Available online @ https://jjem.jnnce.ac.in
https:www.doi.org/10.37314/JJEM.SP0143
Indexed in International Scientific Indiexing (ISI)
Impact factor: 1.395 for 2021-22
Published on: 08 December 2023

Dynamics of Return and Volatility interactions between Exchange Rates and NSE Sectoral Indices: A Comparative Analysis Pre and Post COVID-19 Pandemic.

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ABSTRACT

This paper investigates the dynamics of return and volatility spillover effects between exchange rates and National Stock Exchange (NSE) sectoral indices, with a focus on the distinct periods before and after the outbreak of the COVID-19 pandemic. By employing the robust Dynamic Conditional Correlation GARCH (DCC-GARCH) model, this study assess relationship between these critical financial indicators. Empirical analysis is carried out using daily return data of USD/INR exchange rate and NSE sectoral indices, spanning both the pre-pandemic and post-pandemic eras ranging from 1st January 2018 to 31st October 2023. The DCC-GARCH model is applied to capture the time-varying correlations and conditional volatilities within these datasets. The findings of the study revealed that in short run there is a spillover effect from exchange rates to Indian stock markets. Investors must be cautious to invest in the Indian stock market for the long period of time as there is volatility spillover or volatility transmission observed in few sectors of NSE post covid.

Keywords:

Exchange Rate, NSE Sectoral Indices DCC-GARCH; volatility spillover;COVID-19 Pandemic.

1. Introduction

The COVID-19 pandemic has significantly impacted stock markets, leading to a rapid fall in global financial markets. This has resulted in unexpected downward pressure on global indices, with recent studies showing greater volatility during March 2020 compared to historical crises like Black Monday in 1987 or the Great Depression of 1930(Baker et al., 2020). The Indian stock market experienced major shocks in the first quarter of 2020, with the NSE and BSE paused trading due to the lower circuit threshold of 10% twice in two weeks. The first crash occurred on February 1, 2020, with the Nifty and Sensex experiencing the worst weekly fall in over a decade. The worst crash occurred on March 12, 2020, when the WHO acknowledged COVID-19 as a universal epidemic, causing Sensex to close at 33 months low and Nifty to crash by 8.30%.

Multinational corporations (MNCs) primarily depend on revenue generated from overseas operations. Engaging in various tasks such as hedging decisions, short-term financing, short-term investments, capital budgeting, earnings assessment, and long-term financing becomes imperative for MNCs. This multifaceted involvement exposes them to the impact of exchange rate movements. Consequently, a profound understanding of these movements is essential for MNCs to make informed decisions. This comprehension is particularly beneficial for managing short-term financing, investments, capital budgeting, assessing earnings, handling exposure to foreign contracts, and mitigating exchange rate risks, thereby stabilizing their earnings.

Furthermore, the empirical findings derived from such studies contribute significantly to uphold the theoretical framework related to the determinants of exchange rates or stock market movements.

Due global linkages, Exchange rate plays a significant role in stock market volatility. It is evident from past studies that stock prices are volatile to movement in foreign exchange returns.The objective of this paper is to examine the relationship and volatility spillovers between Indian stock and foreign exchange markets. Understanding volatility spillover between assets or markets is crucial, as it elucidates that a significant shock not only increases volatility within its originating market but also has a cascading effect, amplifying volatility across other interconnected markets (Hong, 2001).There are only a handful of studies examining the volatility spillover between futures-spot commodity market especially in India. Most of the earlier studies examining exchange rate volatility spillover in Indian stock market have used the methods like GARCH, EGARCH, BEKK(Kumar, 2013). But the literature examining volatility spillover of exchange rate in NSE sectoral indices using DCC-GARCH method in India is very limited. Hence the study.

2. Literature review

Numerous studies have applied the volatility spillover model, with a substantial focus in the literature on examining its implications, particularly in the realm of stock markets. The studies have been conducted to inspect the volatility spillover acrossglobal indices. Based on the type of literature they are divided into 4 groups a)volatility transmission in sectoral indices, b) volatility transmission between stock indices of multiple countries, c) volatility spillover between exchange rate and other foreign countries and d) volatility spillover between exchange rate and Indian stock market indices.

Dang et al. (2023)assessed the volatility spillover effect across 14 sectors of Vietnam stock market pre and post pandemic period using vector autoregression (VAR) connectedness approach. The results show the higher degree of volatility during COVID-19 pandemic crisis among Commerce, Transportation, and service sectors.Despite of Higher volatility due to pandemic, the post pandemic returns showed the pre pandemic volatility levels(Datta & Hatekar, n.d.; Laborda & Olmo, 2021; Vo, 2023). Higher rate of volatility wasalso observed due to removal of currency peg (Fasanya & Akinde, 2019).The interdependence of global markets results in dissemination of information across markets resulting in volatility spillover(Natarajan et al., 2014). Unidirectional volatility transmission was observed from stock market to foreign exchange market in India(Jebran & Iqbal, 2016a).

Numerous studies have thoroughly investigated the dynamic relation between exchange rates and stock markets (Mok, 1993; Yadav et al., 1993; Yau et al., 2006). The symmetric spillover from stock returns to exchange rate returns(Kanas, 2000). Bidirectional volatility transmission was observed between stock indices and exchange rate returns(Maitra & Dawar, 2019)**.**Several studies also reveal the price and volatility spillovers between developed and emerging markets(Wang & Wang, 2010). There isevidence of higher amount of volatility transmission from currency market to stock market(Bal et al., 2018; D. Singh et al., 2021).

