Volatility Spillover Among the Sectoral Indices of the Indian Capital Market : Evidence from the COVID Period

Satyaban Sahoo [1]
Sanjay Kumar [2]

Abstract

Purpose : The study aimed to empirically investigate the asymmetric volatility spillover relationship among the sectors of the Indian capital market during the COVID-19 period.

Methodology : The study employed the asymmetric dynamic conditional correlation (ADCC) model to measure volatility spillover among the sectoral indices with asymmetric effects to assess the impact of bad news. The study further calculated the time-varying conditional correlation.

Findings : The empirical analysis indicated short-run and long-run volatility persistence among sectoral indices of the Indian capital market. Furthermore, the results also showed the significant effect of bad news on the volatility of the sectoral indices. The time-varying conditional correlation suggested a high correlation among the sectoral indices during COVID-19. So, there was only a limited opportunity for portfolio diversification among these sectors during the crisis period.

Practical Implications : The findings may assist financial advisors in assessing the relationship among sectors of the Indian capital market during the crisis period. While constructing the equity investment portfolio during the crisis period, financial managers must wait for the market to stabilize before determining whether sector diversification is appropriate or required.

Originality : The ADCC model presented previously unresearched evidence of volatility spillover among the sectors of the Indian capital market during the COVID-19 crisis. The empirical findings would enable investors to make important investment and portfolio diversification decisions in sectors of the Indian capital market.

Keywords : sectoral index, Indian capital market, asymmetric DCC model, time-varying conditional correlation

JEL Classification Codes : C1, C58, N25

Paper Submission Date : October 5, 2022 ; Paper sent back for Revision : June 14, 2023 ; Paper Acceptance Date : June 25, 2023 ; Paper Published Online : September 15, 2023

The COVID-19 pandemic, which emerged in late 2019, and has had a major worldwide impact, has had various consequences on the financial market. The pandemic produced significant disruptions that significantly changed how the global financial market performed. Any country's financial economic system reflects the true state of the economy's health and financial stability. The importance of the financial market is widely acknowledged from an industry and investor standpoint. During a crisis like COVID-19, investors are confronted with a more complicated market, resulting in more significant challenges and opportunities in portfolio construction and decision-making. During the crisis, investors' primary aim is to

[1] *Assistant Professor (Corresponding Author),* Department of Commerce, Manipal Academy of Higher Education (MAHE), Madhav Nagar, Manipal - 576 104, Karnataka. (Email : satyabans40@gmail.com)
ORCID iD : https://orcid.org/0000-0002-5545-6289
[2] *Assistant Professor,* Department of Management, Central University of Rajasthan, Bandarsindri, Kishangarh - 305 817, Distt. Ajmer, Rajasthan. (Email : sanjaygarg@curaj.ac.in) ; ORCID iD : https://orcid.org/0000-0002-5636-1556

DOI : https://doi.org/10.17010/ijf/2023/v17i9/173183

minimize the portfolio's risk, so they may follow different strategies like picking growth and value stocks and stocks from large-cap, mid-cap, and small-cap segments. Another strategy to reduce portfolio risk is to develop an equity sector allocation technique that divides stocks into different sectors with consistent reactions to market conditions. For example, during the COVID-19 crisis, the information technology (IT) and pharmaceutical sectors performed better than others in the Australian and Indian capital markets (Alam et al., 2021; Mittal & Sharma, 2021).

Additionally, even if it contains a variety of securities, putting a sizable amount of the fund in a single economic sector may cause excessive volatility due to its short-term weakness. The sector-based index aids in providing information on a specific industry by considering a group of companies that represent that industry (Yuksel & Bayrak, 2012). The distribution of funds to various sectors is purely based on these sectors' performance and expected growth. Investors are more likely to invest in particular stocks if they receive beneficial information from their target sector. They continuously revise their portfolio in conformity with new information (Aravind, 2017). According to contemporary portfolio theory, when sectors are not perfectly correlated, the return can remain constant while the risk is decreased by decentralized investment simultaneously (Cao et al., 2013). Investment decisions in different sectors are scrutinized for risk-return characteristics (Dhal, 2009). Therefore, understanding the interdependence of various sectors may be helpful for investors and traders. The ongoing COVID-19 outbreak created a question among investors about the uncertainties of the financial market, which increased volatility. Researchers have been productive in terms of the impact of the COVID-19 pandemic on financial markets (Elhini & Hammam, 2021; So et al., 2021; Zehri, 2021; Zhang et al., 2020). Aside from determining statistical significance, different researchers have attempted to establish an economic basis for such relationships. The financial markets across all sectors experienced a significant impact due to the COVID-19 crisis (Dharani et al., 2022); for example, many companies have gone bankrupt, leading to the fall of the banking sector (Barua & Barua, 2021; Darjana et al., 2022; Demirgüç-Kunt et al., 2021; Mohania & Mainrai, 2020). So, the primary motives for studying sectoral interdependence are determining the extent of prospective profits and the benefit of portfolio diversification among different sectors.

