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Volatility Spillover Among Sectoral Indices of the Indian and US Stock Markets

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Abstract: ***The primary objective of this study is to empirically analyse the volatility spillover among sectoral equity returns in the Indian and US markets. The paper extracts the time-varying conditional correlations between the sector indices using the Dynamic Conditional Correlation model. The analysis of the DCC-GARCH model indicates a conditional correlation between the Indian and US stock markets. Furthermore, despite market volatility and a significant disruption caused by the COVID-19 crisis in 2019, the consistent presence of a positive correlation highlights the strong and lasting connection between Indian and foreign stock exchanges in the financial services, FMCG sector, and the Healthcare sector. The fluctuation in conditional correlation coefficients over time highlights the evolving connectivity and volatility spillover effects between the Indian and United Nations stock markets in the Information and Technology sector. The findings indicate that offering proper direction for risk management and developing investment strategies in uncertain and unstable market conditions is essential for understanding the' continuous impact and interconnectedness of global financial markets.***

Keywords: ***Stock Market Integration, Financial Market Interconnectedness, Volatility Spillover, Market Risk Transmission, Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Autoregressive Conditional Heteroskedasticity (ARCH)***

Abbreviations:
GARCH: Generalized Autoregressive Conditional Heteroskedasticity
ARCH: Autoregressive Conditional Heteroskedasticity
DCC: Dynamic Conditional Correlations
FMCG: Fast-moving Consumer Goods

I. INTRODUCTION

With equity investment becoming increasingly significant as a primary investment alternative, the effective management of portfolio risk has become a critical topic for financial analysts. With globalization and regionalization ongoing, equity markets across numerous countries have witnessed increasing levels of integration. This integration reflects the growing interconnectedness and interdependence.

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Among global financial markets, facilitated by technological advancements, improved communication, and trade liberalisation.

Financial markets are dynamic and interconnected systems, influenced by various factors that might affect asset prices and market behaviour. While increased integration might result in greater interdependence and synchronized movements, it's essential to find out that not all markets are equally integrated. Some markets may be more interconnected, and certain countries or regions may have stronger linkages due to trade relationships. Factors widely acknowledged to influence the performance of equity sector returns, such as market conditions, economic growth, investors' trading patterns, and interest rate fluctuation [1]. These variables serve as critical determining factors for market participants, influencing their decisions to improve asset allocations, risk management, and develop effective trading strategies. The degree and direction of volatility spillovers, on the other hand, are determined by market conditions [11], including investor sentiment, economic indicators, geopolitical events, and regulatory changes, all influence the prevailing level of market uncertainty and risk appetite.

Volatility is a crucial aspect of these markets, reflecting the uncertainty and risk associated with investment decisions. In contrast, the transmission of volatility between different markets has been an area of considerable research interest due to its potential impact on investors' portfolios and risk management strategies. The widespread adoption of sector index investing in the last two decades can be attributed to the popularity of exchange-traded funds. These investment vehicles offer a convenient and accessible way for investors to gain exposure to specific sectors of the equity market [10]. By employing the top-down approach, investors systematically navigate their investment decisions, starting with choosing a country, followed by selecting a sector, and ultimately picking individual companies [9]. Hence, considerable research has explored the empirical and theoretical aspects of the relationship between returns within significant equity sectors.

The research paper aims to explore the dynamics of volatility spillover among sectoral indices in two major economies, India and the United States. Both countries boast large and diverse financial markets, offering a unique opportunity to explore cross-border spillover effects and diversification possibilities across sectors. Over the years, economic globalization and technological advancements have increased the integration of international financial markets. The 2008-2009 financial crisis highlighted the importance of understanding cross-market linkages and the potential for contagion; there are plenty of empirical studies focusing on the volatility spillover stock markets [4], commodity and financial markets [8], and foreign exchange markets [13]. While an extensive body of empirical studies has offered valuable insights into equity market integration, the unique dynamics and complexities of sectoral analysis remain largely unexplored.

Given the economic importance of India and the United States, understanding the nature and extent of volatility spillover between their financial markets can be crucial for global investors. Both countries have diverse and thriving economies, and their financial markets serve as critical hubs for domestic and international investments. Investors managing portfolio stocks, who intend to maximise returns while minimising risk, typically focus on identifying the equity sectors in the US market that offer the highest returns with the lowest risk. In the context of US equity sectors, investors emphasize highlighting sectors that exhibit either weak positive correlations or even negative correlations with each other and with alternative financial instruments [1]. Exploring how volatility transmits between these markets, especially at the sectoral level, offers crucial insights for investors diversifying their portfolios across borders.