Many researchers have used GARCH family models namely, GARCH, EGARCH, BEKK GARCH and VAR models to assess the volatility transmission(Jebran & Iqbal, 2016b; Karmakar, 2005; Sahoo & Kumar, 2022) and spillover effects of foreign exchange(Dey & Sampath, 2020).

The consensus emerging from the literature review indicates that most studies acknowledge that the market's assessment and absorption of new information are evident in the volatility process. Consequently, the study of volatility spillover proves beneficial for understanding financial contagion between countries or within different asset classes.

Research Gap

After an in-depth examination of the literature, it is evident that most studies have focused on the volatility of BSE and NSE indices in India in relation toglobal markets, exchange rate and other macro-economic factors. However, there is a limited amount of research specifically examining the spillover volatility effects between exchange rates and NSE sectoral indices. This gap in the literature serves as motivation for undertaking a study to investigate the relationship between exchange rates and NSE sectoral indices. The empirical findings from this study aim to contribute insights into the impact of exchange rate volatility on NSE indices. Additionally, the results will aid in recognizing currency markets that may have contagion effects on volatility within the Indian stock market.

3. Data and Methodology

3.1 Data

The market returns were obtained from the official website of National Stock Exchange by taking the daily closing prices of 16 sectoral indices of the Exchange, namely Nifty Auto, Nifty Bank. The closing prices were taken for the period from January 1, 2018, to October 31, 2023. For the study, the collected datasets divided into three date ranges. Pre-Covid period from January 1,2018 to December 31,2019, Covid period from January 1, 2020, to June 30,2020 and post covid period from July 1, 2021 to October 31, 2023.

3.2 Log returns

The log returns are calculated for closing prices of each sector and exchange rate.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (1)$$

Where R_t=Daily Returns, P_t=price of the current period and $P_{(t-1)}$ = price at the previous period.

3.3 Stationarity test

A variety of tests are available to determine the presence of unit root in data, including the Dickey and Fuller test and the tau test (Dickey & Fuller, 1979) the Phillips–Perron test and ADF test (Phillips & Perron, 1988). ADF is by far the most widely used method for determining time-series data stationarity(N. P. Singh & Sharma, 2018). The null hypotheses proposed in ADF test indicates that all series contains the unit root. Failure of acceptance will result in existence of stationarity in the data considered for the study.

$$\Delta \mathbf{y_t} = \boldsymbol{\alpha} + \boldsymbol{\beta} \mathbf{Y_{t-1}} + \sum_{i=1}^{n} \boldsymbol{\mu}\, \Delta \mathbf{Y_{t-i}} + \boldsymbol{\varepsilon_t}$$

3.4 Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity Model (DCC-GARCH)

The literature provides application of various volatility models to understand the shock transmission among multiple variables. The researchers have extensively used diagonal BEKK model(Zolfaghari et al., 2020), diagonal VECH model, Multivariate GARCH model(Bala & Takimoto, 2017) and DCC-GARCH model(Alqahtani & Chevallier, 2020)

To study the volatility spillover among multiple variables, DCC-GARCH model(Engle, 2002) is employed. The reason lies in the advantages of 2 step estimation procedure. The equation can be specified as below.

$$\boldsymbol{Z_t = u_t + H_t^{1/2} \epsilon_t} \qquad \textbf{(1)}$$

whereZ_t is a vector of historic values of NIFTY sectoral indices$H_t$is a multivariate conditional variance, u_t is a vector of conditional returns and $\epsilon_t$is a vector of standardized returns.The GARCH element is explained in dynamic conditional covariance matrix which is defined as

$$\boldsymbol{H_t = D_t R_t D_t} \tag{2}$$

D_t is diagonal matrix of conditional standard deviationsfrom univariate GARCH model. It is written as below.

$$\boldsymbol{D_t}=\left(\sqrt{\boldsymbol{h_{11t}}} \ldots, \sqrt{\boldsymbol{h_{NNt}}}\right) \tag{3}$$

R_t is conditional correlation matrix which is expressed as:

$$\boldsymbol{R_t = Q_t^{*-1} Q_t Q_t^{*-1}} \tag{4}$$

Q_t is a conditional covariance matrix can be calculated using the following formula.

$$\boldsymbol{Q_t}=(1\text{-a-b})\boldsymbol{Q' + a\epsilon_{t-1}\epsilon'_{t-1} + bQ_{t-1}} \tag{5}$$

Q' is unconditional covariance after residual standardization,$\epsilon_{t-1}\epsilon'_{t-1}$ is a lagged function of the standardized residuals and Q_{t-1} is the past realization of the conditional covariance. The sum of DCC parameters a& b should be less than 1 and H_t should be positive. The conditional correlation can be written as:

$$\boldsymbol{p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}} \tag{6}$$

where $q_{ij,t}$ are the elements of *i*-th and *j*-th market in Qt.

4. Results and Discussion

Table 4.1showing Descriptive statistics of Exchange rate and NSE sectoral indices.

NSE Sectors	Mean	SD	Skewness	Kurtosis	Jarque-Bera
AUTO	10328.59	2478.109	0.295997	2.761927	24.49599
BANK	32444.67	7037.834	0.106132	2.068985	54.86266
COMMODITIES	4443.711	1200.779	0.170855	1.513657	139.9466
CON DURABLE	19904.08	5862.567	0.204763	1.439104	156.6805
ENERGY	19053.92	5011.794	0.393772	1.63005	150.2355
FIN SERVICE	14734.17	3312.366	0.034473	1.588981	120.0763
FMCG	35389.63	7382.92	0.89423	2.725107	196.9952
HEALTHCARE	6830.268	1618.26	0.0313	1.507901	134.1885
HOUSING	6036.392	1624.191	0.214001	1.469512	151.9557
IT	22774.96	7961.915	0.216703	1.559577	136.1367

MEDIA	2074.38	535.8804	0.828258	3.543962	182.9030
METAL	4215.174	1576.083	0.149852	1.589475	125.1107
OIL & GAS	6103.264	1423.828	0.229169	1.496120	148.7156
PHARMA	11218.88	2349.91	-0.060008	1.634948	112.9792
PSU	2800.798	875.2108	0.362624	3.107686	32.34437
SERVICE	19235.89	4385.846	0.04679	1.416677	151.3595
USD	74.46134	4.979041	0.145979	2.422246	25.21219

Table 4.1 presents a comprehensive overview of the summary statistics for the series examined in this study. Notably, all sectors in the NSE exhibit positive average returns, signalling overall profitability. However, distinctive patterns emerge when analysing volatility, skewness, kurtosis, and the normality of the series.