The Indian stock market also could not escape the impacts of COVID-19. In the last two decades, India's financial market has played a critical role in transforming the country into one of the world's fastest-growing economies. Due to the rapid growth of the global financial market, the equity sector of India has become the most attractive avenue for investment for retail investors, institutional investors, and foreign investors. For example, India has seen a massive inflow of foreign direct investment into the automobile sector from 2001 to 2016 (Gupta & Jaiswal, 2017). As a result, the country's stock market has seen a massive increase in value and volume. However, in the early COVID-19 pandemic, the Indian stock market witnessed a precipitous collapse. Government policies, business earnings, general economic conditions, and investor mood all impacted how COVID-19 affected the Indian stock market. Investor attitudes changed as COVID-19 expanded and lockdowns were implemented, resulting in a significant sell-off. The key indices, including the Bombay Stock Exchange's (BSE) Sensex and the National Stock Exchange's (NSE) Nifty, significantly declined. Investors' reactions to news of COVID-19 cases, governmental initiatives, and economic indicators caused daily market movements to become more erratic and turbulent. The volatility brought both possibilities and challenges for investors in trading and investment.

During the pandemic, there were large outflows of foreign institutional investment (FII) from the Indian stock market. Foreign investors withdrew money from emerging markets, particularly India, as uncertainty and risk aversion grew. This had a detrimental effect on market liquidity, ultimately leading to a stock price decline. The performance of sectoral indices showed that COVID-19 had distinct impacts on multiple sectors of the Indian economy. Lockdowns and lower consumer spending badly disrupted the hospitality, tourism, aviation, and retail sectors.

On the other hand, industries, including pharmaceuticals, healthcare, technology, and e-commerce, showed resilience or growth due to the ongoing demand for their goods and services. Investors prefer equities in sectors that offer the best return with the least risk to build optimum portfolios during the crisis. The best return can be achieved if an investor can identify a linkage among the different sectors of the financial market (Patra & Poshakwale, 2008). So, investors need to understand the association among the sectors of the Indian capital market. The need to understand the interdependence among the sectors increases during a crisis period. From an investment standpoint, it is crucial to investigate the structural relationships among the sectors of the Indian capital market. A comprehensive understanding of the volatility spillover relationship could be significant in developing a conducive and appropriate investment strategy, specifically during the crisis period. It enables one to comprehend the evolution and progression of such linkages and the inter-sectoral changes over time (Kaur et al., 2011). Due to the significant ramifications for many parties involved, the sectoral relationship has been a central issue in the finance literature in the last decade.

In the recent past, there has been a surge in academic and financial interest in studying the volatility spillover of various sectoral indices in different markets. However, few studies have addressed the volatility spillover relationship among the sectoral indices of the Indian capital market during a crisis like COVID-19. The transfer of sectoral indices information is an intriguing research subject. Therefore, to address the research gap, this study examines the volatility spillover among sectors of the Indian capital market during the COVID-19 crisis. The research on this topic could potentially provide valuable insights into the dynamics of sectors of the Indian capital market during the COVID-19 period. If the sectoral indices become interdependent over the crisis period, there will be less opportunity for diversification into these sectors. So, the investor should identify relationships among distinct financial market sectors to earn a higher return from the portfolio. Using the NSE's six sectoral indices, an econometric approach is employed in the study to analyze the spillover of both returns and volatility across various sectors.

We make three contributions to the existing literature. First, the study used the closing values of the total return index data. The total return index is unique in encompassing price fluctuations and stock dividend distributions. Second, this study examines the volatility spillover relationship among sectoral indices during the COVID period using the dynamic conditional correlation (DCC) model, which has proven better than other time-series methodologies (Shiferaw, 2019). To capture the influence of negative news on the volatility of sectoral indices, the study employed an asymmetric model of DCC. Last, the study calculated the time-varying conditional correlation among all possible pairs. Therefore, the study holds significance for the Indian capital market because it furnishes a comprehensive empirical assessment of volatility spillover among sectoral indices, especially when investors look for investment options that guarantee optimum portfolio diversification during the crisis.

Literature Review

Much research work has been focused on the area related to our study. The first collection of pertinent work focused on the dynamics and interdependence among sectoral indices and other financial assets. Bagirov and Mateus (2022) investigated the amount and direction of volatility connections between oil prices and Mexico and UK sector indices. Belhassine and Ben Bouzid (2019) and Elyasiani et al. (2013) tested the asymmetric relationship between the Euro and US oil prices and sector indices, respectively. The DCC-GARCH framework was used to study the interaction of sectoral index returns with global oil and gold returns (Civcir & Akkoç, 2021). Degiannakis et al. (2013) found evidence of a contemporary relationship between the oil price and sectoral indices. Exchange rate volatility impacts stock prices because variations in national currencies influence local companies' international competitiveness and cash flows. Mouna and Anis (2017) measured the sensitivity of IT and industrial indices to the exchange rates, market index, and interest rates during the crisis period.