II. LITERATURE REVIEW

Volatility spillover and portfolio diversification have been extensively studied in finance and economics. Researchers have investigated the interconnections between different assets, markets, and countries to better understand how volatility propagates and its implications for investors. Engle (1982) introduced the concept of Autoregressive Conditional Heteroskedasticity (ARCH) models, which were later extended to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models by Bollerslev (1986). These models extensively evaluate volatility spillover effects between stock markets, currencies, and other financial assets. [7], investigate the effect of COVID-19 on the spillover of sectors of the Chinese and US stock markets (Consumer Staples, Consumer Discretionary, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Telecommunication, and Utilities) using Copula and Conditional Value at Risk approach. The result shows bidirectional volatility spillover during bull markets. In contrast to an insignificant downside risk spillover from China to the US, the study found volatility spillovers from the United States to China for only the consumer discretionary, materials, and telecommunications sectors. [6] studied the impact of COVID-19 on volatility spillover among the sector indices listed in BSE India from January 8, 2015, to October 9, 2020. Their findings revealed that during the COVID-19 pandemic, total volatility spillovers reached 69%. The primary net volatility transmitters were the energy sector, followed by the oil and gas sector.

Investigate the volatility spillover among the key US equities sectors (i.e. Financial, Technology, Energy, Health, Consumer, and Industrial). After adjusting for the volatility breaks, the author finds less volatility spillover between equity sector returns [10]. Additionally, it was noted that when volatility breaks were omitted, significant volatility spillover was observed in both directions in each of the six sectors. [2], finds that the COVID-19 emergence increases volatility spillovers across 13 sectors in Australia, in which the main volatility transmitters are consumer staples, industrials, and telecom services. Similarly, [12] aimed to assess the impact of COVID-19 pandemic on sectoral indices including primary, consumer, industrial goods, healthcare, financial services, FMCG, Telecom, IT, real estate, energy, and utilities, along with the significant market index of highly impacted countries such as Argentina, Brazil, France, India, Germany, Italy, Russia, Turkey, and the USA. The research showed that within the sectors examined, the volatility spillover within each industry itself is more pronounced than the spillovers observed between different sectors. During the COVID-19 pandemic, the sectors acted more as volatility transmitters than receivers. examine the integration of Euro- and US-wide sector equity indices, concentrating on the return, volatility, and trend spillover impacts of local and global shocks. They explore that, unlike volatility spillovers, return spillovers are not significant enough to explain sector equity returns. Additionally, their study shows that when the trend-based volatility spillover is considered, some sector stock indexes respond similarly to local and global shocks.

[5], found that the difference over time between sectoral stock return and volatility spillover indices in Nigeria was significant. Meanwhile, the return spillover index shows increased integration among sectoral equities. [3], examined the volatility spillover across 24 sectors in Vietnam. Their findings confirm a substantial spillover effect across all industries following the COVID-19 pandemic. Furthermore, these findings confirm the increased inter-sectoral connectedness among Vietnamese sectors, where aquaculture and building materials have become risk transmitters. The present study makes a further contribution to the recent literature by investigating the extent of volatility spillover among sectoral indices. The paper employs the dynamic conditional correlation (DCC) model within a multivariate framework, utilising daily data from May 2015 to December 2024. Specifically, to measure and quantify the volatility spillover effects between sectoral indices in India and the US.

III. DATA AND METHODOLOGY

The study examines the closing stock prices of India and the United States, covering the period from May 2015 to December 2024. The data were collected from Yahoo Finance. The validity of the data was verified through the official websites of the respective stock exchanges. The data series comprises five sector indices from the National Stock Exchange of India and the Dow Jones of the US: Technology, Healthcare, FMCG, Financial, and Banking. The rate of change in the price series is calculated through continuously compounded returns. $R_{i,t} = \ln [P_{i,t} / P_{i,t-1}]$, where $R_{i,t}$ signifies the continuously compounded return for index I at time t and $P_{i,t}$ represents the price level of index I at time t.

