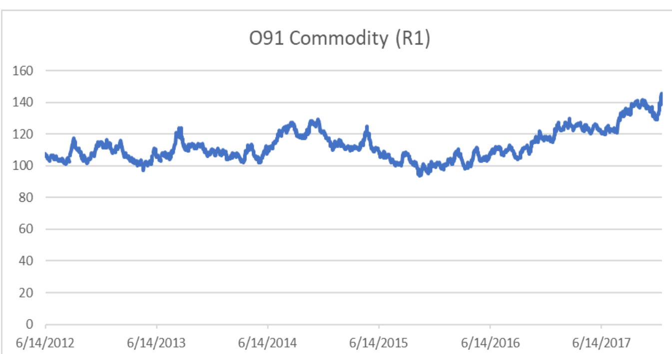


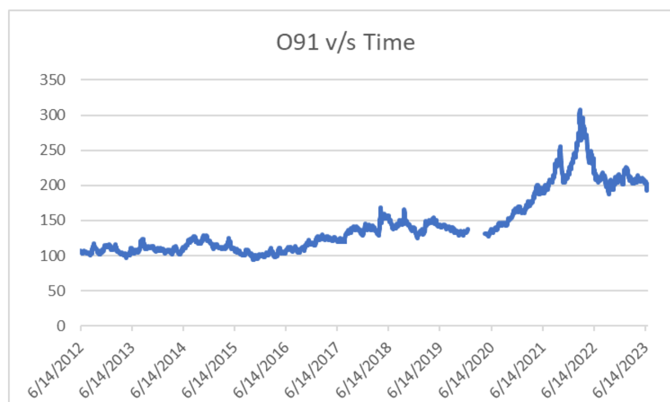
Graph 9 & 10: Silver v/s Time ((For the Year 2012-2017(left) and 2012-2023(right) respectively)



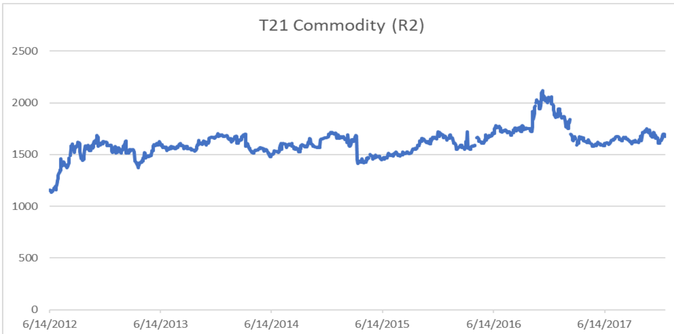


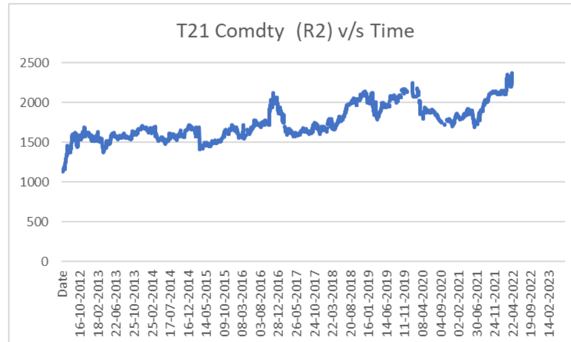
Graph 11 & 12: Aluminum Prices v/s Time ((For the Year 2012-2017(left)(right) and 2012-2023 respectively)





Graph 13 & 14: Wheat Prices v/s Time ((For the Year 2012-2017(left) and 2012-2023(right) respectively)





Methodological framework

Step 1: Data Selection and Preliminary Analysis

Our research delves into the return and volatility spillovers between the Indian stock market, the global oil market, and various commodity markets. The selection of our dataset focuses on the **Nifty50 index** to represent the Indian stock market, **Brent oil prices** as a proxy for the global oil market, and **specific commodity futures** depicting the commodity markets. The time period of the data included in this research spans from July 2, 2012, to June 30, 2017. The data sourced is to capture the market dynamics over a period marked by economic events and trends, thereby providing a robust basis for our investigation.

To ensure the integrity and appropriateness of our data for time-series analysis, preliminary tests, including the Augmented Dickey-Fuller test **(ADF)**, Phillips-Perron **(PP)** and Kwiatkowski-Phillips-Schmidt-Shin **(KPSS)** are done to assess **stationarity**. ADF, KPSS tests are a type of statistical test which are called **unit root test**.Unit root test is a feature of random walk which can cause problems in statistical inference which involves time series data. Hence if a series has a unit root then it is non-stationary. This step is important to validate if the data is suitable for further econometric modeling, as non-stationary data can lead to spurious results in time-series analysis.

Step 2: Testing for Cointegration

In this study, we aim to comprehensively explore the presence of long-term equilibrium relationships between the stock, oil, and commodity markets. To achieve this, we employ cointegration tests, specifically the Johansen and Juselius test, along with the ARDL bounds test. Cointegration testing is crucial in our research as it will reveal whether the examined variables, despite being non-stationary in their individual series, move together over time, thereby indicating a long-term alignment or equilibrium. This is vital for understanding the dynamics that govern these markets, as it provides insights into the underlying fundamental forces or economic mechanisms that connect these variables in the long run.

