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4 April 2022

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Acknowledgement
The authors acknowledge valuable feedback from researchers during online Second SEBI NISM Research Conference 2021 held during February 25 – 26, 2021. The authors also acknowledge Prof. Peter Molnar, Prof. Marcin Faldzinski and Dr. Srikanta Kundu. Due acknowledgement to Dr. Sunila Pillai for proofreading. The usual disclaimer applies. Errors are the authors' responsibility.

Declaration of Conflicting Interests
The authors declared that there is no conflict of interest.

Funding Acknowledgement
We confirm that we have not received any financial grant from any funding agency in the public, commercial, or not-for-profit sectors. We are indebted to the Eviews sales teams and the Gauss sales team for providing free license to carry out this research.

Data availability statement.
The data used for this research is available in public domain and can be retrieved from the National Stock Exchange (NSE), India by selecting indices name and time period using the following weblink:
https://www1.nseindia.com/products/content/equities/indices/historical_index_data.htm

Range Volatility Spillover across Sectoral Stock Indices during COVID 19 Pandemic: Evidence from Indian Stock Market

Susanta Datta, Neeraj Hatekar

Abstract: The study examines volatility spillover across sectoral stock indices from one Emerging Market Economies, viz. India during COVID 19 pandemic. Our contributions are threefold: (a) incorporation of range volatility during pandemic, (b) comparative assessment of volatility spillover at the sectoral level, and (c) identify evidence of volatility spillover across different sectoral indices. Using daily historical price data for 11 sectoral stock indices during first wave of pandemic; we find that Range GARCH (1,1) performs better not only during crisis but also during pandemic periods. The multivariate Range DCC model confirms evidence of volatility spillover across sectoral stock indices.

Keywords: Forecasting, Volatility, Spillover, Return, Range, NIFTY, COVID 19

JEL classification: C58, C22, G17.

I. Introduction:

The sudden outbreak of the COVID 19 pandemic has completely disrupted the economic conditions and livelihood of people across all countries (Baker et. al. 2020). The empirical literature suggests plausible economic impact due to subsequent lockdown (see Padhan et. al. 2021; Baldwin et. al. 2020). We can classify them into three categories: the first category tries to build macroeconomic models (McKibbin et. al. 2020); the second category tries to assess the impact on income and wealth during the pandemic (Hanspal et. al. 2020). However, the third category deals with assessing the impact of the pandemic on the stock market (Xiaolin et. al. 2020, Bohdan, 2020).

The stock market witnessed Black Monday on March 9, 2020, and the World Health Organization (WHO) declared COVID 19 as a Pandemic on March 11, 2020. Blancard et. al. (2020) identifies reactions in the stock market due to (a) initial strong response with increasing cases and volatility, (b) little influence by country-specific characteristics, and (c) intervention by the government and central bank. Xiaolin et. al. (2020) study the impact on China's stock markets due to lockdown and observes reversals for industry and firm-level using cumulative abnormal returns (CARs). It is also observed that (a) overreactions are much stronger for stock owned by retail investors and (b) worse performance of stocks having positive CARs with higher idiosyncratic volatilities and lower book-to-market ratios. Qing et. al. (2020) empirically tests daily return data from selected 8 countries. They suggest that (a) the pandemic has a negative but short-term impact on stock markets of affected countries and (b) impact on stock markets has bidirectional spillover effects. Bohdan (2020) uses a logistic curve model with Bayesian regression for predictive analytics to model COVID 19 spread and its impact on the stock market.

II. Literature review:

Padhan et. al. (2021) confirms that pandemic has increased financial risks and accordingly adversely affecting across the global financial markets. The pandemic negatively affected stock markets return along with increased volatility spillover in stock return.

Literature review on Stock returns volatility during COVID 19

Haroon & Rizvi (2020a) examine sentiment generation and equity volatility between World and United States (US) from 01/01/2020 to 30/04/2020 using the asymmetric GARCH model and confirm that panic news contributes to volatility. Haroon & Rizvi (2020b) study 23 Emerging Market Economies (EMEs) from 01/01/2020 to 30/04/2020 using GARCH and Panel Regression and observe that reducing cases and increasing liquidity leads to a flatter curve which reduces uncertainty. Sharma (2020) check commonality in volatility among 5 Asian Economics from 01/01/2019 to 25/09/2020 using descriptive statistics/ADF test/GARCH and show that there exists a stronger commonality which is more prominent in the case of Singapore. Salisu and Sikiru (2020) examine the hedging potential of Asia - Pacific and Islamic stocks among 15 countries from 31/08/2020 to 15/09/2020 using GARCH based unit root test, UPE based model and suggest a role of global factors due to low hedging effectiveness.

Prabheesh et al (2020a) examine stock market and oil price return relation for net oil-importing nations from 01/01/2020 to 08/06/2020 using summary statistics and DCC – GARCH model which shows positive relations along with giving a signal for future demand contraction, while Prabheesh et al (2020b) conduct the similar study from 01/01/2020 to 10/08/2020 using the same methodology and observe that there exists a positive relationship and suggests for restricted portfolio diversification. Rai and Garg (2021) study the relationship between stock prices and exchange rate among BRICS economies from 02/01/2020 to 15/09/2020 by applying DCC – GARCH and BEKK – GARCH and suggest for significant risk transfer. Akhtaruzzaman et al (2020) examine the occurrence of financial contagion among the World, China, and G7 from 01/01/2013 to 20/03/2020 using VERMA DCC-GARCH and Diebold - Yilmaz and find evidence of an increase in stock return correlation which may lead to a higher role of financial contagion. Corbet et al (2020) examine the contagion effect on the stock market for China from 11/03/2019 to 10/03/2020 using DCC GARCH and confirm the evidence of volatility relationship evolve significantly.