The second collection of research work focused on the interrelationships among the sectoral indices and traditional market indices of the different markets. The GARCH model has been used on the daily sectoral equity index of the Euro to determine the aggregate index of the US and Euro impact on the variability of the Euro sector index (Asal, 2011). The author found that diversification within the sector was more efficient than diversification in international indices. However, Balli and Balli (2011) found that the world sector index did not impact the Euro sector index at the beginning of the Euro. Khalid et al. (2021) investigated the patterns of volatility transmission among several sectors of the Pakistan Stock Exchange (PSX). A multivariate Baba, Engle, Kraft, and Kroner (BEKK) model has been used to capture the volatility interdependencies among the seven sectoral indices of the Moroccan Stock Exchange (El Jebari & Hakmaoui, 2020). The findings validate the presence of bidirectional volatility spillover among the sectoral indices. The dynamic spillover among 10 Dow Jones Islamic (DJI) and traditional sector index pairs was examined (Mensi et al., 2017). Using MGARCH models, the results revealed that all pairs had substantial time-varying conditional correlations.

The third collection of research work concentrated their interest on the volatility of the sectoral indices, which are sensitive to different economic or political events. Samineni et al. (2020) tested the expiration effect of the price volatility of the bank index on the F&O segments; Anoop et al. (2018), Babu et al. (2019), and Chellasamy and Anu (2017) investigated the impact of demonetization on sectoral indices movements in India, and Jiun (2019) investigated the effect of the General Elections on sectoral indices. Furthermore, Muthukamu and Amudha (2020) also examined the influence of GST implementation on the auto sector of the Indian capital market. In addition, Amudha and Muthukamu (2018) also found that the auto sector index reacted more to bad news than good news. During the Euro debt crisis, no such volatility spillover was found among the financial, FMCG, and IT indices (Majumder & Nag, 2018); however, evidence of spillover was found during the global financial crisis (GFC). The authors used the BEKK model for the analysis. Using the BEKK model, Bellelah et al. (2017) investigated the effect of GFC on the sectoral indices of the French equity market.

The COVID-19 crisis impacted the volatility of the sectoral indices. Bhatia and Gupta (2020) found that the bank index was unaffected by COVID-19. MGARCH uncovers a significant negative correlation between COVID-19 and sectors of S&P across the COVID period (Elhini & Hammam, 2021). Costa et al. (2022) and Curto and Serrasqueiro (2022) investigated sectoral connectedness among the sectoral indices of the US market during the COVID period. During the COVID, volatility connectedness among the sectors increased, as suggested by the Diebold and Yilmaz approach (Costa et al., 2022). Curto and Serrasqueiro (2022) used the asymmetric power GARCH model and found that some US sectors were heavily influenced and others were not. The European studies also suggested that Europe's sector prices were strongly linked with gold. Kyriazis (2021) used the DCC model to establish the relationship among sector indices, gold, crude oil, and COVID-19 deaths. The author discovered an indirect relationship between COVID-19 deaths and European markets. Similar results were reported by Pandey (2023), where the author found a higher correlation among the gold, crude oil, and sectoral indices of the Indian capital market. Bouri et al. (2021) found higher-order integration and volatility connections between the rare earth index and other traditional indices. Using daily market return data from 10 worldwide sectors, the authors discovered a similar pattern in the behavior of Islamic and conventional sectoral indices throughout time (Rizvi & Arshad, 2018). Ahmed (2012) examined the interrelationship among the Qatar Stock Exchange's banking, industrial, insurance, and service sector indices. The asymmetric Power GARCH model helped Curto and Serrasqueiro (2022) determine whether COVID-19 impacted the volatility of stocks and sectors.

The last collection of research concentrated on the studies conducted on the sectoral indices of the Indian capital market. The studies on volatility spillover among the sectoral indices in India are not limited. The interdependence among the Indian sectoral indices and other financial assets has also been discussed in previous literature. The DCC model has been deployed to experimentally study the time-varying correlations between crude oil returns and the Indian stock market at sectoral levels (Singhal & Ghosh, 2016). Tiwari et al. (2021)

analyzed the interdependencies and volatility spillover between the returns of sectoral indices of the BSE and oil prices. Trabelsi et al. (2021) assessed the association between gold and seven sectoral indices of the BSE. The authors used MGARCH models to discover that gold returns largely depended on the performance of the BSE sectoral index. Similar results were reported by Mishra (2019), where the author found that the realty index dominated and gold remained neutral in the Indian market. In another study, volatility spillover among the sectoral indices and gold was analyzed using the VAR-ADCC-BVGARCH model (Kumar, 2014). The author found significant volatility spillover from the gold to Indian sector indices. Guha et al. (2016) established a linear relationship between the sectoral indices and the traditional market index of the NSE. The studies of Hasnat (2021), John et al. (2019), Mallikarjuna and Rao (2017), Manimaran and Anand (2017), Anbukarasi and Nithya (2014), and Shanmugasundram and Benedict (2013) attempted to confirm volatility spillover among the Indian sectoral indices.