The IT sector stands out with the highest volatility, as reflected in its substantial standard deviation of 7961.915. Following closely is the Banking sector with a standard deviation of 7037.834, emphasizing its notable price fluctuations. In contrast, the USD exhibits lower volatility with a standard deviation of 4.97. This discrepancy in volatility underscores the comparatively higher price fluctuations in the Indian stock market represented by the NSE.

The pharma sector is distinctly negatively skewed, suggesting a distribution with a longer left tail. Conversely, the returns of other NSE sectors and exchange rate demonstrate positive skewness, indicating longer right tails. This skewness provides insights into the asymmetry of return distributions for different sectors.

The leptokurtic nature of the distribution is observed in the commodities sector, as indicated by its kurtosis values. A leptokurtic distribution has fatter tails, suggesting a higher likelihood of extreme values. This implies that the commodities sector may exhibit more pronounced fluctuations in returns compared to a normal distribution.

The application of the Jarque–Bera test reveals that the series under consideration are not normally distributed. Sectors like FMCG, HEALTHCARE, and BANK exhibit relatively higher Jarque-Bera values, signalling potential deviations from normality in their return distributions. The outcomes substantiate the presence of asymmetric, highly volatile, and non-normally distributed patterns within the NSE sectors, and the exchange rate price series examined in the study.

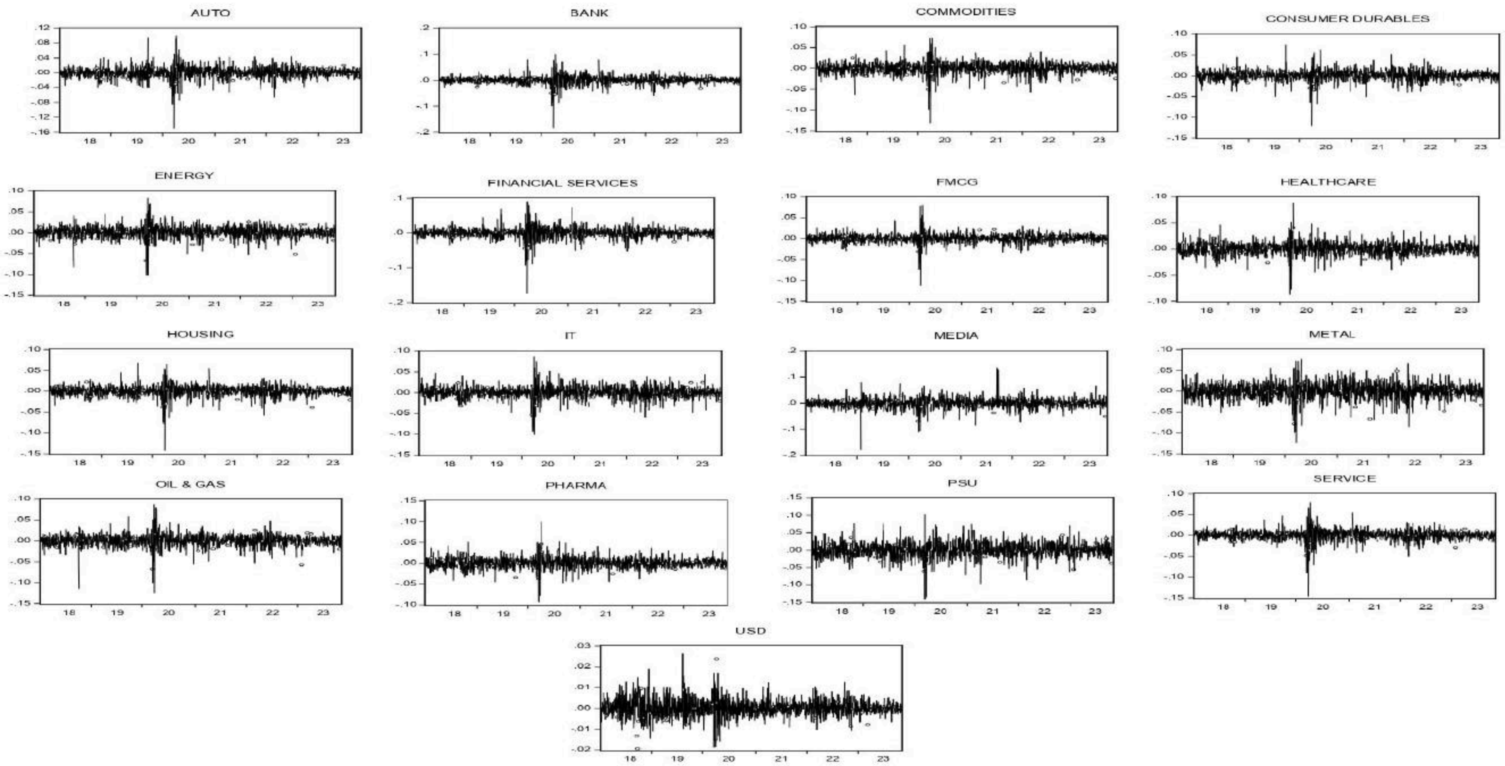
4.2Table showing Cross Correlation between Exchange Rate and NSE sectoral Indices.