However, still there is a gap in literature to capture extreme daily price movements during the pandemic. Especially in the turbulent days with drops and recoveries of the market, the traditional close-to-close volatility (i.e., GARCH model) indicates low volatility while the daily price range shows correctly that volatility is high (Chou, 2005). Return-based volatility models are inaccurate and inefficient because they are based on the closing prices, failing to use the information contents inside the reference daily historical price range which is the difference between highest and lowest prices of an asset. Alternatively, by utilizing full information contained in the price range, range volatility models can be used as an alternative measure to fill such gaps in literature.

Literature review on Range Volatility

The main studies include Parkinson (1980), Garman and Klass (1980), Wiggins (1991), Rogers and Satchell (1991), Andersen and Bollerslev (1997), Yang and Zhang (2000), Alizadeh, Brandt, and Diebold (2002), Brandt and Jones (2006), Chou (2005, 2006, 2009, 2010), Molnar (2016). Parkinson (1980) developed from its measure for more efficient than the Classical return-based estimators and extended by others. Molnar (2012) derived the properties of range-based estimators and Molnar (2016) suggests a simple way to improve the GARCH model using the intraday range between the highest and lowest as proxy volatility and performed empirical test on 30 stocks and 6 stock indices and simulated data show that the RGARCH (1,1) model outperforms the standard GARCH (1,1) model, both in terms of in-sample fit and out of sample forecasting. It is thus empirically verified that using the high/low range data of asset prices to do estimation can acquire more efficient results than the return data based on close prices [Molner (2016), Datta and Hatekar (2018), Datta (2019)].

One of the popular multivariate volatility models viz. Dynamic Conditional Correlation (DCC) model, introduced by Engle (2002) and Tse and Tsui (2002), explains how covariance changes and therefore describe temporal dependencies among asset class. Engle (2002) model is based on closing prices. Fiszeder, Faldzinski, and Molnar (2019) incorporates high and low prices into the DCC framework and empirical evaluation suggests that range based DCC model outperforms return based DCC model across currencies, stocks, and commodity exchange-traded funds.

Under this backdrop, this paper tries to explore new methodological aspects of modelling volatility spillover during a pandemic scenario. Our contributions are threefold: (a) incorporation of range volatility in literature as an alternative measure during Pandemic, (b) comparative assessment of spillover in price and volatility between return based and range-based volatility models at sectoral level, and (c) identify evidence for volatility spillover across different sectoral indices with reference to an Emerging Market Economies (EMEs) viz. India for better policy-making purposes.

III. Objectives of this paper:

We try to explore daily historical open, high, low and close (OHLC) prices of NIFTY sectoral indices to check their comparative performance of forecasting and volatility spillover across different sectors during pandemic and identify the best performing sector-specific model.

IV. Research Methodology:

Data

The unit of analysis is NIFTY daily OHLC historical price data of 11 NIFTY sectoral indices viz. auto, bank, FMCG, financial services, information technology (IT), metal, media, pharma, PSU bank, private bank, and realty. Secondary data retrieves from the website of National Stock Exchange, India. The period for this study is considered from January 1, 2020, to November 30, 2020 (See, Figure 1).

Methodology

We calculate both close-to-close and open-to-close return and plot them graphically along with OHLC price for all. We also estimate descriptive Statistics – Mean, Median, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis for 229 observations for close-to-close return (Table 2) and 230 observations for open-to-close return (Table 3). We further carry out diagnostic tests – Normality test (JB test), unit root test (ADF and PP), Autocorrelation test (Portmanteau Q Statistic, Ljung Box Squared Q statistic at lag 5 and lag 10), Stability check (UDmax and WDmax using Bai –Perron (1998, 2003) tests.

We need to determine the optimal lag length for every sectoral stock index. We consider the minimum AIC value among 10 lags to determine optimal lag length (P*). Secondly, we try to satisfy that (a) there is no linear autocorrelation in the error term, (b) there is linear autocorrelation in squared error term and (c) reject the null hypothesis with zero autoregressive conditional heteroskedasticity effect by using ARCH Lagrange Multiplier (LM) test for optimal lag length.

GARCH (1, 1) specification

We adopted Engle (1982) for estimating GARCH (1,1) and the specification of GARCH (1,1) is as follows:

(a) Mean equation is an AR (p*) process using close-to-close return:

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \varepsilon_t \qquad (1)$$

where $\varepsilon t \sim N(0, ht)$ and p* is optimal lag length selected based on table (4).

(b) Conditional variance equation for GARCH (1,1) using close-to-close return and open-to-close return are as follows:

$$h_t = \beta_0 + \beta_i \varepsilon^2_{t-1} + \beta_j h^2_{t-1} \qquad (2)$$

The necessary and sufficient conditions are as follows: (a) $\beta 0 > 0$; $\beta i \geq 0$ and $\beta j \geq 0$ and (b) $(\beta i + \beta j) < 1$ for all i & j.

RGARCH (1, 1) specification

We adopted Molnar (2012) and Molnar (2016) for estimating Range GARCH (1,1) or RGARCH (1,1) or GARCH (0,1) with exogenous volatility proxy such as using range volatility proxies as follows: (i) Parkinson (1980) volatility proxy = (lnHt- lnLt)/4ln2; (ii) Garman and Klass (1980) volatility proxy = 0.5[ln (Ht/Lt)]2 - [2ln2 -1] [ln(Ct/Ot)]2 and (iii) Rogers and Satchell (1991) volatility proxy = (1/N) ∑ln (Hn/On) [ln (Hn/On) – ln (Cn/On)] + ln(Ln/On)[ln(Ln/On) – ln(Cn/On)]; where 'O' stands for Open price, 'H' stands for High price, 'L' stands for Low price, and 'C' stands for Close price.