Our methodology is not only geared towards capturing the short-term interactions that are reflected in the day-to-day market movements but also seeks to anchor these observations within the broader context of long-standing, stable relationships. The equations utilized in these tests, along with the interpretation of their outcomes, are pivotal in providing a robust framework that guides our analysis.

Through this approach, we aim to unravel the complex web of interactions among these crucial economic variables, offering insights that are deeply rooted in both the immediate and enduring connections that shape market behaviors and trends.

Step 3: VAR Model for return spillover

The core of our analysis rests on the development and implementation of the Vector Autoregression (VAR) model, which is used to deconstruct the return spillovers across the Indian stock market, the global oil market, and an assortment of commodity markets. This model demonstrates our thorough methodology, accurately capturing the direct connections between these markets with precision. Through the mathematical formulation of the VAR model, we map out how past returns in one market exert influence over the present returns in another, providing a window into the complex dynamics that underpin these financial ecosystems. The selection of an appropriate lag order is a critical step in this process, determined through empirical tests that ensure our model captures the most relevant temporal relationships.

This careful adjustment of the VAR model not only improves the accuracy of our analysis but also enhances our understanding of how global financial markets are interconnected. By using this model, our goal is to study the complex network of return spillovers, providing insights that are both deep and practical for investors and policymakers as they navigate the landscape of global financial markets.

To determine the cointegration connections among the Pt^{st} , Pt^{oil} *and* Pt^{cm} series, we performed bound tests according to Johansen and Juselius (1990) and Pesaran et al. (2001). The VAR equation is as follows:

$$\mathbf{P_t = A_0 + \sum^{p}_{i=1} A_i P_{t-i} + e_i} \tag{1}$$

where $\mathbf{P_t = (P_t^{st}, P_t^{oil}, P_t^{cm})}$

Equation (1) can be written as:

$$\mathbf{\Delta P_t = A_0 + \pi P_{t-p} + \sum^{p-1}_{i=1} \tau_i \Delta P_{t-i} + \varepsilon_i} \tag{2}$$

where $\Delta P_t = A_0 + \Pi P_{t-p} + \sum^{p-1}_{i=1} \Gamma_i \Delta P_{t-i} + \varepsilon_i$

Trace statistic : $\mathbf{\lambda_{Trace}(r) = -T \sum^{n}_{i=r+1} \ln (1 - \lambda_{r+1})}$

Maximum eigenvalue statistic: $\mathbf{\lambda_{Max}(r) = -T \ln (1 - \lambda_{r+1})}$,

The sample size is denoted by T, while λ_i represents the highest canonical correlation.

The Autoregressive Distributed Lag (ARDL) technique, which can be applied without taking into account whether the time series are I(0) or I(1), is necessary for the limits testing procedure. The ARDL approach allows test co-integration among time series integrated of different orders smaller than I(2), in contrast to other widely used cointegrating approaches. We can write our equation as follows:

We can thus specify our equation as:

$$\Delta P^{st}_{t} = a_i + \Sigma^{qi}_{i=1} b_i \,\Delta P^{st}_{t-i} + \Sigma^{q2}_{i=1} c_i \,\Delta P^{oil}_{t-i} + \Sigma^{q3}_{i=1} d_i \,\Delta P^{cm}_{t-i} + \lambda_1 P^{st}_{t-1} + \lambda_2 P^{oil}_{t-1} + \lambda_3 P^{cm}_{t-1} + \varepsilon_t \quad (3)$$

Step 4: Dynamic Volatility Spillovers in Global Markets: Insights from a BEKK-GARCH

Model Analysis of Stock, Oil, and Commodity Interactions Our research paper showcases a comprehensive analysis of the intricate dynamics governing volatility spillovers among the stock, oil, and commodity markets. We employ the highly sophisticated BEKK-GARCH model, which allows us to thoroughly explore how market volatilities interact and influence each other over time. With this framework, we construct a detailed picture of the conditional variance-covariance matrix, which plays a pivotal role in understanding the complex web of volatility transmissions among these financial markets. The BEKK-GARCH model's structure is designed to capture the dynamic interplay of volatilities, enabling us to identify the direct impacts of market-specific shocks and the cross-market effects that such shocks may trigger. By employing this approach, we can unravel the nuanced mechanisms through which volatility spillovers occur, offering invaluable insights into the broader market dynamics. Furthermore, our analysis sheds light on the conditional variances and covariances that underpin these markets, providing a robust foundation for developing more effective risk management and hedging strategies. This is particularly important in the current volatile landscape of global markets. Applying the BEKK-GARCH model in our study significantly enhances our understanding of financial market volatility, contributing to the broader discourse on financial econometrics. It offers practical implications for investors and policymakers aiming to navigate the complexities of global markets.

We examine the return and volatility transmission in India using the trivariate BEKK-GARCH approach (Engle and Kroner, 1995). We can express our model under the conditional mean equation and conditional variance equation by including the VAR(1) element in BEKK-GARCH. The following summarizes the conditional mean model of VAR(1):

The below equation gives conditional mean model of VAR(1):

$$\mathbf{R_t = \mu + GR_{t-1} + \varepsilon_t, \ \ \varepsilon_t | \Omega_{t-1} \sim N(0,H_t)} \quad \mathbf{(4)}$$

Where Rt stands for a vector representing the returns on the stock, oil, and commodity markets. G is a three-by-three matrix containing the VAR coefficients, and εt is a Gaussian error vector. μ is a constant vector.