Furthermore, Batra and Taneja (2020) concluded that the traditional index, Nifty 50, and the sector index, Nifty Pharma, were the most volatile. Aravind (2017) found bidirectional solid causality among the sectoral indices. Sarkar et al. (2009) found global indices caused the volatility in the Sensex, and domestic sectors of capital goods and consumer durables played a lead role in the volatility of the Sensex.

From the review of prior literature, it could be seen that many studies have been carried out on relationships among global stock indices, sectoral indices, and other financial assets. However, there is hardly any study investigating the volatility spillover of sectoral indices of the Indian stock market considering the crisis period like COVID-19. So, the study examines the possible interdependence among the different sectoral indices of the Indian capital market during COVID-19.

Methodology

To fulfill the objectives of the paper and to find out the volatility spillover among the sectoral indices of the Indian capital market, the study was carried out in four different steps: The first was the conduct of preliminary tests, including the stationary checking of indices; in the next step, the data were tested for the existence of serial correlation and ARCH effects; and the third step was to measure both return and volatility spillover among the sectoral indices during COVID-19. The estimation of the time-varying conditional correlation has been carried out in the last step.

Data and Preliminary Analysis

The empirical analysis relies on the six sectoral indices of the NSE, namely Nifty Oil & Gas (Oil & Gas), Nifty Financial Services (Financial Services), Nifty FMCG (Fast Moving Consumer Goods), Nifty Bank (Bank), Nifty Auto (Automobile), and Nifty IT (Information and Technology). Out of the 15 sectoral indices of the NSE, these six sectors represent around 82% of the Nifty 50 index. Daily closing values of six sectors' total return index, from January 31, 2020, to December 31, 2021, were collected from the website of NSE. On January 31, 2020, the World Health Organization (WHO) officially declared COVID-19 a global public health emergency, leading to the recognition of the period's start date in the context of the pandemic (He et al., 2020). The return series is considered for further statistical analysis, which is calculated as follows:

$$R_t = \ln (P_t / P_{t-1}) \qquad (1)$$

Descriptive statistics of the sectoral indices are depicted in Table 1. During the COVID period, the IT index generated the highest average return ; whereas, the Bank index generated the lowest average return. It can also be

Table 1. *Descriptive Statistics of Sectoral Index*

	Oil & Gas	Financial Services	FMCG	Bank	Auto	IT
Mean	0.000963	0.000419	0.000489	0.000303	0.000690	0.001916
Median	0.001934	0.001478	0.000928	0.001033	0.001484	0.002391
Maximum	0.086763	0.089107	0.079905	0.099951	0.098994	0.086406
Minimum	–0.112858	–0.173624	–0.111998	–0.182997	–0.149051	–0.100652
Std. Dev.	0.017497	0.021436	0.013428	0.022527	0.019486	0.017558
Skewness	–0.738196	–1.454729	–0.776716	–1.340637	–0.978559	–0.749248
Kurtosis	11.75904	14.80781	20.56952	14.59795	13.54532	9.902078
Jarque–Bera	1561.572*	2926.978*	6157.214*	2804.512*	2276.717*	987.2910*
ADF Test	–6.1464*	–6.1068*	–6.8233*	–7.0339*	–4.6169*	–7.1012*
PP Test	–24.0663*	–21.9125*	–24.5279*	–21.2998*	–22.6364*	–23.7123*

Note. (*) indicates the significance at a 1% level.

evidenced that all the series are negatively skewed. The skewness defines that the considered series has deviated from the standard distribution curve. The Kurtosis confirms that all series are leptokurtic with a value greater than three. The significant Jarque–Bera value provides evidence to reject the null hypothesis of normality. The augmented Dickey–Fuller test (ADF) and Phillips-Perron (PP) test of the stationary test of all series are also presented in Table 1. The significant value of the ADF and PP tests indicates that all the return series are stationary at a level that satisfies the prerequisite condition to use the GARCH models.