The specification of RGARCH (1,1) is as follows:

(c) Mean equation: AR (p*) process using open-to-close return:

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + \varepsilon_t \, ; \qquad (3)$$

where εt ~N (0, ht) and p* is optimal lag length selected based on table (4).

(d) Conditional variance equation:

(i) RGARCH (1,1) using Parkinson (1980):

$$h_t = \beta_0 + \beta_i \sigma^2_{Park,\, t-1} + \beta_j h^2_{t-1} \qquad (4)$$

(ii) RGARCH (1,1) using Garman and Klass (1980):

$$h_t = \beta_0 + \beta_i \sigma^2_{GK,\, t-1} + \beta_j h^2_{t-1} \qquad (5)$$

(iii) RGARCH (1,1) using Rogers and Satchell (1991):

$$h_t = \beta_0 + \beta_i \sigma^2_{RS,\, t-1} + \beta_j h^2_{t-1} \qquad (6)$$

The necessary and sufficient conditions are as follows: (a) $\beta 0 > 0$; $\beta i \geq 0$ and $\beta j \geq 0$ and (b) $(\beta i + \beta j) < 1$ for all i & j. We check whether βi increases and βj decreases in RGARCH (1,1) as compared by standard GARCH (1,1).

In sample estimation

We consider around 72% sample from initial 167 out of 230 observations from January 2020 to August 2020 for in sample estimation. We estimate and compare in-sample estimates and out-of-sample forecasting among 2 GARCH (1, 1) and 3 RGARCH (1, 1) models using selected optimal lag length as reported in Table 4 and check necessary conditions as mentioned under GARCH (1,1) and RGARCH (1,1) specification. Then, we report estimated value of the parameters and corresponding probability of rejection at 1% and 5% level of significance and values of information criteria such as AIC, SIC, HQC. We need to check whether βi increases and βj decreases in RGARCH (1,1) as compared by standard GARCH (1,1) to carry out comparative analysis among all 5 models.

Out of sample forecasting

We consider remaining 28% at the end part of sample i.e., last 63 out of 230 observations from September 2020 to November 2020.Accordingly, we carry out dynamic forecasting and report Root Mean Squares Error (RMSE) and Mean Absolute Error (MAE).

We check whether estimated GARCH (1,1) and RGARCH (1,1) are significant or not and identify best performing model using information criteria from in sample estimation and RMSE and MAE from out of sample forecasting results.

Multivariate Volatility Model

DCC GARCH and DCC RGARCH

We carry out multivariate volatility models and estimate pair-wise dynamic conditional correlations between two NIFTY sectoral indices, separately for close-to-close return and open-to-close return, for both DCC GARCH and DCC RGARCH models. DCC GARCH using close-to-close returns without considering fluctuation in price range, while DCC RGARCH – using open-to-close returns and fluctuations in the high and low-price range. We estimate both alpha (α) coefficient following a MA structure and beta (β) coefficient following an AR structure and also check their level of significance to ensure whether there exist any dynamic conditional correlations (DCC) or not. This will ensure us whether any external shock in one sector is transmitted to another sector through error term.

V. Empirical Findings:

Figure 2 provides daily movement of OHLC prices along with its close to a close return and open-to-close return for 11 NIFTY sectoral indices viz. Auto, Bank, Financial Services, FMCG, Information Technology, Media, Metal, Pharma, PSU Bank, Private Bank, and Realty. It was found that there was a sharp decline in the OHLC price range around the declaration of the first lockdown due to unprecedented uncertainty prevailing in the market.

<<<Insert Figure 2 here>>>

However, it is important to note that gradually the whole price range is moving toward its earlier position. These results also support that the recovery was even quicker than earlier crises including the dot.com bubble and financial crisis and the stock market behaved contrary to the current gloomy situation as compared to other markets. (Banerjee and Chauhan, 2020)

<<<Insert Table 2 here>>>

Table 2 depicts descriptive statistics and other diagnostic test results for close-to-close return, while Table 3 depicts for open-to-close return. Out of 11 NIFTY sectoral indices, we found 8 close-to-close returns are positive (except 3 viz. Media, PSU Bank, Realty), while except for information technology, the rest 10 open-to-close returns are negative. It is important to note that close-to-close return consists of overnight volatility and opening jump, in addition, to open-to-close return which mainly considers intraday fluctuation within a given time interval. Median, Maximum, Minimum, and Standard Deviation values are as expected. While all close-to-close return series follows a negatively skewed distribution, on the other hand, except Private Bank, the remaining 10 open-to-close return series follow a positively skewed distribution. Both return series for all 11 NIFTY sectoral indices have kurtosis greater than 3 reflecting leptokurtic distribution and confirm non- normality due to the fat tail nature of financial data.

<<<Insert Table 3 here>>>

Jarque - Bera (JB) test for Normality confirms non-normality which is a common feature of financial time series for both return series of all 11 indices for both return series at 1% level of significance. Augmented Dickey-Fuller test (ADF) test, as well as Phillips Perron (PP) test for stationarity, reject the null hypothesis of non-stationarity at 1% level of significance for all 11 indices for both return series. We carry out UDmax and WDmax to ensure stability conditions. UDmax test statistic suggests that Information Technology and Pharma are significant at 5% level of significance for close-to-close return and Financial Services, Information Technology, PVT bank are significant at 5% level of significance for open-to-close return. WDmax test statistics show that Metal and Pharma are significant at 5% level of significance for close-to-close return and Bank, Financial Services, Information Technology, Media, Pharma and PVT bank are significant at 5% level of significance for open-to-close return. However, it is difficult to carry out sub-sample basis estimates for those sectors having structural breaks due to the paucity of large sample data and hence we restrict to do so.