A BEKK-GARCH model was presented by Engle and Kroner (1995) to address VECH parameterization issues by streamlining the estimation procedure. This approach significantly streamlines the estimate procedure by releasing the positive limitation on the conditional variance matrix through the usage of quadratic forms. The following is the specification of the conditional variance equations:

$$\mathbf{H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B} \quad \mathbf{(5)}$$

Where the matrices A,B and C are:

$\begin{aligned} & H_t=\left[\begin{array}{lll}h_{11, t} & h_{12, t} & h_{13, t} \\ h_{21, t} & h_{22, t} & h_{23, t} \\ h_{31, t} & h_{32, t} & h_{33, t}\end{array}\right], C=\left[\begin{array}{lll}c_{11} & & \\ c_{21} & c_{22} & \\ c_{31} & c_{32} & c_{33}\end{array}\right], \\ & A=\left[\begin{array}{lll}a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33}\end{array}\right] \text { and } B=\left[\begin{array}{lll}b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33 .}\end{array}\right]\end{aligned}$ (**using Mathpix)**

$$\begin{aligned} & H_t=\left[\begin{array}{lll}h_{11, t} & h_{12, t} & h_{13, t} \\ h_{21, t} & h_{22, t} & h_{23, t} \\ h_{31, t} & h_{32, t} & h_{33, t}\end{array}\right], C=\left[\begin{array}{lll}c_{11} & & \\ c_{21} & c_{22} & \\ c_{31} & c_{32} & c_{33}\end{array}\right], \\ & A=\left[\begin{array}{lll}a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33}\end{array}\right] \text { and } B=\left[\begin{array}{lll}b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33 .}\end{array}\right]\end{aligned}$$

The conditional variance for each market, ignoring the constant coefficients, can be expanded as follows:

$$h_{11,t} = a^2_{11}\varepsilon^2_{st,t-1} + 2a_{11}a_{12}\varepsilon_{st,t-1}\varepsilon_{oil,t-1} + 2a_{11}a_{31}\varepsilon_{st,t-1}\varepsilon_{cm,t-1} + a^2_{21}\varepsilon^2_{oil,t-1} + 2a_{21}a_{31}\varepsilon_{oil,t-1}\varepsilon_{cm,t-1} + a^2_{31}\varepsilon^2_{cm,t-1} + b^2_{11}h_{11;t-1} + 2b_{11}b_{12}h_{12,t-1} + 2b_{11}b_{31}h_{13,t-1} + b^2_{21}h_{22;t-1} + 2b_{21}b_{31}h_{23,t-1} + b^2_{31}h_{33,t-1} \quad (6)$$

$$h_{22,t} = a^2_{12}\varepsilon^2_{st,t-1} + 2a_{12}a_{22}\varepsilon_{st,t-1}\varepsilon_{oil,t-1} + 2a_{12}a_{32}\varepsilon_{st,t-1}\varepsilon_{cm;t-1} + a^2_{22}\varepsilon^2_{oil;t-1} + 2a_{22}a_{32}\varepsilon_{oil,t-1}\varepsilon_{cm,t-1} + a^2_{32}\varepsilon^2_{cm,t-1} + b^2_{12}h_{11,t-1} + 2b_{12}b_{22}h_{12,t-1} + 2b_{12}b_{32}h_{13,t-1} + b^2_{22}h_{22,t-1} + 2b_{22}b_{32}h_{23,t-1} + b^2_{32}h_{33,t-1} \quad (7)$$

$$h_{33,t} = a^2_{13}\varepsilon^2_{st,t-1} + 2a_{13}a_{23}\varepsilon_{st,t-1}\varepsilon_{oil,t-1} + 2a_{13}a_{33}\varepsilon_{st,t-1}\varepsilon_{cm,t-1} + a^2_{23}\varepsilon^2_{oil,t-1} + 2a_{23}a_{33}\varepsilon_{oil,t-1}\varepsilon_{s3t,t-1} + a^2_{33}\varepsilon^2_{cm,t-1} + b^2_{13}h_{11,t-1} + 2b_{13}b_{23}h_{12,t-1} + 2b_{13}b_{33}h_{13,t-1} + b^2_{23}h_{22,t-1} + 2b_{23}b_{33}h_{23,t-1} + b^2_{33}h_{33,t-1} \quad (8)$$

The effect of past shocks and historical volatility to the current conditional variance are captured by the diagonal elements of matrices A(a11, a22, and a33) and B(b11, b22, and b33), respectively. Conversely, the volatility spillovers across the markets are measured by the off-diagonal elements of matrices A (e.g., a12, a13, and a21) and B (e.g., b12, b13, and b21). During the estimate procedure, the error terms' normal distribution should be used to maximize the following logarithm likelihood function:

$$L(\theta) = \sum^{T}_{t=1} \{L_t(\theta)\} \quad (9)$$

The log-likelihood function of the joint distribution is given as:

$$L_t(\theta) = -\ln(2\pi) - 1/2 \ln|H_t| - ½\, \varepsilon_t' H^{-1}_t \varepsilon_t \quad (10)$$

Step 5: Unveiling Market Dynamics: A VAR-BEKK-GARCH Model Analysis of Return and Volatility Spillovers Among Stock, Oil, and Commodity Market