The preliminary analysis of stock return data for sectoral indices is conducted using descriptive statistics. Unit root tests, specifically the

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Augmented Dickey-Fuller Test and the Phillips-Perron test, were employed to assess the stationarity of the series. Unlike earlier studies that utilised econometric tools such as the Vector Error Correction Model, Granger's Causality, and Linear Correlation to study volatility spillovers, our approach employs a more sophisticated and versatile technique known as DCC-GARCH (Dynamic Conditional Correlation-Generalised Autoregressive Conditional Heteroskedasticity). The DCC-GARCH technique is well-suited for handling the dynamic and evolving nature of the data, capturing varying levels of correlation among variables as conditions change over time. Additionally, the DCC-GARCH model considers dynamic conditional correlation coefficients while accounting for heteroskedasticity in the error terms. This is achieved by modelling conditional correlations within a dynamic framework, where lagged values are employed for computation [8]. This approach provides a comprehensive and robust method for analysing volatility spillover dynamics across sectoral indices, thereby enhancing our understanding of market interdependencies and risk transmission mechanisms.

Table-I: Analysis of Descriptive Statistics of Nifty in Different Sectors

	Information & Technology	Healthcare	FMCG	Financial Services	Banking
	NIFTY	NIFTY	NIFTY	NIFTY	NIFTY
Mean	18310.06	6457.850	29983.65	12163.03	27435.83
Median	14999.90	6174.300	29463.85	11213.90	26433.95
Maximum	39370.70	9229.600	52440.20	20057.70	44747.35
Minimum	9434.600	4018.850	18094.00	5689.900	13555.00
Std. Dev.	8367.092	1308.407	7990.395	4050.479	8054.569
Skewness	0.841616	0.402497	0.598063	0.319986	0.350040
Kurtosis	2.255170	1.937314	2.655306	1.792736	2.018534
Jarque-Bera	304.2176	159.5883	139.1351	167.6455	130.5021
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	39458182	13916666	64614766	26211330	59124208
Sum Sq. Dev.	1.51E+11	3.69E+09	1.38E+11	3.53E+10	1.40E+11
Observations	2155	2155	2155	2155	2155

Source: Author's Calculations

Table-II: Analysis of Descriptive Statistics of Dow Jones in Different Sectors

	Information & Technology	Healthcare	FMCG	Financial Services	Banking
	DJ	DJ	DJ	DJ	DJ
Mean	172640.3	75465.29	49444.84	88172.00	30481.14
Median	138601.2	69194.49	42297.73	82304.64	30568.77
Maximum	373272.1	122894.5	80055.31	149030.7	57026.75
Minimum	63005.63	44856.16	31650.69	40633.77	17289.19
Std. Dev.	92988.93	24176.28	14106.37	33517.25	7434.912
Skewness	0.511191	0.438362	0.627115	0.329146	0.219998
Kurtosis	1.797132	1.689009	1.790178	1.719023	2.147781
Jarque-Bera	223.7751	223.3428	272.6760	186.2502	82.52047
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	3.72E+08	1.63E+08	1.07E+08	1.90E+08	65625896
Sum Sq. Dev.	1.86E+13	1.26E+12	4.29E+11	2.42E+12	1.19E+11
Observations	2155	2155	2155	2155	2155

Table-III: ADF Test and PP Test at Level and Level 1 of Nifty in Different Sectors

Stock Return	Augmented Dickey–Fuller unit root test		Phillips-Perron unit root test	
Nifty	(t-statistics)	p-values	(t-statistics)	p-values
Information & Technology- ADF at Level ADF at Level 1	-0.372965 -34.47231	0.9113 0.0000	-0.382916 -45.21040	0.9097 0.0001
Healthcare- ADF at Level ADF at Level 1	-0.691831 -45.11447	0.8469 0.0001	-0.691831 -45.12061	0.8469 0.0001
FMCG- ADF at Level ADF at Level 1	0.865703 -46.57353	0.9951 0.0001	0.865666 -46.57330	0.9951 0.0001
Financial Services- ADF at Level ADF at Level 1	-0.305790 -45.29633	0.9217 0.0001	-0.305790 -45.29645	0.9217 0.0001
Banking- ADF at Level ADF at Level 1	-0.299680 -45.03344	0.9226 0.0001	-0.352519 -45.03313	0.9146 0.0001

Source: Author's Calculations

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Table-IV: ADF Test and PP Test at Level and Level 1 of Dow Jones in Different Sectors