<<<Insert Table 4 here>>>

Empirical results suggest that 8 out of 11 sectors satisfy all three conditions for both returns, however, there are 3 exceptional cases we found for Auto, Media, and PVT sector for close-to-close return and Media, Metal, and PSU Bank for open-to-close return. Instead, we consider the proximate lag length which satisfies all 3 pre-requisite conditions as optimal lag length (see notes section under Table 4, for details).

<<<Insert Table 5 here>>>

Table 5 presents estimated coefficients (based on optimal lag length), level of significance, 3 information criterion values for AIC, SIC, and HQC for 5 estimated models: 2 GARCH (1,1) models and 3 RGARCH (1,1) models. It is found that AIC gives minimum value as compared to SIC and HQC values. Except for PSU bank and Media, GARCH using open-to-close return outperforms as compared to GARCH using close-to-close return. Estimated βi and βj are significant at 1% level of significance. It is evident that the value of estimated βi increases and βj decreases for all nifty indices.

Among the 3 RGARCH (1, 1) models using Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991), it is found that AIC gives minimum value as compared to SIC and HQC information criteria. RGARCH with Parkinson (1980) volatility proxy outperforms as compared to Garman and Klass (1980) and Rogers and Satchell (1991) among sample estimates. Empirical evidence suggests that estimated coefficients βi increase and βj decreases for all stock indices as compared to GARCH close-to-close which are consistent with the findings of Peter Molnar (2016).

<<<Insert Table 6 here>>>

DCC GARCH and DCC RGARCH

The rule of thumb suggests that if both α and β coefficients are not significant, then there do not exist any dynamic conditional correlations. However, if at least one coefficient from α and β depicts significant results, then it confirms that there exists a dynamic conditional correlation. Due to numerical optimisation issues, we can estimate 34 pairs (Table 7) of open-to-close return along with pairs of close-to-close return and estimates only 21 pairs (Table 8) of close-to-close return series out of 55 pairs of respective return series.

<<<Insert Table 7 here>>>

Except for Auto-FMCG, Financial Services-FMCG, and Financial Services-Pharma, rest 31 pair of open-to-close return shows that β coefficient is significant at 1% level of significance for both DCC GARCH and DCC RGARCH (Table 7).

<<<Insert Table 8 here>>>

Except for, PSU – Pvt Bank and Metal-Realty pair, rest 19 pair based on close-to-close return shows that β coefficient is significant at 1% level of significance for both DCC GARCH and DCC RGARCH (Table 8).

VI. Conclusion

We have explored new methodological aspects of modelling volatility spillover during COVID 19 Pandemic and contributed in literature in terms of (a) exploring possible impact in vulnerable Emerging Market Economies (EMEs) concerning India's stock market, (b) carrying out a comparative assessment of volatility spillover at sectoral level and (c) identify evidence for volatility spillover across different sectors for better policy-making purposes. We contribute in terms of identifying optimal lag length so that comparison of GARCH (1,1) and RGARCH (1,1) can be made across all models in terms of both in sample estimates and out of sample forecasting. Our initial findings suggest that all selected sectoral stock indices perform better in forecasting while using open-to-close return instead of close-to-close return. Irrespective of all 3 information criteria, the RGARCH (1,1) using Parkinson (1980) model outperforms better as compared to

Garman and Klass (1980) and Rogers and Satchell (1991) models. This result confirms the fact that the range volatility model utilizes a full set of information contains in the price range while return volatility only considers the price information and throws away other relevant information. Our empirical findings confirms that range based GARCH model not only capture true intraday fluctuation during turbulent crisis time period, but also capture true intraday volatility due to outbreak of COVID 19 pandemic. Empirical findings will help SEBI to understand the underlying volatility regime across sectors during a pandemic and help to develop market surveillance strategy at the sectoral level, instead of an ongoing script-based market surveillance strategy in future.

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Table 1: Description of dataset consisting of 11 Nifty Sectoral Indices

Nifty Sectoral Indices	Observations	Start Date	End Date
Auto	230	01-Jan-2020	27-Nov-2020
Bank	230	01-Jan-2020	27-Nov-2020
Financial Services	230	01-Jan-2020	27-Nov-2020
FMCG	230	01-Jan-2020	27-Nov-2020
Information Technology	230	01-Jan-2020	27-Nov-2020
Media	230	01-Jan-2020	27-Nov-2020
Metal	230	01-Jan-2020	27-Nov-2020
Pharma	230	01-Jan-2020	27-Nov-2020
PSU Bank	230	01-Jan-2020	27-Nov-2020
Pvt Bank	230	01-Jan-2020	27-Nov-2020
Realty	230	01-Jan-2020	27-Nov-2020

Source: Authors compilation based on NSE Sectoral indices historical data

Table 2. Descriptive Statistics and results of Diagnostic test for Close-to-Close returns of 11 NIFTY Sectoral Stock Indices.