In our research, we leverage the VAR-BEKK-GARCH model as a pivotal tool, enabling a detailed investigation into the behavior and interaction of return and volatility spillovers among stock, oil, and commodity markets. This comprehensive econometric approach combines the strength of the VAR model in analyzing return spillovers with the BEKK-GARCH model's ability to map out the intricate patterns of volatility interactions. Through careful examination of the model's results, we systematically explore how historical returns and volatilities in these markets affect future market dynamics. This thorough analysis helps us identify the paths and strengths of these spillovers, offering a deep dive into the complex relationships between markets. By unraveling these sophisticated connections, our research not only reveals the fundamental mechanisms of market interplay but also provides valuable guidance for developing strategies in portfolio management and risk reduction. The insights derived from the VAR-BEKK-GARCH model analysis greatly enhance our comprehension of financial markets, delivering critical information useful to investors, policy makers, and scholars.

Results and Discussions

Two set of results have been obtained:
1. Results for 2012-2023
2. Pre Covid(2012-2017, only till 2017 due to data constraints of wheat)

Following are the assumptions that were used to obtain these results:

Assumptions:

1. The analysis is divided into two parts, one includes both post-covid and pre-covid period and the second one includes only pre-covid period.
2. The unavailable values in the data set are replaced by the average value of data in that column.
3. Since data for commodity Wheat is not available since the Year 2017, the commodity is not included in the complete analysis of the data, instead is only included in pre-covid analysis.
4. Values in the data set are converted into log values.

Table 1: Descriptive Statistics for Indian Market Returns (For the Year 2012-2023)

	Nifty Returns	Crude Oil Returns	Copper Returns	Gold Returns	Silver Returns	Aluminium Returns
nobs	2932	2932	2932	2932	2932	2932
NAs	0	0	0	0	0	0
Minimum	-0.129805	-3.008357	-0.064568	-0.079102	-0.112211	-0.089813
Maximum	0.087632	0.459085	0.077251	0.05698	0.092629	0.111194
1. Quartile	-0.003479	-0.003953	-0.005987	-0.004128	-0.006566	-0.006056
3. Quartile	0.005121	0.011168	0.006409	0.004574	0.006785	0.005865
Mean	0.000586	0.001964	0.000226	0.000234	0.000156	0.000219
Median	0.00052	0.002916	0.00022	0.00023	0.00015	2.00E-04
Sum	1.718724	5.757614	0.663771	0.687342	0.457372	0.642926
SE Mean	0.000181	0.001135	0.000214	0.00016	0.000276	0.000215
LCL Mean	0.000232	-0.000262	-0.000194	-7.90E-05	-0.000385	-0.000203
UCL Mean	0.000941	0.00419	0.000646	0.000548	0.000697	0.000642
Variance	9.60E-05	0.003779	0.000135	7.50E-05	0.000223	0.000136
Stdev	0.009786	0.061474	0.011598	0.008661	0.014937	0.011666
Skewness	-1.014701	-39.864479	0.035916	-0.124268	-0.19016	0.413569
Kurtosis	19.317559	1960.4071	2.893969	6.906319	6.936298	7.29834

Table 2: Descriptive Statistics for Indian Market Returns (For the Year 2012-2017)

	NIFTY Index	Crude Oil	Copper	Gold	Silver	Aluminum	Wheat
Mean	0.000474	-0.0001592	0.00007436	-0.00002399	-0.0001761	0.0001138	0.0003282
Median	0.0000	0.000	0.000	0.000	0.000	0.000	0.00
Maximum	0.036631	0.0894309	0.06221	0.05698	0.0926288	0.0482456	0.0846325
Minimum	-0.059151	-0.0690731	-0.05288	-0.07910	-0.092493	-0.0525253	-0.1369
Std. Dev.	0.00813	0.018500	0.01127	0.0088	0.013	0.0103	0.0111
Skewness	-0.3576	0.3965	0.1531	0.1468	0.1545	0.3828	-1.2816
Kurtosis	4.20124	2.5768	2.4411	9.2442	5.8648	1.870589	27.93668
JB	1153.1	461.95	384.83	5425.8	2188.88	259.83	49892

Table 3: Unit Root Tests (For the Year 2012-2023)

	NIFTY Index	Crude Oil	Copper	Gold	Silver	Aluminum
ADF^L	-2.82	-1.8686	-1.6385	-1.636	-2.0804	-2.124
PP^L	-2111.5	-12.991	-16.893	-10.474	-10.283	-30.727
$KPSS^L$	25.531	4.6784	18.19	23.156	11.535	21.958
ADF^R	-20.025	-15.399	-15.932	-15.548	-14.415	-14.953,
PP^R	-3448.3	-3413.2	-3501.6	-3369.2	-3528.8	-3375.9
$KPSS^R$	0.0072337	0.056409	0.073701	0.20178	0.136	0.037953

Table 4: Unit Root Tests (For the Year 2012-2017)

	NIFTY Index	Crude Oil	Copper	Gold	Silver	Aluminum	Wheat
ADF^L	-2.4155	-1.5696	-2.7796	-3.0342	-2.4824	-2.8707	-2.4479
PP^L	-1136.3	-18.527	-14.248	-19.519	-11.695	-21.71	-24.788
$KPSS^L$	16.07	12.249	7.6808	2.6533	10.475	5.1833	6.0222
ADF^R	-17.848	-14.243	-10.868	-11.34	-10.715	-11.8	-12.006
PP^R	-1781	-1731.1	-1849.5	-1746.4	-1847.8	-1820	-1740.5
$KPSS^R$	0.0065195	0.06135	0.15817	0.036791	0.063651	0.12146	0.10552