Stock Return	Augmented Dickey–Fuller Unit Root Test		Phillips-Perron Unit Root Test	
Dow Jones	**(t-statistics)**	**p-values**	**(t-statistics)**	**p-values**
Information & Technology- ADF at Level ADF at Level 1	0.319790 -51.46455	0.9793 0.0001	0.434683 -51.86356	0.9844 0.0001
Healthcare- ADF at Level ADF at Level 1	-0.257871 -15.79615	0.9285 0.0000	-0.319856 -53.59913	0.9196 0.0001
FMCG- ADF at Level ADF at Level 1	-0.625588 -14.53704	0.8625 0.0000	-0.562546 -50.88907	0.8762 0.0001
Financial Services- ADF at Level ADF at Level 1	-0.658232 -15.59940	0.8549 0.0000	-0.594651 -51.53248	0.8694 0.0001
Banking- ADF at Level ADF at Level 1	-2.055224 -40.86057	0.2633 0.0000	-2.222968 -67.01249	0.1982 0.0001

Source: Author's Calculations

The NIFTY and DJ indices exhibit positive and minor right skewness, but these values are close to zero. These findings indicate that the distributions are predominantly symmetrical, with a slight inclination towards right skewness. The kurtosis values for all the distributions are less than 3, suggesting that they possess a less pronounced tail compared to a normal distribution, and are therefore classified as platykurtic. The p-value for each Jarque-Bera test is 0.000000, indicating that the normality null hypothesis should be rejected. The findings suggest an essential deviation from normality in the distributions. Furthermore, the Jarque-Bera test verifies that these datasets show considerable deviations from normality.

The augmented Dickey-Fuller test and the Phillips-Perron test were employed to evaluate the stationarity of the series of sectoral index returns [**Error! Reference source not found.**]. The Augmented Dickey-Fuller test is employed to test the null hypothesis of a unit root, and subsequently, the Phillips-Perron test is used to confirm the results [**Error! Reference source not found.**]. The results from conducting Augmented Dickey-Fuller and Phillips-Perron tests, both at the level and level 1, on stock exchanges within various sectors, indicate variations in the stationarity of time series among different stock indices. Therefore, sectoral indices do not show signs of stationarity, as their corresponding p-values do not reject the null hypothesis of a unit root. The t-statistics for the Banking, Financial, Healthcare, and Technology sectors are negative for both Nifty and Dow Jones, whereas the t-statistics for the FMCG sector are positive. However, the p-values exceed the standard threshold of 0.05, indicating a lack of statistical significance.

The Augmented Dickey-Fuller and Phillips-Perron tests provide strongly negative t-statistics and p-values near zero, significantly lower than the conventional significance level of 0.05. This indicates that after undergoing first-order differencing (at level 1), the time series for all sectoral indices becomes stationary.

IV. VOLATILITY SPILLOVER AMONG SECTORAL INDICES

A. DCC-GARCH Model

Engle (2002) introduced the multivariate generalised autoregressive conditional heteroskedasticity (GARCH) model, which is applied to estimating dynamic conditional correlations (DCC). The DCC-GARCH model calculates correlation coefficients of standardized residuals, directly addressing heteroskedasticity as it permits the inclusion of additional explanatory variables in the mean equation, ensuring proper model specification [5]. In this paper, the DCC-GARCH model developed by Engle in 2002 is utilised to investigate the presence of volatility spillover among sectoral indices of India and the US.

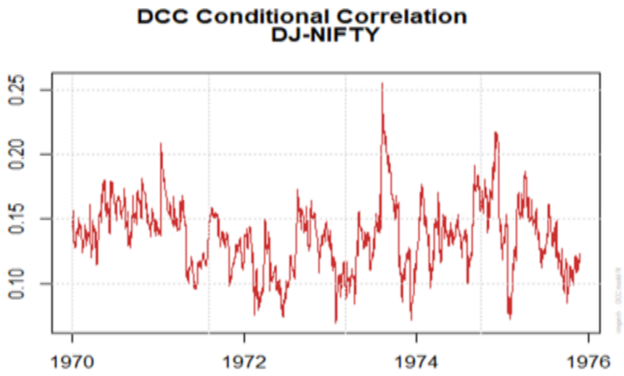
Table-V: DCC-GARCH Conditional Correlation

	NIFTY/DJ	Information & Technology	Healthcare	FMCG	Financial Service	Banking
S.NO		**Estimate**	**Estimate**	**Estimate**	**Estimate**	**Estimate**
1	[A]α1	0.047934	0.064708	0.071778	0.082347	0.085531
2	[A]β1	0.928920	0.897098	0.891177	0.901608	0.901376
3	[B]α1	0.119885	0.117224	0.126600	0.138213	0.058392
4	[B]β1	0.859135	0.829126	0.861412	0.815424	0.906249
5	[Joint]dccα1	0.006351	0.008651	0.000959	0.011505	0.019327
6	[Joint]dccβ1	0.961538	0.878238	0.956568	0.908514	0.946169