NSE SECTORS	AUTO	BANK	COMMODITIES	CONSUMER DURABLES	ENERGY	FINANCIAL SERVICES	FMCG	HEALTH CARE	HOUSING	IT	MEDIA	METAL	OIL& GAS	PHARMA	PSU	SERVICE	USD
AUTO	1.0000																
BANK	0.7066	1.0000															
COMMODITIES	0.7479	0.7081	1.0000														
CON_DURABLE	0.7130	0.6472	0.6913	1.0000													
ENERGY	0.6373	0.6118	0.8576	0.5805	1.0000												
FIN_SERVICE	0.7106	0.9714	0.7082	0.6657	0.6124	1.0000											
FMCG	0.5970	0.5605	0.6178	0.5905	0.5427	0.5751	1.0000										
HEALTHCARE	0.5054	0.4138	0.5733	0.4749	0.4686	0.4184	0.5357	1.0000									
HOUSING	0.8004	0.8564	0.9129	0.7678	0.7471	0.8658	0.6691	0.5617	1.0000								
IT	0.4345	0.4179	0.4859	0.4509	0.4128	0.4431	0.4502	0.4488	0.4944	1.0000							
MEDIA	0.5808	0.5160	0.6061	0.5157	0.5098	0.5007	0.4260	0.4261	0.6058	0.3651	1.0000						
METAL	0.6316	0.5981	0.8917	0.5800	0.6647	0.5912	0.4701	0.4983	0.7961	0.4177	0.5376	1.0000					

OIL & GAS	0.6437	0.6043	0.8525	0.5824	0.9437	0.6076	0.5517	0.4779	0.7385	0.4131	0.5167	0.6601	1.0000				
PHARMA	0.4786	0.3901	0.5474	0.4380	0.4496	0.3915	0.5054	0.9815	0.5302	0.4221	0.4026	0.4795	0.4587	1.0000			
PSU	0.5800	0.7145	0.6539	0.5175	0.5715	0.6557	0.4303	0.3947	0.6909	0.2836	0.5267	0.5819	0.5729	0.3812	1.0000		
SERVICE	0.7323	0.9334	0.7572	0.6902	0.6647	0.9569	0.6232	0.4964	0.8849	0.6607	-0.0683	0.6392	-0.1137	0.4668	0.6437	1.0000	
USD	-0.1134	-0.1412	-0.1192	-0.1243	-0.1009	-0.1492	-0.0872	0.0170	-0.1298	-0.1030	0.5418	-0.0912	0.6543	0.0257	-0.1121	-0.1509	1.0000

Table 2 presents a correlation matrix, indicating the degree of linear association between different NSE sectors and the USD.Except Healthcare and Pharma sector, the unconditional correlations between the USD/INR exchange rate returns and majority of the NSE sector returns are negative, but with different magnitudes. In contrast, correlations within NSE sectoral indices are strongly positive.

Figure 1 Log return series of 16 sectors of NSE and USD/INR exchange rate



The return series volatilities as represented in Figures 1 change over time and demonstrate positive serial correlation, known as "volatility clustering". It is evident that large changes tend to be followed by large changes and small changes tend to be followed by small changes,

Table 4.3 Augmented Dickey–Fuller Test

NSE SECTORS	AT LEVEL	AT FIRST DIFFERENCE
AUTO	0.6967	0
BANK	0.4844	0
COMMODITIES	0.5097	0
CON_DURABLE	0.5181	0
ENERGY	0.4676	0
FIN_SERVICE	0.3263	0
FMCG	0.6273	0
HEALTHCATE	0.5558	0
HOUSING	0.5576	0
IT	0.8684	0
MEDIA	0.6274	0
METAL	0.5791	0
O_G	0.3469	0
PHARMA	0.5304	0
PSU	0.9046	0
SERVICE	0.5833	0
USD	0.5833	0

Table 4.3presents the outcomes of the Augmented Dickey-Fuller (ADF) test. Upon examining the p-values for all series after the first difference, their statistical significance is evident, resulting in the rejection of the null hypothesis. This indicates that after a single differencing operation, the resultant series achieves stationarity. Consequently, it implies the existence of a first-order trend component in the series, emphasizing the necessity of differencing to attain stationarity in the data.

DCC-GARCH model is applied to examine the spillover from exchange rate to NSE sectoral indices. The results are segregated into 3 tables. **Table 4.4a**presents the spillover effect from USD/INR exchange rate to NSE sectoral indices during pre-covid period. **Table 4.4b**and **Table 4.4c**presents the spillover effect during covid and post covid period respectively.

Series A reports the estimated ARCHparameter, which measures the response of the conditionalvolatility to external shocks. In pre-Covid time (Table 4.4a) almost all estimates of are statistically significant,except for NIFTY Auto, NIFTY IT, NIFTY Oil & Gas. In terms of magnitudes, 10 sectors are above 0.1, which implies that the volatility of returns of NSE sectoral indices is responsive to the shocks from USD/INR exchange rate.During Pandemic (Table 4.4b)all the sectors have experienced the effect of exchange rate shocks. Among them 9 sectoral returns observed negligible volatility.NIFTY Commodities, Consumer Durables and Service sectors have not experienced considerable variations due to exchange rate fluctuations during Post-Covid Period.