Note: Return data, or descriptive statistics, are expressed in percentages. We include an intercept in the test equation for ADF and PP tests. Level data are represented by ADF^L, PP^L, and $KPSS^L$, whereas return series, or the first difference of the level data, are represented by ADF^R, PP^R, and $KPSS^R$. While ADF^L and PP^L are not significant, with the exception of t21, ADF^R and PP^R are all significant at the 1% level. With the exception of wheat, $KPSS^R$ are not significant, while $KPSS^L$ are all significant at the 1% level in the KPSS test, which uses the time series as its null hypothesis.

Table 5: Correlations Matrix (For the Year 2012-2023)

	NIFTY	Crude Oil	Copper	Gold	Silver	Aluminum
NIFTY	1.000	0.380	0.842	0.833	0.606	0.904
Oil	0.380	1.000	0.637	0.366	0.494	0.538
Copper	0.842	0.637	1.000	0.858	0.828	0.928
Gold	0.833	0.366	0.858	1.000	0.828	0.839
Silver	0.606	0.494	0.828	0.828	1.000	0.674
Aluminum	0.904	0.538	0.928	0.839	0.674	1.000

Table 6: Correlations Matrix (For the Year 2012-2017)

	NIFTY	Crude Oil	Copper	Gold	Silver	Aluminum	Wheat
NIFTY	1	0.0344	-0.0088	-0.23	-0.077	-0.0316	0.0257
Crude Oil	0.0344	1	0.291	0.086	0.1501	0.2342	0.032
Copper	-0.009	0.291	1	0.214	0.325	0.533	0.051
Gold	-0.237	0.086	0.214	1	0.7653	0.19018	-0.03
Silver	-0.077	0.150	0.325	0.765	1	0.2156	-0.033
Aluminum	-0.032	0.234	0.53	0.191	0.2156	1	0.0174
Wheat	0.025	0.032	0.05	-0.0317	-0.033	0.017	1

Table 7: Cointegration Test Results (For the Year 2012-2023)

H*0*	Copper		Gold		Silver		Aluminum		Wheat	
	Tr	Max	Tr	Max	Tr	Max	Tr	Max	Tr	Max
None	38.81	25.73	26.27	13.43	30.49	15.85	107.7	96.33	-	-
At most 1	13.08	9.15	12.84	8.60	14.64	9.76	11.37	7.95	-	-
At most 2	3.93	1.62	4.24	4.24	4.89	4.89	3.42	3.42	-	-

Johansen and Juselius Cointegration Test Results

Table 8: Cointegration Test Results (For the Year 2012-2017)

H*0*	Copper		Gold		Silver		Aluminum		Wheat	
	Tr	Max	Tr	Max	Tr	Max	Tr	Max	Tr	Max
None	27.01	14.09	25.64	14.84	20.12	13.77	33.09	19.19	-	-
At most 1	12.92	11.31	10.80	8.69	6.35	4.41	13.90	11.84	-	-
At most 2	1.62	1.62	2.12	2.12	1.94	1.94	2.06	2.06	-	-

Johansen and Juselius Cointegration Test Results

Note:Our approach to the Johansen and Juselius cointegration test, we incorporate both a linear deterministic trend and an intercept within the cointegration equation, opting for lag selection based on the Akaike Information Criterion (AIC). Given that wheat prices have been found to be stationary by the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, employing the Johansen and Juselius Cointegration Test is not suitable. The terms "Tr" and "Max" correspond to the Trace statistics and the Max-Eigen statistics, respectively.

Table 9: VAR-BEKK-GARCH results(For the Year 2012-2017)

	Gold	Silver	Copper	Aluminum	Wheat
Mean Equations					
Dependent Variable : R_{st}					
Constant	3.85 ***	4.81***	2.69 ***	2.82 ***	1.988 ***
R_{st} (-1) – g_{11}	0.7529 ***	0.699 ***	0.748 ***	0.578 ***	0.73 ***
R_{oil} (-1) – g_{12}	-0.089 ***	-0.069 ***	-0.125 ***	-0.15 ***	-0.088 ***
R_{cm} (-1) – g_{13}	-0.088 *	-0.145 ***	0.100 **	0.47 ***	0.148 ***
Dependent Variable : R_{oil}					
Constant	0.634 *	0.344	0.300 *	0.472 ***	0.45 *
R_{st} (-1) – g_{21}	-0.029 **	-0.023*	-0.0383 ***	-0.047 ***	-0.028 **
R_{oil} (-1) – g_{22}	0.9724 ***	0.97 ***	0.940 ***	0.965 ***	0.972 ***
R_{cm} (-1) – g_{23}	-0.0142	0.010	0.089 ***	0.049 *	0.0037
Dependent Variable : R_{cm}					
Constant	0.117 *	0.161 *	6.34 **	0.084 **	0.104 *
R_{st} (-1) – g_{31}	0.0012	-0.006 .	-0.00009 ***	-0.0001	0.00515 .
R_{oil} (-1) – g_{32}	0.0015	0.0011	0.00032	-0.0004	0.0006
R_{cm} (-1) – g_{33}	0.986 ***	0.988 ***	0.98	0.98 ***	0.978 ***
Conditional Variance Equations					
C(1,1)	0.18625448	0.18625448	0.18625448	0.18625448	0.18625448
C(2,1)	0.19656072	-0.19656072	-0.19656072	-0.19656072	-0.19656072
C(2,2)	0.24482756 ***	0.24482756	0.24482756	0.0.24482756	0.24482756
C(3,1)	0.01625345	-0.10517928	-0.04740207	0.04504578	0.03203480
C(3,2)	0.00228450	0.03463444	0.08582168	0.03247693	-0.00286265