	Auto	Bank	Financial Services	FMCG	Information Technology	Media	Metal	Pharma	PSU Bank	Pvt Bank	Realty
Mean	0.0003	-0.0004	-0.0001	0.0002	0.0014	-0.0008	0.0002	0.0017	-0.0021	-0.0003	-0.0006
Median	0.0021	0.0019	0.0022	0.0011	0.0021	0.0010	0.0030	0.0013	-0.0005	0.0024	0.0011
Maximum	0.099	0.100	0.089	0.080	0.086	0.064	0.076	0.099	0.102	0.105	0.062
Minimum	-0.149	-0.183	-0.174	-0.112	-0.101	-0.109	-0.123	-0.094	-0.141	-0.197	-0.121
Std. Dev.	0.024	0.029	0.027	0.017	0.021	0.025	0.026	0.020	0.027	0.030	0.026
Skewness	-1.039	-1.336	-1.421	-0.729	-0.764	-0.920	-0.959	-0.098	-0.848	-1.418	-1.072
Kurtosis	11.757	10.945	10.854	16.282	8.822	5.768	6.787	8.075	8.740	12.063	6.560
Jarque-Bera	772.94***	670.41***	665.64***	1703.57***	345.66***	105.41***	171.95***	246.11***	341.79***	860.47***	164.83***
Observations	229	229	229	229	229	229	229	229	229	229	229
ADF	-16.21***	-15.40***	-15.84***	-4.18***	-18.05***	-14.13***	-17.20***	-9.17***	-16.22***	-14.96***	-14.33***
PP	-16.17***	-15.40***	-15.85***	-18.05***	-17.76***	-14.47***	-17.06***	-15.77***	-16.18***	-14.96***	-14.37***
UDMax	9.03	9.90	7.95	7.57	12.68**	5.59	11.11	12.27**	10.32	8.17	5.00
WDMax	9.03	12.31	10.91	7.57	12.68	8.39	13.08**	14.43**	11.87	9.73	8.69

Source: Authors calculation based on NIFTY sectoral stock indices

Note: Jarque-Bera test is used to check the normality condition of the given time series. Unit root test is based on Augmented Dickey-Fuller (ADF) test and Phillips –Perron (PP) test with the linear trend and intercept terms (Reported at the intercept, although trend gives the same result for both return series). UDmax and WDmax are the tests for structural stability following Bai and Perron (1998, 2003). The critical value at 5 % level of significance is 11.70 for UDMax and 12.81 for WDMax.

Table 3. Descriptive Statistics and results of Diagnostic test for Open-to-close returns of 11 NIFTY Sectoral Stock Indices.

	Auto	Bank	Financial Services	FMCG	Information Technology	Media	Metal	Pharma	PSU Bank	Pvt Bank	Realty
Mean	-0.0009	-0.0023	-0.0017	-0.0018	0.0003	-0.0028	-0.0011	-0.0012	-0.0043	-0.0023	-0.0021
Median	-0.0017	-0.0012	-0.0007	-0.0019	-0.0010	-0.0039	-0.0016	-0.0020	-0.0044	-0.0008	-0.0030
Maximum	0.091	0.102	0.111	0.069	0.083	0.079	0.126	0.103	0.188	0.099	0.123
Minimum	-0.063	-0.085	-0.089	-0.046	-0.058	-0.067	-0.057	-0.065	-0.086	-0.097	-0.085
Std. Dev.	0.020	0.023	0.022	0.014	0.016	0.020	0.021	0.018	0.025	0.024	0.023
Skewness	0.743	0.165	0.397	0.657	0.733	0.104	0.844	0.626	1.817	-0.057	0.338
Kurtosis	7.241	6.683	8.370	7.459	8.618	4.236	8.361	7.898	18.520	6.644	7.804
Jarque-Bera	193.49***	131.03***	282.43***	207.07***	323.05***	15.04***	302.67***	244.96***	2434.78***	127.41***	225.57***
Observations	230	230	230	230	230	230	230	230	230	230	230
ADF	-13.02***	-13.19***	-7.68***	-13.98***	-16.52***	14.98***	-16.42***	-17.52***	-16.17***	-13.18***	-15.71***
PP	-15.37***	-15.82***	-15.75***	-18.10***	-16.52***	-14.98***	-16.51***	-17.52***	-16.32***	-15.41***	-15.77***
UDMax	9.57	14.92	12.03**	5.12	16.03**	11.51	10.77	11.04	7.36	15.10**	7.03
WDMax	10.70	22.14**	19.12**	7.07	25.57**	13.54**	12.67	12.99**	11.73	21.58**	12.00

Source: Authors calculation based on NIFTY sectoral stock indices

Note: Jarque-Bera test is used to check the normality condition of the given time series. Unit root test is based on Augmented Dickey-Fuller (ADF) test and Phillips –Perron (PP) test with the linear trend and intercept terms (Reported at the intercept, although trend gives the same result for both return series). UDmax and WDmax are the tests for structural stability following Bai and Perron (1998, 2003). The critical value at 5 % level of significance is 11.70 for UDMax and 12.81 for WDMax.

Table 4. Selection process of optimal lag length for close-to-close return and open-to-close return for 11 NIFTY sectoral indices.