Asymmetric DCC Model

The DCC model has been developed to capture time-varying conditional correlation, which measures the volatility spillover among the return series. The number of parameters to be assessed in the DCC MGARCH model increases linearly instead of exponentially, as in the multivariate GARCH model, by resolving the dimensionality issue (Singhal & Ghosh, 2016). The ADCC model proposed by Cappiello et al. (2006) was employed in this study. It is a generalized version of Engle's (2002) DCC model that includes an asymmetric term. It enables the measurement of asymmetric information on time-varying conditional correlation. The dependent correlation coefficient is lower in the situation of joint negative returns, i.e., when both returns are negative.

Conversely, when there is joint positive news, the coefficient tends to be higher (Jain & Sehgal, 2019). The DCC model's covariance matrix is expressed as $H_t = D_t R_t D_t$. H_t is the conditional covariance matrix. D_t is the conditional variance in the $k \times k$ diagonal matrix. It is a matrix of time-varying standard deviations for return series. R_t presents a time-varying conditional correlation (Gabauer, 2020). R_t is computed as follows:

$$R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t)^{-1/2}) \qquad (2)$$

Where, $Q_t = (1 - \psi - \phi)\overline{Q} + \psi\mu_{t-1}\mu'_{t-1} + \phi Q_{t-1}$.

Where, Q_t refers to positive definite matrix, the ψ and Φ are the scalars parameters such that $\psi + \Phi < 1$ (Chittedi, 2015; Perumandla & Kurisetti, 2018). Further $\overline{Q}$ refers to the $k \times k$ matrix of standardized residuals (Seth & Singhania, 2019). The previously indicated DCC model does not capture the asymmetric model. As a result, Cappiello et al. (2006) developed the ADCC model described below:

$$Q_t = (1-\psi-\phi)\,\overline{Q} - \omega\overline{N} + \psi\mu_{t-1}\mu'_{t-1} + \phi\, Q_{t-1} + \omega n_{t-1} n'_{t-1} \quad (3)$$

Here, ω is the asymmetric parameter term. The unconditional correlation matrix of residuals of μ_t is represented by $\overline{Q} = E[\mu_t \mu'_t]$. $\overline{N} = E[n_t n'_t]$ is the unconditional covariance matrix of n_t. Furthermore, ψ and ϕ are the nonnegative parameters of standardized residuals and shock in the dynamics of the conditional correlation matrix, respectively. If the sum of ψ and ϕ is less than 1, then the model is mean reverting.

Empirical Analysis and Results

Testing Serial Correlation and ARCH Effects

The results of serial correlation and ARCH effects of the return series of the sectoral indices are presented in Table 2. The ARCH Lagrange multiplier test's significant value (LM) indicates heteroscedasticity in all return series at lag five. Furthermore, the Ljung-Box test (LB) applied to squared residuals yielded an important result supporting serial correlation in all sectoral return series. The results of both tests confirm that the GARCH models can be used to measure the volatility spillover among the sectoral indices.

Return Spillover

Table 3 presents the return spillover among the sectoral indices computed from the ADCC MGARCH model. It is clear from the data that the Oil & Gas index coefficient is negative and significant, indicating that its return has a sizable negative impact on the return of the Financial Services and Bank index. Similarly, the previous return of the IT index has an asymmetric effect on the current return of the Oil & Gas, Financial Services, and Bank index. A bidirectional return spillover exists among the Financial Services, Auto, Bank, and IT indices. The current return

Table 2. ***Results of Serial Correlation and ARCH Effects***

	Oil & Gas	Financial Services	FMCG	Bank	Auto	IT
ARCH LM Test (5)	22.633*	56.0073*	71.3839*	30.1991*	38.0457*	81.4040*
L–B Q^2 Stat (5)	23.787*	68.635*	82.436*	35.736*	42.658*	92.358*

Note. (*) indicates the significance at a 1% level.

Table 3. ***Return Spillover Effects***

Spillover To	Spillover From					
	Oil & Gas	Financial Services	FMCG	Bank	Auto	IT
Oil & Gas	–0.0494	0.0255	0.0866	0.0876	0.0603	–0.1735*
Financial Services	–0.1906*	–0.0447	–0.0146	0.1956	0.0811*	–0.0859*
FMCG	–0.0503	0.0628	0.0258	–0.0782	0.0638*	–0.0809*
Bank	–0.2170*	0.0120	–0.0372	0.1741	0.1123*	–0.1118*
Auto	–0.0645	0.3118**	–0.0768	–0.1516	0.0519	–0.0783*
IT	–0.0031	0.2234*	0.0757	–0.1825**	0.0493	–0.0456

Note. (*) and (**) indicates the significance at a 1% and 5% level, respectively.

of the Auto and FMCG index is negatively impacted by bad news relating to the IT index, as indicated by the strong negative coefficients. Information detrimental to the prior Auto index return affects the present return of the Bank index.