C(3,3)	0.06113411 ***	0.11904677	0.07470287	0.06177110	0.07231627
A(1,1)	0.10000000	0.10000000	0.10000000	0.10000000	0.10000000
A(1,2)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
A(1,3)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
A(2,1)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
A(2,2)	0.10000000	0.10000000	0.10000000	0.10000000	0.10000000
A(2,3)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
A(3,1)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
A(3,2)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
A(3,3)	0.10000000	0.10000000	0.10000000	0.10000000	0.10000000
B(1,1)	0.80000000	0.80000000	0.80000000 ***	0.80000000 ***	0.80000000 ***
B(1,2)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
B(1,3)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
B(2,1)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
B(2,2)	0.80000000	0.80000000 ***	0.80000000 ***	0.80000000 ***	0.80000000 ***
B(2,3)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
B(3,1)	0.02000000	0.02000000	0.02000000	0.02000000	0.02000000
B(3,2)	0.02000000 ***	0.02000000	0.02000000	0.02000000	0.02000000
B(3,3)	0.80000000 ***	0.80000000 ***	0.80000000 ***	0.80000000 ***	0.80000000 ***

Table 10: VAR-BEKK-GARCH results(For the Year 2012-2023)

	Gold	Silver	Copper	Aluminum
Mean Equations				
Dependent Variable : R_{st}				
Constant	-0.575 ***	0.23	1.58309*	2.928***
R_{st} (-1) – g_{11}	0.675	0.835***	0.65195*	0.3765 ***
R_{oil} (-1) – g_{12}	0.339 ***	-0.0006	-0.13582*	0.784059***
R_{cm} (-1) – g_{13}	-0.088 *	0.1198 ***	0.44959*	0.47 ***
Dependent Variable : R_{oil}				
Constant	0.073	0.0417	0.141980 *	0.179 ***
R_{st} (-1) – g_{21}	0.0013	-0.00038	-0.011973*	-0.017 *
R_{oil} (-1) – g_{22}	0.985 ***	0.982***	0.974452*	0.978***
R_{cm} (-1) – g_{23}	0.006224	0.0097949	0.029687*	0.031065 **
Dependent Variable : R_{cm}				
Constant	0.0418 *	0.0642 **	-0.021760	0.0098
R_{st} (-1) – g_{31}	0.001	0.000877	0.011469*	0.0028
R_{oil} (-1) – g_{32}	0.001748	0.003612	0.012658*	0.0045 *
R_{cm} (-1) – g_{33}	0.994 ***	0.990467	0.969041*	0.984 ***
Conditional Variance Equations				
C(1,1)	0.069484452	0.069484452	0.0694845	0.06948445 ***
C(2,1)	0.024053847 ***	0.025965528 ***	0.0236498 ***	0.02740453 ***
C(2,2)	0.064568110 ***	0.064568110	0.0645681	0.06456811 ***
C(3,1)	0.040272370 ***	0.022115468 ***	0.0389658	0.04623604
C(3,2)	0.005840639 ***	0.017947812 ***	0.0241612	0.01288460 ***
C(3,3)	0.03142006 ***	0.035726160 ***	0.0248732 ***	0.02105830 ***
A(1,1)	0.869707948 ***	0.872125533 ***	0.831538 ***	0.77528164 **

A(1,2)	0.018584591 *	0.016579090 *	0.00624363	0.00808119
A(1,3)	0.031481923 **	0.033513278 **	0.0463639 **	0.09052866 ***
A(2,1)	-0.01685335 *	-0.013761463 *	-0.0254479 **	-0.01607198
A(2,2)	0.989257011 ***	0.995285875 ***	0.951007 ***	0.96068837 ***
A(2,3)	0.008921059	-0.001155144	0.0149291	-0.01407049
A(3,1)	0.002371171	-0.008740703 *	0.0000175837	0.02056333
A(3,2)	-0.001235899	-0.000823562	-0.000190603	-0.00869206
A(3,3)	0.98462519 ***	0.995776326 ***	0.955461 ***	0.93876208 ***
B(1,1)	0.510490192 ***	0.492425388 ***	0.544514 ***	0.56357351 ***
B(1,2)	-0.042342524 ***	-0.041959781 ***	-0.0224487 ***	-0.04767637 ***
B(1,3)	-0.067763374 ***	-0.078567638 *	0.02000000 ***	-0.05971454 **
B(2,1)	0.011156227	0.018017959 ***	0.0283646 ***	-0.01241564
B(2,2)	0.272189199 ***	0.242277122 ***	0.337706 ***	0.29831130 ***
B(2,3)	0.003451003	0.004143105	0.02000000 *	0.05693787 **
B(3,1)	-0.000106484	0.011986279 ***	-0.00407618	-0.00689925
B(3,2)	0.007651022 *	0.009118545 ***	-0.00648869	0.00152333
B(3,3)	0.264130995 ***	0.233983896 ***	0.316478 ***	0.31062951 ***

Note: *, **, * indicate statistical significant levels at 10%, 5%, and 1% respectively.**

VAR-BEKK-GARCH Results

Table 10 comprises two sections that present our estimation findings for VAR(1)-BEKK-GARCH(1,1). Predicted on the estimation of conditional mean equations, the first section displays the VAR results. The objective is to determine the return spillovers between these markets using these estimations. The second section presents the findings from our analysis of volatility spillovers using the conditional variance equations described by BEKK GARCH.