Sector	Close-to-close Return				Open-to-close Return			
	Max Lag Length	Q statistics (prob)	Squared Q Statistics (prob)	ARCH LM Test (F Statistics) (prob)	Max Lag Length	Q statistics (prob)	Squared Q Statistics (prob)	ARCH LM Test (F Statistics) (prob)
Auto[#]	2	0.011 (0.995)	28.441 (0.000)	15.336 (0.000)	2	0.006 (0.997)	9.393 (0.009)	4.163 (0.017)
Bank	7	0.352 (1.000)	81.546 (0.000)	11.046 (0.000)	6	0.0941 (1.000)	43.670 (0.000)	5.038 (0.000)
Financial service	7	0.9246 (0.988)	73.792 (0.000)	14.239 (0.000)	6	0.0666 (1.000)	34.773 (0.000)	4.154 (0.001)
FMCG	9	1.0331 (0.999)	91.681 (0.000)	8.286 (0.000)	8	0.4441 (1.000)	65.323 (0.000)	4.907 (0.000)
Information Technology	7	0.5104 (0.999)	87.376 (0.000)	8.420 (0.000)	1	0.00001 (0.997)	11.665 (0.001)	11.977 (0.001)
Media[#$]	7	0.6901 (0.998)	23.016 (0.002)	2.990 (0.005)	8	0.1578 (1.000)	24.408 (0.002)	2.915 (0.004)
Metal[$]	6	0.9676 (0.987)	52.974 (0.000)	6.199 (0.000)	3	0.0788 (0.994)	14.223 (0.003)	4.759 (0.003)
Pharma	2	0.0248 (0.988)	9.7514 (0.008)	4.264 (0.015)	1	0.0018 (0.966)	20.511 (0.000)	21.951 (0.000)
PSU bank[$]	7	0.3754 (1.000)	32.540 (0.000)	4.088 (0.000)	1	0.0199 (0.888)	3.5525 (0.059)	3.515 (0.062)
Pvt bank[#]	2	0.0005 (1.000)	8.7296 (0.013)	4.361 (0.014)	6	0.1128 (1.000)	73.879 (0.000)	8.293 (0.000)
Realty	7	0.3284 (1.000)	32.800 (0.000)	3.894 (0.001)	1	0.0009 (0.997)	3.1467 (0.076)	3.109 (0.079)

Source: Authors calculation based on NIFTY sectoral stock indices

Note: (1) Q(.) and Q2(.) represent the Ljung Box test statistics of returns and squared returns respectively. (2) For close-to-close return, for auto[#], media[#], and private bank[#] sector, lag 1, 6, and 1 were determined, however, to satisfy Q(.), Q^2(.) statistics and ARCH test, lag length 2,7 and 2 were selected respectively. (3) For open-to-close return, for media[$], metal[$] and PSU bank[$] sector, lag 2, 2, and 2 were determined, however, to satisfy Q(.), Q2(.) statistics and ARCH test, lag length 8, 3 and 1 were selected respectively.

Table 5. Comparative performance of return-based and range-based Volatility modelling in terms of estimated coefficients and Information Criteria (In Sample forecasting).

NIFTY Sectoral Indices	GARCH (1,1) using Close-to-close return		GARCH (1,1) using Open-to-close return		RGARCH (1,1) using Parkinson (1980)		RGARCH (1,1) using Garman and Klass (1980)		RGARCH (1,1) using Roger and Satchell (1991)	
	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria
	C	AIC	C	AIC	C	AIC	C	AIC	C	AIC
	RESID (-1)^2	SIC	RESID (-1)^2	SIC	PARK (-1)	SIC	GK (-1)	SIC	RS (-1)	SIC
	GARCH (-1)	HQC	GARCH (-1)	HQC	GARCH (-1)	HQC	GARCH (-1)	HQC	GARCH (-1)	HQC
Auto	1.68E-05	-4.773697	8.43E-05***	-4.967056	0.000148***	-5.095207	0.013242***	-5.074708	1.23E-06	-5.056616
	0.158273	-4.660287	0.428709***	-4.854113	0.877385***	-4.982263	0.000417***	-4.961765	0.000389***	-4.943672
	0.824310	-4.727657	0.457441***	-4.921209	-0.055692***	-5.049359	-0.612870	-5.028860	0.999825***	-5.010768
Bank	1.41E-05	-4.485192	2.10E-05	-4.783747	2.54E-05	-4.795067	0.013443***	-4.764274	2.08E-05*	-4.602792
	0.188738***	-4.272878	0.271533***	-4.592355	0.282281***	-4.603675	0.000322***	-4.572882	0.000160	-4.411401
	0.820544***	-4.398974	0.739370***	-4.706034	0.707366***	-4.717354	-0.518930	-4.686561	0.961561***	-4.525080
Financial Services	1.58E-05**	-4.621053	2.51E-05*	-4.912264	3.21E-05*	-4.951372	0.012558***	-4.848435	2.35E-05*	-4.718694
	0.178522***	-4.408739	0.308472***	-4.720872	0.432522***	-4.759981	0.000351***	-4.657044	0.000250***	-4.527303
	0.817658***	-4.534834	0.696278***	-4.834551	0.579338***	-4.873659	-0.455216	-4.770723	0.949890***	-4.640982
FMCG	5.05E-06*	-5.716032	9.86E-06*	-5.782711	4.29E-05***	-5.952722	0.000197	-5.525808	0.000324***	-5.660801
	0.184287***	-5.462967	0.169374***	-5.551096	0.982333***	-5.721106	0.000000	-5.294193	-0.000198***	-5.429185
	0.816469***	-5.613254	0.788860***	-5.688654	-0.112257***	-5.858665	0.171429	-5.431751	-0.638080**	-5.566744
Information Technology	2.18E-05	-5.219157	7.79E-06	-5.705480	9.70E-06	-5.734990	0.008665***	-5.595594	1.50E-05***	-5.539754
	0.985196***	-5.006842	0.220929***	-5.611745	0.322669***	-5.641256	0.000232***	-5.501859	0.000442***	-5.446019
	0.341050***	-5.132938	0.772024***	-5.667432	0.654506***	-5.696943	-0.366519	-5.557547	0.941759***	-5.501707
Media	2.80E-05	-4.489101	0.000295***	-4.779313	0.000249	-4.759619	0.004585	-4.741359	0.000677**	-4.724754
	0.122305**	-4.276787	0.494579***	-4.547698	0.386840**	-4.528003	0.000190	-4.509743	0.000268	-4.493139
	0.848804***	-4.402883	-0.031312	-4.685257	0.048871	-4.665562	-0.615005	-4.647302	-0.512841	-4.630698
Metal	2.33E-05	-4.500033	2.83E-05	-4.855875	0.000298***	-4.954182	0.007717***	-4.828431	1.10E-05	-4.831915
	0.119962**	-4.307835	0.172926**	-4.723564	0.388927***	-4.821871	0.000307***	-4.696120	0.000351***	-4.699603
	0.851481***	-4.421988	0.787719***	-4.802162	-0.151696**	-4.900469	-0.583551	-4.774718	0.968434***	-4.778201
Pharma	1.49E-05	-5.122988	1.15E-05	-5.256794	6.88E-05**	-5.229999	0.000196***	-5.152258	3.32E-06	-5.170083
	0.133631***	-5.009578	0.118965***	-5.163059	0.447522***	-5.136264	5.66E-06***	-5.058523	0.000396***	-5.076348
	0.844344***	-5.076948	0.862945***	-5.218746	0.416251**	-5.191951	0.961870***	-5.114210	0.974306***	-5.132035