Series B reports the estimated GARCH parameter, which measures the response of the conditional volatility from past shocks.The estimated β are statistically significant and positivein all 3 periods of study except Energy and Consumer Durable sectors in pre-Covid(Table 4.4a). The magnitudes of theβin rest of the sectors are above 0.75. This suggests that the conditional volatility in Energy consumer durables sector market takes a relativelyshort time to diminish from past shocks compared to NSE sectoral Indices. Furthermore,all estimated models have satisfied the mean-reverting condition, where $0 < \alpha_{ij} + \beta_{ij} < 1$.

The DCCα signifies the spillover effect in the short run. Except NIFTY Housing sector during pre-Covid and NIFTY Healthcare sector during Covid period,short run spillover effect was not observed in rest of the NSE sectoral indices.

DCC β parameter is insignificant for NIFTY Bank, Commodity, Energy, Housing, Oil & Gas, Pharma and Service sectorindicates that there exists volatility transmission from Exchange rate to NSE sectoral indices in long run period during pre-Covid period (Table 4.4a). The findings of the study postulate that investor can invest in the Indian stock market for short-run period as there is no sign of volatility spillover from the exchange rate fluctuations considered in the study.

NSE Commodities(0.7439)Energy(0.7762) Healthcare(0.5613) IT (0.6096) Oil & Gas (0.5827) and Pharma (0.9446) during post covid are indicatingthat there is no lingering spillover fromthe Exchange rate to the respective sectors.

Table 4.4a DCC GARCH ESTIMATION PRE COVID-PERIOD 1/1/2018-31/12/2019

NSE SECTORAL INDICES	Shock from USD/INR (490 observations)			
	Series A	Series B	Series C	
	α	β	DCC α	DCC β
AUTO	0.123997 (0.0316)	0.845239 (0.0000)	0.0000034 (0.9584)	0.864295 (0.1527)
BANK	0.182691 (0.2552)	0.733527 (0.0019)	0.0000001 (0.99985)	0.824917 (0.0000)
COMMODITIES	0.081003 (0.2671)	0.800634 (0.0000)	0.011361 (0.6004)	0.939767 (0.0000)
CON DURABLE	0.210010 (0.1270)	0.010415 (0.9814)	0.0000002 (0.8902)	0.816536 (0.0481)
ENERGY	0.183816 (0.0739)	0.369529 (0.5800)	0.025844 (0.4166)	0.760388 (0.0037)
FIN SERVICE	0.128115 (0.1028)	0.801432 (0.0000)	0.0000001 (0.3078)	0.853959 (0.0013)
FMCG	0.084967 (0.2230)	0.742517 (0.0240)	0.0000002 (1.0000)	0.830657 (0.9540)
HEALTHCARE	0.115059 (0.0585)	0.787808 (0.0000)	0.0000011 (0.9206)	0.866148 (0.6315)
HOUSING	0.034027 (0.0207)	0.913008 (0.0000)	0.0000001 (0.0000)	0.794553 (0.0001)
IT	0.034010 (0.0241)	0.913094 (0.000000)	0.014716 (0.277496)	0.969965 (0.0000)
MEDIA	0.107499 (0.2596)	0.571112 (0.0000)	0.0000007 (0.9989)	0.872382 (0.0446)
METAL	0.021359 (0.0961)	0.934517 (0.0000)	0.0000004 (0.9480)	0.852048 (0.7712)
OIL & Gas	0.132398 (0.0072)	0.766092 (0.0000)	0.008073 (0.4043)	0.954953 (0.0000)
PHARMA	0.022902 (0.4525)	0.931099 (0.0000)	0.0000004 (0.7806)	0.834664 (0.0002)

PSU	0.034799 (0.1220)	0.924299 (0.0000)	0.069803 (0.1940)	0.002289 (0.9887)
SERVICE	0.143850 (0.0949)	0.793992 (0.0000)	0.0000001 (0.2354)	0.809975 (0.0000)

Table 4.4b DCC GARCH ESTIMATION DURING COVID PERIOD 1/1/2020-30/6/2021

NSE SECTORAL INDICES	**Shock from USD/INR(374observations)**			
	Series A	**Series B**	**Series C**	
	α	**B**	**DCC α**	**DCC α**
AUTO	0.120387 (0.0087)	0.828200 (0.0000)	0.0000002 (0.9972)	0.843618 (0.0201)
BANK	0.151533 (0.0050)	0.818480 (0.0000)	0.0000001 (1.0000)	0.858552 (0.0004)
COMMODITIES	0.137991 (0.0678)	0.789205 (0.0000)	0.0000001 (1.0000)	0.883238 (0.0277)
CON DURABLE	0.117283 (0.0683)	0.841517 (0.0000)	0.0000004 (0.9579)	0.828681 (0.0488)
ENERGY	0.159219 (0.0456)	0.738946 (0.0000)	0.012797 (0.7473)	0.889583 (0.0000)
FIN SERVICE	0.186871 (0.0046)	0.785902 (0.0000)	0.0000003 (0.8440)	0.848905 (0.0000)
FMCG	0.152616 (0.0027)	0.811113 (0.0000)	0.0000004 (1.0000)	0.829082 (0.0018)
HEALTHCARE	0.134595 (0.1205)	0.795426 (0.0000)	0.0000005 (0.0000)	0.872004 (0.9743)
HOUSING	0.201144 (0.0816)	0.708487 (0.0000)	0.0000001 (0.9974)	0.856420 (0.3206)
IT	0.230348 (0.0305)	0.745949 (0.0000)	0.0000142 (0.5116)	0.828541 (0.0254)
MEDIA	0.095502 (0.0179)	0.839147 (0.0000)	0.0000004 (0.9334)	0.860718 (0.0015)