Volatility Spillover Effect

The results of the ADCC MGARCH model, which assesses the volatility dynamics among the sectoral indices of the Indian stock market, are presented in Table 4. "*C*" signifies the constant term, "*A*" represents the ARCH effects, "*B*" is the GARCH effects, and "*D*" is the asymmetric term. The "*DCC*(1)" and "*DCC*(2)" present the combined ARCH and GARCH effects. The ARCH effect assesses the impact of volatility for a short period, including the previous period's persistence of residuals. GARCH effects evaluate the conditional correlation of

Table 4. *Volatility Spillover Effects*

Variables	Coefficient	Standard Error	*t*-Statistics	Significance
C(Oil & Gas)	0.0000	0.0000	0.6439	0.5196
C(Financial Services)	0.0000	0.0000	3.5723	0.0004
C(FMCG)	0.0000	0.0000	5.3321	0.0000
C(Bank)	0.0000	0.0000	3.5801	0.0003
C(Auto)	0.0000	0.0000	3.7788	0.0002
C(IT)	0.0000	0.0000	4.7800	0.0000
A(Oil & Gas)	–0.0540	0.0082	–6.6178	0.0000
A(Financial Services)	0.0367	0.0204	1.7999	0.0719
A(FMCG)	0.0729	0.0219	3.3337	0.0009
A(Bank)	0.0232	0.0154	1.5121	0.1305
A(Auto)	0.0748	0.0135	5.5379	0.0000
A(IT)	0.0303	0.0200	1.5168	0.1293
B(Oil & Gas)	0.9996	0.0094	106.3158	0.0000
B(Financial Services)	0.9144	0.0192	47.7227	0.0000
B(FMCG)	0.8553	0.0221	38.6284	0.0000
B(Bank)	0.9294	0.0154	60.3804	0.0000
B(Auto)	0.8975	0.0131	68.6395	0.0000
B(IT)	0.8787	0.0202	43.4095	0.0000
D(Oil & Gas)	0.1023	0.0126	8.1434	0.0000
D(Financial Services)	0.0434	0.0173	2.5170	0.0118
D(FMCG)	0.0300	0.0221	1.3597	0.1739
D(Bank)	0.0475	0.0136	3.5031	0.0005
D(Auto)	–0.0078	0.0188	–0.4173	0.6765
D(IT)	0.0516	0.0272	1.8964	0.0579
DCC(1)	0.0122	0.0036	3.3509	0.0008
DCC(2)	0.9617	0.0147	65.5653	0.0000
DCC(3)	–13.2948	0.0000	0.0000	0.0000

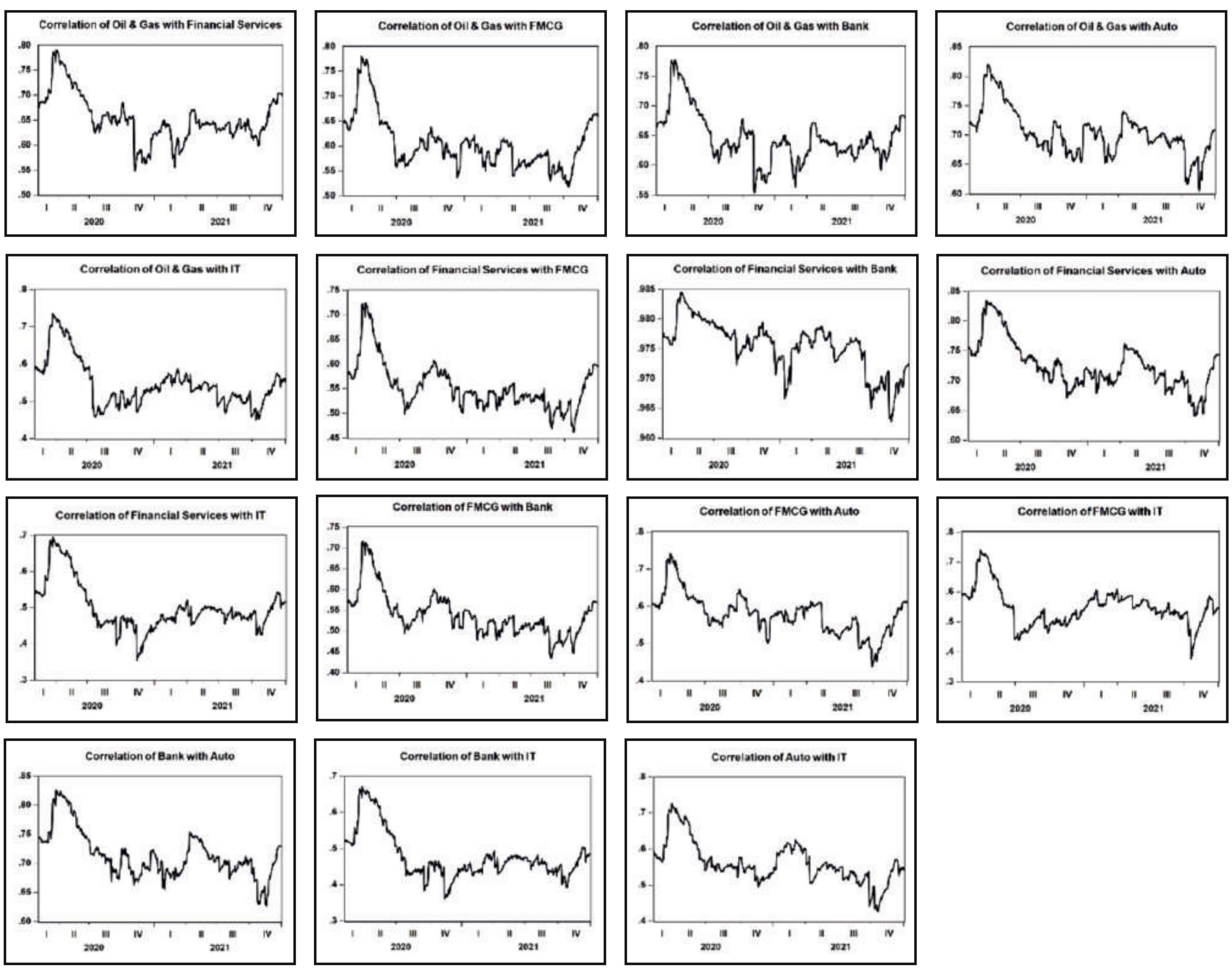
long-term shock (Yadav & Pandey, 2019). The significant ARCH term indicates volatility that persists for a short time. Like the ARCH term, the significant GARCH term also suggests long-run volatility persistence.