Table 5. Comparative performance of return-based and range-based Volatility modelling in terms of estimated coefficients and Information Criteria (In Sample forecasting). (Contd.)

	GARCH (1,1) using Close-to-close return		GARCH (1,1) using Open-to-close return		RGARCH (1,1) using Parkinson (1980)		RGARCH (1,1) using Garman and Klass (1980)		RGARCH (1,1) using Roger and Satchell (1991)	
	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria	Estimated Coefficients	Information Criteria
	C RESID (-1)^2 GARCH (-1)	AIC SIC HQC	C RESID (-1)^2 GARCH (-1)	AIC SIC HQC	C PARK (-1) GARCH (-1)	AIC SIC HQC	C GK (-1) GARCH (-1)	AIC SIC HQC	C RS (-1) GARCH (-1)	AIC SIC HQC
PSU Bank	3.02E-05 0.147228*** 0.829855***	-4.412823 -4.200509 -4.326605	0.000244*** 0.690343*** 0.116815	-4.605623 -4.511888 -4.567575	0.000170** 1.052582*** - 0.021149	-4.598406 -4.504671 -4.560358	0.006837*** 0.000274*** -0.464422	-4.422052 -4.328318 -4.384005	0.000588*** 0.000403*** 0.122463	-4.436365 -4.342630 -4.398317
Private Bank	1.56E-05 0.201349*** 0.810108***	-4.430298 -4.316888 -4.384258	1.98E-05 0.278201*** 0.739196***	-4.736461 -4.545069 -4.658748	2.20E-05 0.268599*** 0.730882***	-4.751819 -4.560428 -4.674107	0.013846*** 0.000373*** -0.535926	-4.694021 -4.502630 -4.616308	2.27E-05 0.000168 0.962318***	-4.512414 -4.321022 -4.434701
Realty	6.43E-05 0.072701 0.837179***	-4.387027 -4.174713 -4.300808	0.000180*** 0.309314*** 0.423648***	-4.669251 -4.575517 -4.631204	0.000119*** 0.518736*** 0.388091***	-4.721724 -4.627989 -4.683677	0.003558** 0.000232** -0.580971	-4.572855 -4.479120 -4.534807	0.000451 0.000569*** 0.202243	-4.573000 -4.479265 -4.534952

Source: Authors calculation based on Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991) and Molnar (2016).

Note:

*(1) ***; ** and * represents level of significance at 1%, 5% and 10%.*

(2) Violation first set of GARCH (1,1) and RGARCH (1,1) necessary conditions: (a) violation of first condition [$\beta_0 < 0$]: NIL; (b) violation of second condition: [$\beta i < 0$]: OC – GARCH (Media only), RGARCH using @RS (-1) (FMCG only), (c) Violation of third condition: [$\beta j < 0$]: RGARCH using PARK (-1) (auto, FMCG, metal, PSU bank), RGARCH using GK(-1): auto, bank, financial services, information technology, media, metal , PSU bank, PVT bank, realty, RGARCH using RS(-1) (FMCG, media).

(3) Violation second set of GARCH (1,1) and RGARCH (1,1) necessary conditions [($\beta i + \beta j$) <1 for all i & j]**:** GARCH using CCRET: ($\beta i + \beta j$) >1: bank, IT, PVT bank, GARCH using OCRET : ($\beta i + \beta j$) >1: bank, PVT bank, $\beta j < 0$ but ($\beta i + \beta j$) <1: media; RGARCH using PARK(-1): ($\beta i + \beta j$) >1: financial services, ($\beta i + \beta j$) = 1: PSU bank, PVT bank, $\beta j < 0$ but ($\beta i + \beta j$) <1: auto, FMCG, metal; RGARCH using GK(-1): Violating condition (at least one from three conditions) but ($\beta i + \beta j$) <1: Auto, bank, financial services, PVT bank, IT, media, metal, PSU bank, Reality; GARCH using RS(-1) : Violating condition (at least one from three conditions) but ($\beta i + \beta j$) <1: FMCG, Media.

Table 6. Dynamic Forecasting of 5 Volatility model along with reported RMSE and MAE value.