METAL	0.080621 (0.0008)	0.872483 (0.0000)	0.0000001 (0.9905)	0.865600 (0.6827)
OIL & GAS	0.143571 (0.0109)	0.761799 (0.0000)	0.0000001 (1.0000)	0.850215 (0.0463)
PHARMA	0.134704 (0.1362)	0.804268 (0.0000)	0.0000001 (0.9999)	0.867834 (0.9265)
PSU	0.094583 (0.0279)	0.846510 (0.0000)	0.000019 (0.9357)	0.850509 (0.2293)
SERVICE	0.179496 (0.0053)	0.781112 (0.0000)	0.0053 (1.0000)	0.846364 (0.0517)

Table 4.4c DCC GARCH ESTIMATION POST COVID PERIOD 1/7/2021 - 31/10/2023

NSE SECTORAL INDICES	**Shock from USD/INR (579 observations)**			
	Series A	**Series B**	**Series C**	
	α	**β**	**DCC α**	**DCC α**
AUTO	0.061969 (0.3057)	0.928278 (0.0000)	0.009062 (0.5083)	0.869054 (0.0000)
BANK	0.056692 (0.0724)	0.934799 (0.0000)	0.012763 (0.1265)	0.967381 (0.0000)
COMMODITIES	0.037593 (0.0250)	0.958082 (0.0000)	0.000003 (0.9913)	0.843413 (0.7439)
CON DURABLE	0.039625 (0.0092)	0.955391 (0.0000)	0.029653 (0.2357)	0.868046 (0.0000)
ENERGY	0.169301 (0.2342)	0.688509 (0.0000)	0.0000022 (0.9363)	0.828201 (0.7762)
FIN SERVICE	0.047249 (0.0073)	0.945737 (0.0000)	0.009915 (0.2921)	0.968026 (0.0000)
FMCG	0.032042 (0.1282)	0.957724 (0.0000)	0.000007 (0.3509)	0.826261 (0.0000)
HEALTHCARE	0.019060 (0.0054)	0.974909 (0.0000)	0.0000013 (0.9704)	0.857581 (0.5613)

HOUSING	0.060507 (0.0272)	0.934445 (0.0000)	0.000012 (0.9754)	0.865132 (0.3056)
IT	0.022001 (0.0399)	0.970892 (0.0000)	0.0000008 (1.0000)	0.838502 (0.6096)
MEDIA	0.231463 (0.1079)	0.659199 (0.0000)	0.029800 (0.0547)	0.949749 (0.0000)
METAL	0.047730 (0.2885)	0.938322 (0.0000)	0.003548 (0.7239)	0.963513 (0.0000)
OIL & GAS	0.156644 (0.2244)	0.744126 (0.0065)	0.000002 (0.9806)	0.837361 (0.5827)
PHARMA	0.016196 (0.0218)	0.977902 (0.0000)	0.000001 (0.9996)	0.855782 (0.9446)
PSU	0.091512 (0.3698)	0.762287 (0.0000)	0.029631 (0.0284)	0.934523 (0.0000)
SERVICE	0.047572 (0.0044)	0.946641 (0.0000)	0.0000001 (0.8973)	0.873972 (0.0152)

The conditional correlation displayed in Figure 2.a to 2.c portrays the dynamic correlation between USD and NSE sectoral indices for 3 categorised period under study. Majority of the indices shows negative Conditional Correlation in all the 3 periods. It indicates that higher volatility in USD exchange rate induces lower stock returns in sectoral indices. Highest correlation is found in PSU and Oil and Gas sectors during pre-covid period. Positive conditional correlationis observed in NIFTY healthcare sector during Covid period. Rangebound dynamic conditional correlation is found in NSE PSU sector across all the 3 period under study.