The sum of the ARCH *(A)* and GARCH *(B)* coefficients in Table 4 is close to 1, indicating significant volatility and persistence over time. Furthermore, *DCC*(3) represents the joint asymmetric term. The negative and significant joint asymmetric coefficient shows that bad news has a greater influence on sectoral indices during the COVID period than good news. One important observation from the results is that all GARCH terms are positive and significant, implying that long-run volatility persistence exists in all the sectoral indices. The coefficients of *DCC*(1) and *DCC*(2) are significant and positive, suggesting that interdependence existed among the sectoral indices of the Indian stock market during the COVID period. So, it is worth mentioning that an asymmetric volatility spillover relationship existed among the sectoral indices of the Indian capital market during the COVID period.

Conditional Correlations

Figure 1 illustrates the time-varying conditional correlations derived from the ADCC MGARCH model. The

Figure 1. ***Conditional Correlations***



significant fluctuation in dynamic conditional correlations during the sample period suggests that reliance on constant correlations might be deceptive. The graphs show that volatility is accumulating over the series. It is worth noting that the conditional correlation between most of the pairs is positive and typically more than 0.50. As a result, portfolio investors have limited opportunities to diversify their investments between the pair of sectors.

The conditional correlations between the Oil & Gas and Financial Services and Oil & Gas and Bank show similar patterns and magnitudes. Similar trends can be seen in the conditional correlations between FMCG and Auto, Financial Services and Auto, and Oil & Gas and Auto. The financial services and banking industries have the largest conditional correlations estimated using the ADCC model, indicating less room for diversification in these two areas. It is also evident from the graph plot (Figure 1) that during the early phase of the COVID period, all pairs presented a sudden spike, showing higher conditional correlations among the sectors; however, with the passage of time, correlations between the sectors started to decline and remained within a range.

Discussion

The COVID-19 outbreak is regarded as a global disaster and a major financial disruption worldwide, far exceeding previous catastrophic events such as the GFC. The spread of COVID-19 has significantly impacted the global economy, affecting everything from the tourism industry to international trade, manufacturing to the service sector, and airlines to various other sectors. Despite the escalating economic recession, the global IT and food industries remain balanced and have exceeded expected demand. In short, the COVID-19 outbreak is expected to have widely divergent effects across sectors. So, this study investigated the volatility spillover among sectoral indices of the Indian capital market during the COVID period. The daily total return index of six sectoral indices was collected from NSE to fulfill the study's objective. The ADCC MGARCH model is the principal methodology for establishing the variables' volatility spillover relationship. This asymmetric GARCH model identifies bad news's impact on the volatility of sectoral indices.