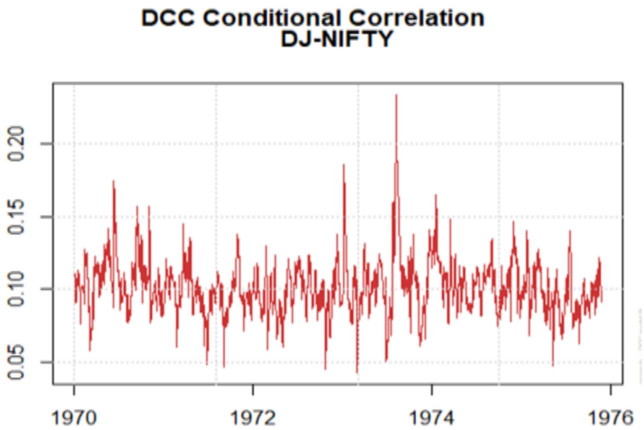
Source: Author's Calculations

Table-VI: DCC-GARCH Conditional Correlation

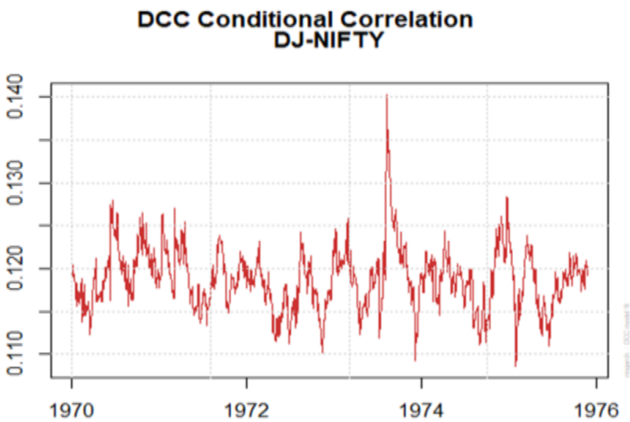
	NIFTY/DJ	Information & Technology	Healthcare	FMCG	Financial Service	Banking
S.NO		Pr (>|t|)	Pr (>|t|)	Pr (>|t|)	Pr (>|t|)	Pr (>|t|)
1	[A]α1	0.00000	0.00000	0.000000	0.000025	0.000309
2	[A]β1	0.00000	0.00000	0.000000	0.000000	0.000000
3	[B]α1	0.00000	0.00000	0.029182	0.000000	0.714405
4	[B]β1	0.00000	0.00000	0.000000	0.000000	0.522569
5	[Joint]dccα1	0.21845	0.31981	0.855963	0.219887	0.889379
6	[Joint]dccβ1	0.00000	0.00000	0.000000	0.000000	0.000000



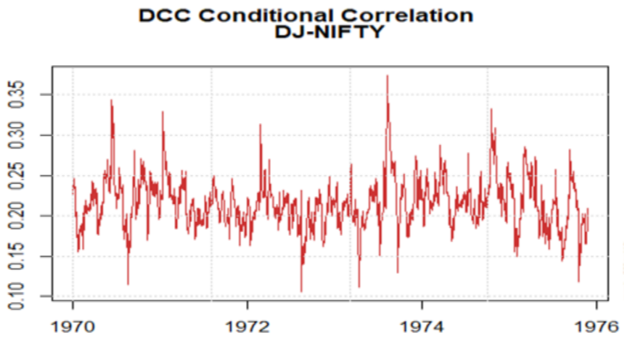
[Fig.1: DCC-GARCH Conditional Correlation Between Stock Markets in the Information and Technology Sector]



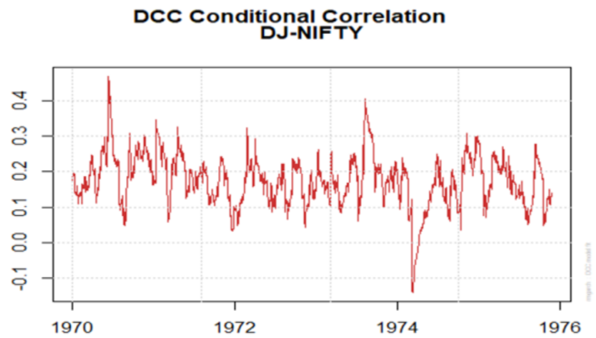
[Fig.2: DCC-GARCH Conditional Correlation Between Stock Markets in the Healthcare Sector]