Figure 2.a DCC Conditional Correlation Pre-Covid Period

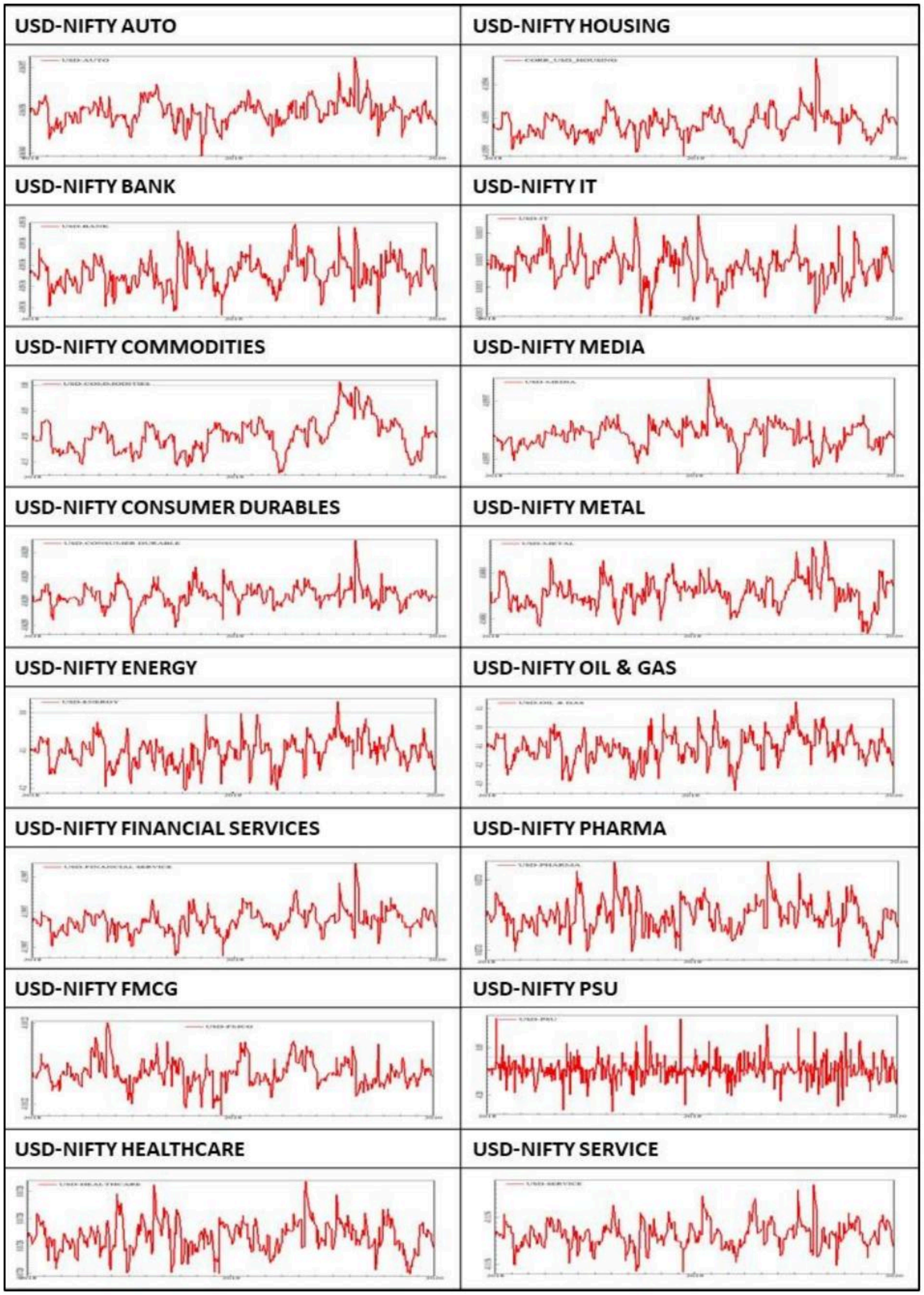


Figure 2.b DCC Conditional Correlation during Covid Period

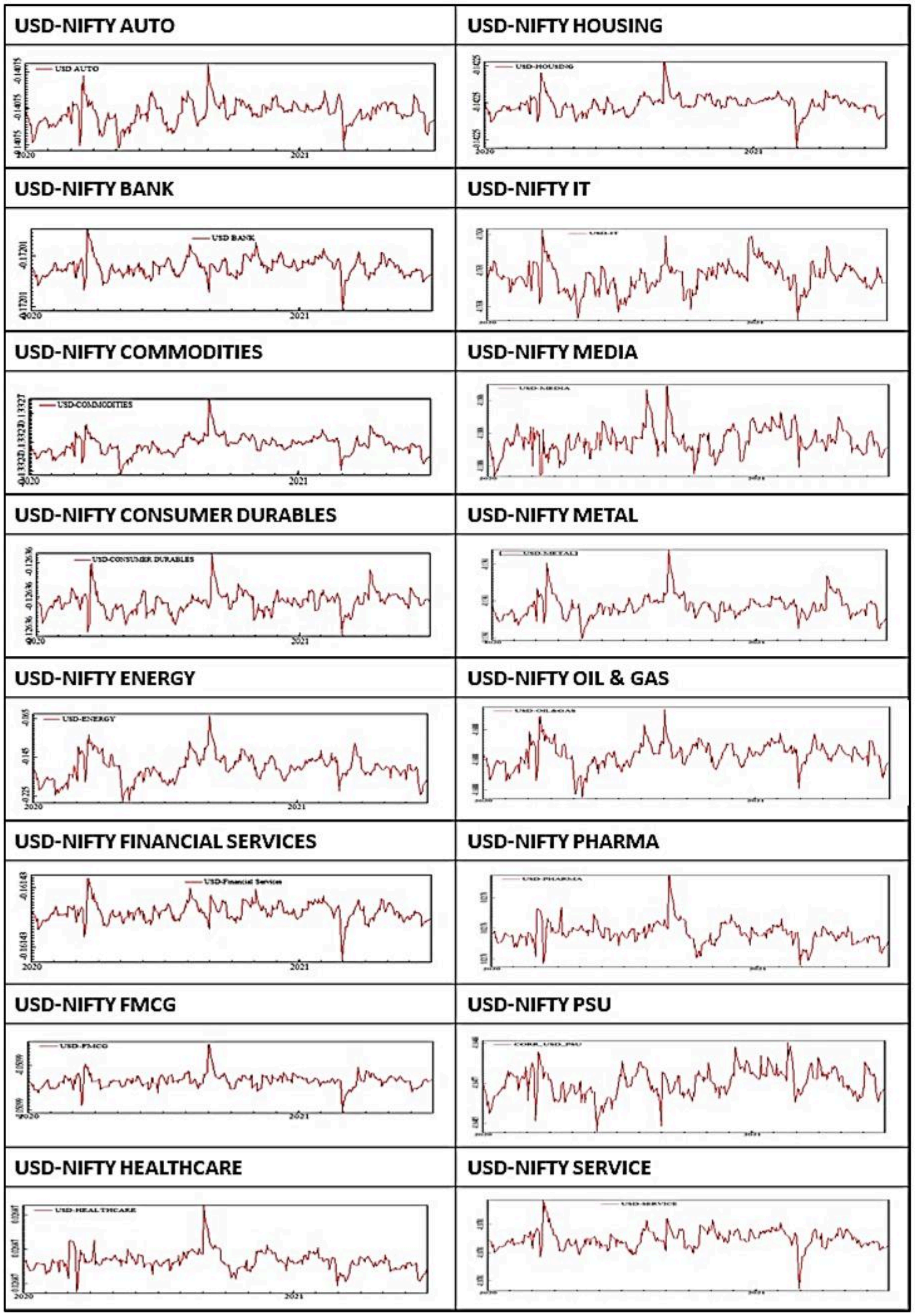
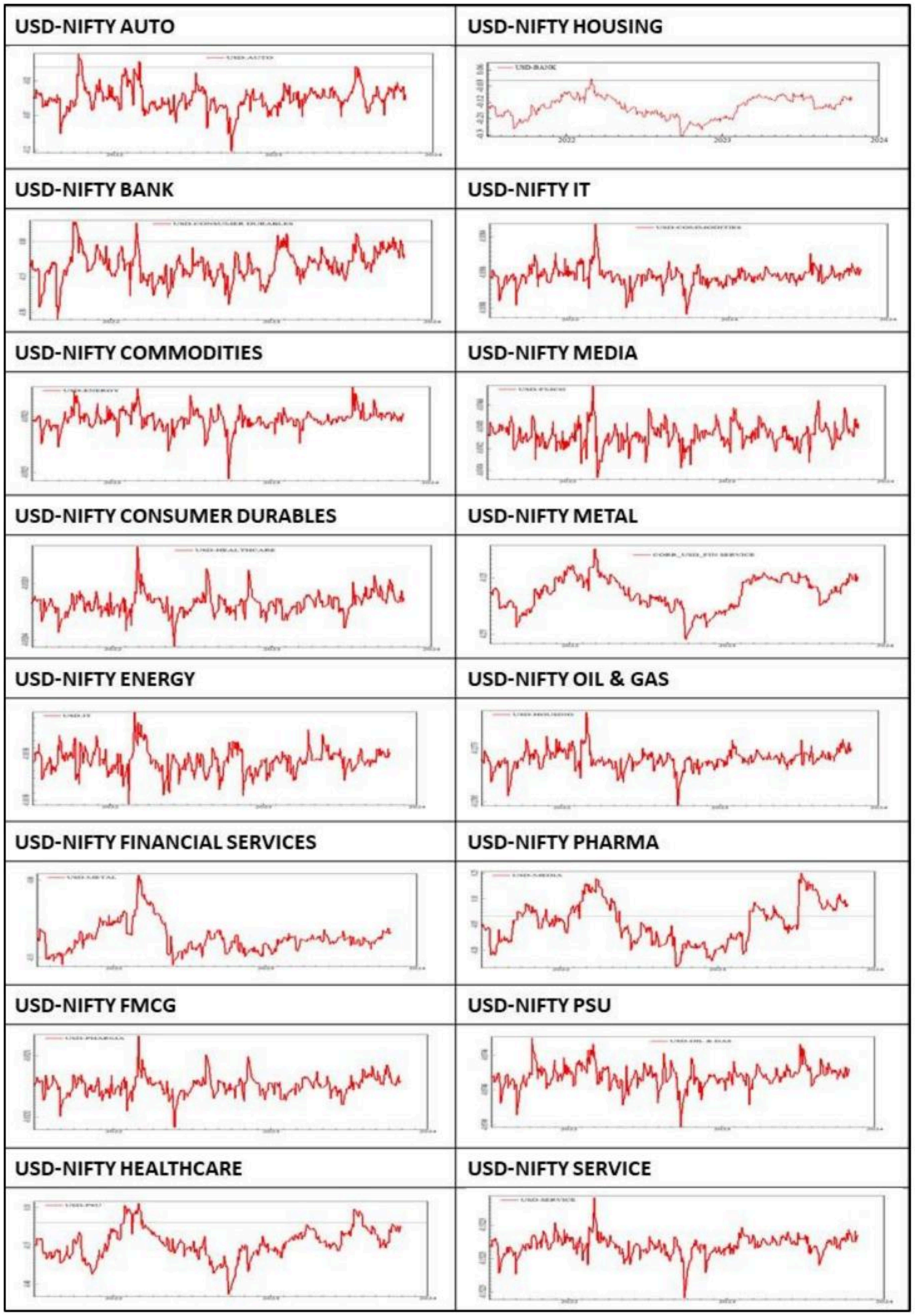


Figure 2.c DCC Conditional Correlation Post-Covid Period



5. Conclusion

This research attempts to examine the volatility spillover from the USD/INR exchange rate to select NSE sectoral indices, employing daily data spanning from January 2018 to October 2023. The objective of the study is intended to identify the spillover effect before and after Covid-19 pandemic. The analytical approach integrates the univariate ARCH-GARCH framework to model volatility, while addressing the complexities of modelling conditional variances and covariances across NSE sectoral indices through the application of the DCC-GARCH model, a refinement over the ARCH model.The findings reveal that there is a spillover effect from the exchange rate to NSE sectoral indices in the short run during pre-covid. 10 of 16 NSE sectoral indices are showing lingering volatility transmission. There is no volatility spillover or transmission in the short run during post-covid period.

The study's outcomes not only contribute significantly to the body of knowledge but also offer practical implications. Investors stand to benefit from an enhanced understanding of volatility transmission and the intricate interrelationship between exchange rates and stock returns, facilitating informed investment decisions, diversification strategies, and portfolio optimization. This, in turn, serves to mitigate the financial risks inherent in investment endeavours. Furthermore, financial practitioners, policymakers, and regulators can leverage this newfound knowledge of volatility spillover to inform the development and implementation of judicious regulatory frameworks. Additionally, a careful consideration of volatility-based trading strategies is recommended. A vigilant monitoring of foreign exchange patterns is essential for investors aiming to stay informed about currency fluctuations and market trends.

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