Furthermore, the study used the time-varying conditional correlation to find diversification opportunities among the indices. Our findings indicate a volatility spillover among the sectoral indices during the COVID period. The return spillover shows that the IT index negatively and significantly impacted the current movements of the Oil & Gas, Financial Services, FMCG, Bank, and Auto indices. Some underlying reasons are the adoption of remote work practices and the expedited digital transition during COVID-19. The IT sector showed resiliency as many businesses quickly adopted remote work arrangements and ensured continuity in the organization. While the IT industry outperformed throughout COVID-19, it's crucial to highlight its overall impact on other varied sectoral indices. The significant ARCH and GARCH terms indicate the presence of both short- and long-run volatility persistence among the sectoral indices. The results also suggest that bad news contributes more significantly than good news to the volatility of the sectoral indices. The graph plot of time-varying conditional correlation depicts that the correlation among the pairs is so high during the beginning of the COVID period that it suggests avoiding diversification among the pairs. Several reasons contributed to the significant correlation among Indian sectoral indices during COVID-19. Several sectors were affected by the widespread COVID-19 outbreak, lockdowns, and uncertainty. As a result, challenges such as decreasing consumer demand, supply chain disruptions, and economic downturns have impacted the financial performance of enterprises in all sectors. Negative shocks and disruptions in one area have a knock-on effect on other sectors due to the interdependence of supply chains, consumer bases, and financial links.

Conclusion

At the onset of COVID-19, the volatility of the Indian stock market's sectoral indices reached unusually high levels, and these indices began to react negatively to COVID-related information. However, based on the findings, it is reasonable to conclude that sectoral indices rebounded and were relatively efficient in the long run. The various measures implemented by federal and state governments to curb the spread of the coronavirus made this achievable. The study also concludes from the conditional connection that pandemics have had the greatest short-term influence on sectoral indices, which gradually declined over time as the market restored to normalcy and headed toward long-term advantage.

The current research can contribute to the academic literature on the Indian capital market during COVID-19. This study may offer empirical evidence that confirms or refutes accepted ideas or conclusions in the field of research on the sectoral indices of the Indian capital market. The current research supports the findings of Guru and Das (2021), where the authors indicated that volatility spillover among sectoral indices increased significantly during the COVID-19; however, the current study also reveals that bad news has a greater impact on sectoral indices than good news. The findings show that the capital market sectors have a spillover relationship within a given economy. Investors may benefit from our study. Investors are advised to avoid investing actively during crises like COVID, where the correlation among the sectors is too high. Policymakers may use this study to assist them in developing targeted policies to reduce systemic risks and control cross-sectoral spillover effects.

Managerial Implications

The outcomes of this study have significant implications for investment diversification strategies. Portfolio managers who attempt to allocate investors' resources efficiently must be aware of the extent to which sector-specific stock indices are more volatile in a given economy, specifically during a crisis period. Investment portfolios built on relatively independent economic sectors are more likely to generate value and improve the ability to reduce the primary component of investment risk. The findings may provide fund managers with insights into sectoral integration, allowing them to learn about the interdependencies among sectors in the Indian capital market. Finally, portfolio managers must assess if sector diversification is appropriate or required when establishing an equity investment portfolio. Understanding volatility spillover can have implications for policymakers and regulators. Sectors that were more vulnerable to spillover effects during the COVID-19 period may be identified, and this information can be used to direct policy initiatives targeted at boosting market stability and resilience.

Limitations of the Study and Scope for Future Research

The research is restricted to the sectoral indices of India. A formal assessment of the volatility spillover among various sectoral indices of well-established and emerging financial markets would be an interesting issue for future research. There is also scope for further research in studying the integration of the Indian capital market sectoral indices with neighboring countries' capital markets, such as Pakistan, China, Bangladesh, and Sri Lanka. Future studies can also use other MGARCH models like BEKK to investigate the volatility spillover among the stock market indices.

Authors' Contribution

Satyaban Sahoo designed the conceptual framework for the empirical study. He also conducted data collection, data analysis, and finalization of the research design. Dr. Sanjay Kumar was involved in the supervision and review of the manuscript. Satyaban Sahoo and Dr. Sanjay Kumar jointly wrote the manuscript.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript.

Funding Acknowledgment

The authors received no financial support for the research, authorship, and/or for publication of this article.

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About the Authors

Satyaban Sahoo is currently working as an Assistant Professor at the Department of Commerce, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka. He did his Ph.D. from the Department of Management, Central University of Rajasthan, Rajasthan. He has published three research papers in international journals of repute. His current research interests include capital market, sustainable finance, and econometrics.

Dr. Sanjay Kumar is currently working as an Assistant Professor at the Department of Management, Central University of Rajasthan, Rajasthan, India. He has been a Visiting Scholar and did his post-doctorate from the College of Business and Public Administration, California State University, San Bernardino, USA. He was awarded with the INDO - US UGC Raman Fellowship in 2014 by the University Grants Commission, New Delhi. He was also honored with the “Best Teacher Award” in 2013 by the Central University of Rajasthan. He has attended and presented papers at many national and international conferences. He has published many articles in national and international journals of repute. He has completed many projects, which include projects from ICSSR and the Society for Technology Incubation & Development of Entrepreneurs (STIDE).