[Fig.3: DCC-GARCH Conditional Correlation between Stock Markets in FMCG Sector]



[Fig.4: DCC-GARCH Conditional Correlation Stock Exchanges in Financial Services Sector]



[Fig.5: DCC-GARCH Conditional Correlation Between Stock Exchanges in the Banking Sector]

The results from the DCC-GARCH model analysis for the information and technology sector, particularly focusing on the NIFTY/DJ pair, indicate a substantial degree of volatility spillover effects between the Indian and US stock exchanges. The α1 and β1 coefficients for the NIFTY/DJ pair are estimated to be 0.047934 and 0.928920, respectively. It is important to emphasize that all p-values are close to zero, with $p < 0.000001$ to indicate statistical significance. This suggests that the Indian NIFTY index has considerable unidirectional spillover effects on the DJ, DAX, and SSE indices. Similarly, the coefficients of β1 confirm the presence of significant unidirectional spillover effects from the Indian NIFTY index to the Dow Jones Index. Also, the β1 coefficients for the B component, which are indicative of bi-directional spillover effects, are estimated to be 0.859135 for the NIFTY/DJ pair, highlighting the considerable bi-directional volatility spillovers that occur between the DJ and the Indian NIFTY index. Shifting the focus to the banking sector, the estimations of α1 and β1 coefficients for the NIFTY/DJ pair reveal significant uni-

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directional spillover effects
from the Indian NIFTY index to the DJ indices. The p-values are close to zero, indicating a strong statistical significance.

The financial services industry analysis showed considerable volatility spillover effects between the Indian and US stock exchange. Specifically, when examining the NIFTY/DJ pair, the computation of α1 and β1 coefficients indicates the existence of significant one-way spillover effects from the Indian NIFTY index to the DJ indices. The p-values, close to zero, indicate a high statistical significance. Similarly, the calculated β1 coefficients for the B component showed substantial bi-directional spillover effects between the NIFTY index and the DJ indices. The results underscore the importance of considering worldwide interconnections and the diffusion of the impact when examining fluctuations in volatility within the financial services sector.

The parameters assessed through the DCC-GARCH model reveal significant volatility spillover effects between the Indian and US stock markets, particularly within the Healthcare sector. The α1 and β1coefficients for the NIFTY/DJ pair are predicted to be 0.064708 and 0.897098, respectively. The p-values are close to zero ($p < 0.000001$) showing strong uni-directional spillover effects from the Indian NIFTY index to the DJ indices. The β1 coefficients for the B component, representing spillover effects in both directions, are calculated to be 0.829126 for the NIFTY/DJ pair, showing high bi-directional spillover effects. When shifting the focus to the FMCG sector, the α1 and β1 coefficients for the NIFTY/DJ pair indicate substantial uni-directional spillover effects from the Indian NIFTY index to the DJ indices. The p-values, which are close to zero, demonstrate strong statistical significance. Also, the estimated β1 coefficients for the B component suggest considerable bi-directional spillover effects between the NIFTY index and the DJ, DAX, and SSE indices.

V. CONCLUSION

The academic literature extensively documents the interdependence of economies worldwide, particularly emphasising the interconnectedness of global stock markets. The focus is specifically on the interconnectedness of global stock markets, emphasizing the economic interdependence reflected in the financial markets. In recent years, researchers have shown an increasing interest in studying how stock markets integrate and communicate information across borders. Researchers have specifically focused on examining the consequences of stock returns and volatilities that extend across diverse indexes. A noteworthy aspect is the specific attention given to understanding the direction of spillover, particularly from industrialized markets to developing and emerging economies. The primary objective of the present study is to examine the volatility spillover and dynamic conditional correlation between India and the US. The findings indicate that the joint DCC coefficients hold statistical significance, indicating the presence of dynamic and time-varying conditional correlations between Indian and US stock indexes. When examining stock market dynamics, it is crucial to consider estimates of conditional heteroscedasticity, especially when high correlations are present. These findings are consistent with earlier research conducted by, offering further confirmation of the empirical evidence regarding the interdependencies of stock markets. Many avenues for future research can enhance our understanding of this phenomenon and its implications for investors and financial markets. Future research could expand the analysis to include other countries or regions. Comparing volatility spillover dynamics across different regions can provide a more comprehensive understanding of global financial market interdependencies. Investigating the effects of volatility spillover on risk management practices and diversified portfolios can be a fruitful area for future research. Analyzing how investors can effectively reduce the impact of volatility transmission on their portfolios can provide valuable insights to participants in the financial markets.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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