VAR Table Predictions (For the Year 2012-2017)

At the 1% significance level, we find that the AR(1) parameter g22 for oil return is statistically significant for the majority of groups. As a result, the oil return exhibits an autoregressive characteristic, indicating that the current values are greatly influenced by oil returns that are one period behind. Similar to this, as g33 are statistically significant for their market returns, several Indian commodity markets—such as those for gold, silver, and copper—also exhibit autoregressive characteristics. As a result, the present market returns for copper, silver, and gold are highly influenced by their historical values and exhibit short-term predictability.

Since the coefficient g12 is statistically significant for all groups, it can be concluded that, when considering return spillover effects, the lagged values of returns in the oil market have a considerable impact on the present returns of the Indian stock market. This demonstrates how the returns on the Indian stock market now are heavily influenced by the performance of the oil market in the past. This suggests that the Indian stock market benefits greatly from the oil's return spillover. The coefficient's negative sign suggests that a higher return in the oil market may result in a potential decrease in the return on the stock market. Given that the coefficient g21 is statistically significant for all groups, we note that there is a return spillover from the Indian stock market to the oil market. As a result, it is evident that the Indian stock market influences the oil market. We find large unidirectional return spillovers from the stock market to the copper markets, respectively, when examining the return spillovers between the Indian stock and commodity markets. For copper, the coefficient g31 is statistically significant at least when regarded at the 1% level. The Indian stock market has a negative effect on copper. This suggests that the copper markets will decline in response to an increase in stock returns.

Given that the coefficient g32 is statistically insignificant at all levels, it is determined that the markets for gold, silver, copper, and aluminum are not likely to be impacted by oil returns.

BEKK-GARCH Table Predictions (For the Year 2012-2017)

Next, we investigate the spillovers of volatility using conditional variance equations. Ross (1989) highlights that the rate of information flow has a major impact on market volatility. Thus, correlations across financial markets may exist not just for profits but also for market volatility.

At the 1% significant level, all of the groups' estimated coefficients for the ARCH and GARCH models [B(1,1), B(2,2), and B(3,3)] in our conditional variance equations are statistically significant. This indicates that there are significant ARCH and GARCH impacts in the Indian stock market, crude oil market, and all commodities markets in India (gold, silver, copper, aluminum, and wheat). These findings indicate that these financial markets' own lagging shocks and lagging conditional variance have a substantial impact on their conditional variances.

We first examine the nature of spillover mechanisms between the worldwide oil market and Indian stocks in order to assess volatility transmissions. The variance equation of the BEKK model's matrix A and B, together with the statistical significance of the off-diagonal coefficients. The coefficients A(1,2) are significant at the 10% level for all groups, indicating that our results demonstrate a considerable transmission of shock spillovers from the Indian stock market to the oil price. The volatility of the oil market during the study period is thus significantly influenced by previous shocks to the Indian stock market.
On the other hand, as the coefficients A(2,1) are significant for every group, we can observe that the shock volatility spillover effect from crude oil to the Indian stock market is intermediate.
Regarding spillovers of volatility, we observe that the variation in oil returns results in positive and noteworthy spillovers to returns primarily in gold, copper, and aluminum.

VAR Table Predictions (For the Year 2012-2023)

At the 10% significance level, we find that the oil return AR(1) parameter g22 is statistically significant for the majority of the groups. As a result, the oil return exhibits an autoregressive characteristic, indicating that the current values are greatly influenced by oil returns that are one period behind. Similarly, autoregressive characteristics like g33 that are statistically important for their market returns are present in some Indian commodity markets, such as those for gold, aluminum, and copper. As a result, the present market returns for copper, gold, and aluminum are highly influenced by their historical values and exhibit short-term predictability.

The lagged values of returns in the oil market are found to have a considerable impact on the present returns of the Indian stock market when looking at return spillover effects, as the coefficient g12 is statistically significant for the majority of the groups (gold, copper, and aluminum). This demonstrates how the returns on the Indian stock market now are heavily influenced by the performance of the oil market in the past. This suggests that the Indian stock market receives a sizable return spillover from the oil industry. Based on the coefficient's positive value, it can be inferred that a better return in the oil market may contribute to a higher return in the stock market.

The return spillover from the Indian stock market to the oil market is observed, given that the coefficient g21 for copper and aluminum is statistically significant. As a result, it is evident that the Indian stock market influences the oil market. Since the coefficient g31 is statistically significant for copper at least at the 1% level, we may conclude that there are large unidirectional return spillovers from the stock market to the copper markets in India when examining the return spillovers between the commodities and stock markets. The Indian stock market has a beneficial effect on copper. This suggests that rising stock returns will cause copper markets to expand. This result is contrary to the pre-covid period where increase in stock returns would have caused decrease in copper markets.

Considering that the coefficient g32 is statistically significant at 1%, it is determined that the markets for copper and aluminum are impacted by oil return. Due to covid-19, change in results has been observed. pre-covid , g32 was statistically insignificant suggesting that there is no impact of oil returns on metal.

BEKK-GARCH Table Predictions (For the Year 2012-2023)

At the 1% significant level, all of the groups' estimated coefficients for the ARCH and GARCH models [A(1,1), A(2,2), A(3,3), B(1,1), B(2,2), and B(3,3)] in our conditional variance equations are statistically significant. This indicates that there are significant ARCH and GARCH impacts in the Indian stock market, crude oil market, and all commodities markets in India (gold, silver, copper, aluminum, and wheat). These findings indicate that these financial markets' own lagging shocks and lagging conditional variance have a substantial impact on their conditional variances.
We first examine the type of spillover mechanisms that exist between the worldwide oil market and Indian stocks in order to analyze volatility transmissions. We may investigate the transmission of shocks and volatility spillovers thanks to the statistical relevance of the off-diagonal coefficients in the matrices A and B of the variance equation (Eq. (5)5) of the BEKK model. The findings indicate a noteworthy degree of shock spillovers from the Indian stock market to the oil price, with the exception of Gold and Silver, for which the coefficients A(1,2) are significant at the 10% level. The volatility of the oil market during the study period is thus significantly influenced by previous shocks to the Indian stock market. In contrast, we observe that the impact of shock volatility spillover from crude oil to the Indian stock market is moderate, as indicated by the fact that A(2,1) coefficients are significant for most of the groups. When it comes to volatility spillovers, we discover that changes in oil returns have a positive and notable impact on returns in gold, silver, copper, and aluminum. The coefficient B(1,2), has significance for the gold, silver and copper groups. These subsequent findings suggest that there are few volatility spillovers from the stock market to the oil market. Results show a unidirectional volatility spillover from the oil to the stock market, but a bidirectional shock spillover between the Indian stock and oil markets. For the majority of commodities markets, as shown in Table 10, the off-diagonal elements of matrix A—A(1,3) are statistically significant at the 5% level (e.g. gold, copper, and silver). This data demonstrates notable shock spillovers from commodity markets to the stock market. The copper market appears to be the most vulnerable to shocks from the Indian stock market, as indicated by

the largest absolute value of coefficient A(1,3) for copper, which is 0.0463. This value is significant at the 5% level. Given that the associated coefficients for the off-diagonal elements of matrix B—B(1,3) are significant at the 1% level, we do see a volatility spillover impact from the stock market to gold, silver and copper. Conversely, we discover no proof that shock and volatility have trickled down from commodity to stock markets, as neither A(3,1) For every group, neither B(3,1) nor is statistically significant. Regarding the interconnection of the Indian commodity markets and the oil market, there is substantial evidence of shock spillovers from oil prices to the wheat and gold markets. We are only able to identify contagion from the oil to copper market for volatility spillovers because the corresponding B(2,3) coefficient is significant at the 10% level.

Conclusion

Using extensive data from India, the research article examines how volatility is transmitted across global stock markets, commodity futures, and oil markets. Using a complex trivariate VAR-BEKK-GARCH model, the research provides a significant understanding of the relationships between these important financial domains.

The results highlight the strong impact of oil prices on the dynamics of India's equities market by demonstrating considerable unidirectional return spillover effects from the oil market to the Indian stock market. This demonstrates how vulnerable the Indian stock market is to changes in the price of oil globally, which has ramifications for investors and decision-makers managing market volatility.

The research paper also suggests that the oil returns and the commodity markets (like gold, aluminum, and copper) are highly impacted by their previous values (lag values). Which indicates these variables exhibit an autoregressive characteristic.

The analysis also reveals interesting return connections between domestic commodities like copper and aluminum, the global oil market, and the Indian stock market.
The analysis indicates that there is a degree of reliance between the oil and Indian stock markets, indicating return spillovers from one market to the other. Due to its reliance on historical changes in the oil market, the Indian stock market stands out for its distinct qualities.

Additionally, the study finds significant unidirectional return spillovers from the Indian stock market to some Indian commodity markets, such as copper. This demonstrates how the equities and commodities markets in India are intertwined, providing investors with chances to diversify their holdings and protect themselves from market volatility.

It has been indicated that oil return affects metals such as aluminum and copper. Oil has a marginally beneficial effect on some metals. which contrasts with findings from the pre-COVID era. Policymakers in the fields of mining, agriculture, and general policy will benefit from an understanding of these relationships.

There is no significant relationship found between wheat prices and global oil prices and vice versa. This result is similar to the conclusion found by Zhang and Reed who had stated that there is no relationship between fluctuation in oil prices and agricultural commodity which in this case is wheat.

These findings have significant policy implications and provide useful information for hedge strategies and portfolio management in India's financial markets. It is crucial to comprehend the complex interdependencies and transmission mechanisms between various financial time series in order to mitigate risks and make well-informed decisions properly.

In conclusion, this study adds a great deal to our knowledge of the financial landscape of India by shedding light on the workings of the country's stock, commodities, and oil markets. Investors and regulators can improve financial resilience and promote sustainable growth in India's dynamic economy by acknowledging and capitalizing on these interdependencies.

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