Sector	Lag Length for Close-to-Close Return	GARCH (1,1) using Close-to-close return		Lag Length for Open-to-Close Return	GARCH (1,1) using Open-to-Close return		RGARCH (1,1) using Parkinson (1980)		RGARCH (1,1) using Garman and Klass (1980)		RGARCH (1,1) using Roger and Satchell (1991)	
		RMSE	MAE		RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
Auto	2	0.014	0.010	2	0.013	0.009	0.012	0.009			0.012	0.009
Bank	7	0.019	0.016	6	0.016	0.016	0.016	0.013	0.016	0.014	0.016	0.014
Financial Services	7	0.017	0.014	6	0.014	0.011	0.014	0.012	0.014	0.012	0.014	0.012
FMCG	9	0.009	0.007	8	0.008	0.006	0.008	0.006	0.008	0.006	0.008	0.006
Information Technology	7	0.015	0.011	1	0.013	0.010	0.013	0.010			0.013	0.010
Media	7	0.018	0.014	8	0.017	0.013	0.017	0.013	0.017	0.013	0.017	0.013
Metal	6	0.019	0.014	3	0.017	0.012	0.017	0.012	0.017	0.013	0.017	0.012
Pharma	2	0.017	0.013	1	0.015	0.012	0.015	0.012	0.015	0.012	0.015	0.012
PSU Bank	7	0.020	0.016	1	0.016	0.013	0.016	0.013	0.016	0.013	0.016	0.013
Pvt Bank	2	0.020	0.016	6	0.016	0.014	0.016	0.014	0.016	0.014	0.017	0.014
Realty	7	0.020	0.017	1	0.018	0.014	0.018	0.014	0.017	0.014	0.018	0.014

Source: Authors calculation based on Parkinson (1980), Garman and Klass (1980), Rogers and Satchell (1991) and Molnar (2016).

Note: RGARCH using Garman and Klass (1980) volatility proxy, we cannot estimate RMSE and MAE values for Auto and Information sector values due to getting squared root of negative number problem during numerical optimization.

Table 7. Comparison of DCC GARCH and DCC RGARCH separately for open-to-close return.

Sector	Open to close return							
	GARCH				RGARCH			
	Alpha(α)	Beta(β)	LR	AIC	Alpha(α)	Beta(β)	LR	AIC
Auto-Bank	0.078	0.721***	53.660	-0.451	0.069	0.767***	49.808	-0.418
Auto-Financial Services	0.076	0.751***	56.143	-0.473	0.067	0.772***	52.143	-0.438
Auto-Fmcg	0.143	0.191	39.339	-0.326	0.124	0.387	31.150	-0.255
Auto-IT	0.048	0.879***	33.071	-0.271	0.038	0.897***	34.043	-0.280
Auto-Metal	0.025	0.955***	101.218	-0.867	0.020**	0.964***	104.139	-0.892
Auto-Pharma	0.145**	0.704***	32.463	-0.266	0.169***	0.702***	35.565	-0.293
Auto-Pvt	0.093	0.668***	53.199	-0.447	0.077	0.737***	49.305	-0.413
Bank-Financial Services	0.146**	0.518***	322.044	-2.795	0.145**	0.504***	317.302	-2.754
Bank-Fmcg	0.093	0.563***	32.178	-0.264	0.070	0.580**	24.888	-0.200
Bank-IT	0.035	0.909***	9.865	-0.069	0.041	0.903***	8.260	-0.055
Bank-Media	0.023	0.946***	43.639	-0.364	0.036	0.929***	42.583	-0.354
Bank-Metal	0.101	0.771***	50.654	-0.425	0.102	0.754***	48.079	-0.402
Bank-Pharma	0.061	0.679***	12.719	-0.094	0.074	0.660***	10.570	-0.075
Bank-Pvt	0.200***	0.683***	483.718	-4.207	0.163***	0.695***	486.303	-4.230
Financial Services-Fmcg	0.081	0.601**	33.575	-0.276	0.062	0.581*	25.677	-0.207
Financial Services-IT	0.073	0.681*	9.793	-0.068	0.036	0.907***	8.294	-0.055
Financial Services-Media.	0.024	0.946***	43.555	-0.363	0.033	0.939***	41.965	-0.349
Financial Services-Metal	0.125*	0.686***	50.625	-0.425	0.164**	0.575***	48.234	-0.404
Financial Services-Pharma	0.077	0.612**	12.792	-0.094	0.099	0.566*	10.994	-0.079
Financial Services-Pvt	0.173**	0.404**	280.470	-2.432	0.168***	0.451***	280.044	-2.428
FMCG –IT	0.050	0.717***	18.600	-0.145	-0.016	0.999***	15.067	-0.114
FMCG -Media	0.006	0.895*	28.594	-0.232	-0.016	0.997***	26.240	-0.212
FMCG -Metal	-0.014	0.987***	40.334	-0.335	-0.024**	0.987***	33.409	-0.274
FMCG –Pvt	0.116*	0.525**	32.205	-0.264	-0.032***	0.998***	25.876	-0.209
IT-Media	0.039	0.904***	10.531	-0.075	0.043	0.892***	10.331	-0.073
IT-Metal	0.026	0.937***	17.215	-0.133	0.051	0.855***	18.817	-0.147
IT-Pharma	0.082**	0.784***	20.244	-0.159	0.074*	0.795***	21.495	-0.170
IT-Pvt	0.085	0.566	9.871	-0.069	0.040	0.892***	8.034	-0.053
Media-Metal	0.037	0.876***	44.933	-0.375	0.040	0.844***	45.332	-0.378
Media-Pharma	0.074	0.764***	16.767	-0.129	0.062	0.778***	17.379	-0.134
Media-Pvt	0.019	0.938***	41.108	-0.342	0.030	0.924***	39.545	-0.328
Metal-Pharma	0.081**	0.773***	29.413	-0.239	0.076*	0.771***	25.045	-0.201
Metal-Pvt	0.120	0.714***	48.183	-0.403	0.121	0.692***	44.943	-0.375
Pharma-Pvt	0.064	0.678***	11.655	-0.084	0.080	0.657***	9.657	-0.067

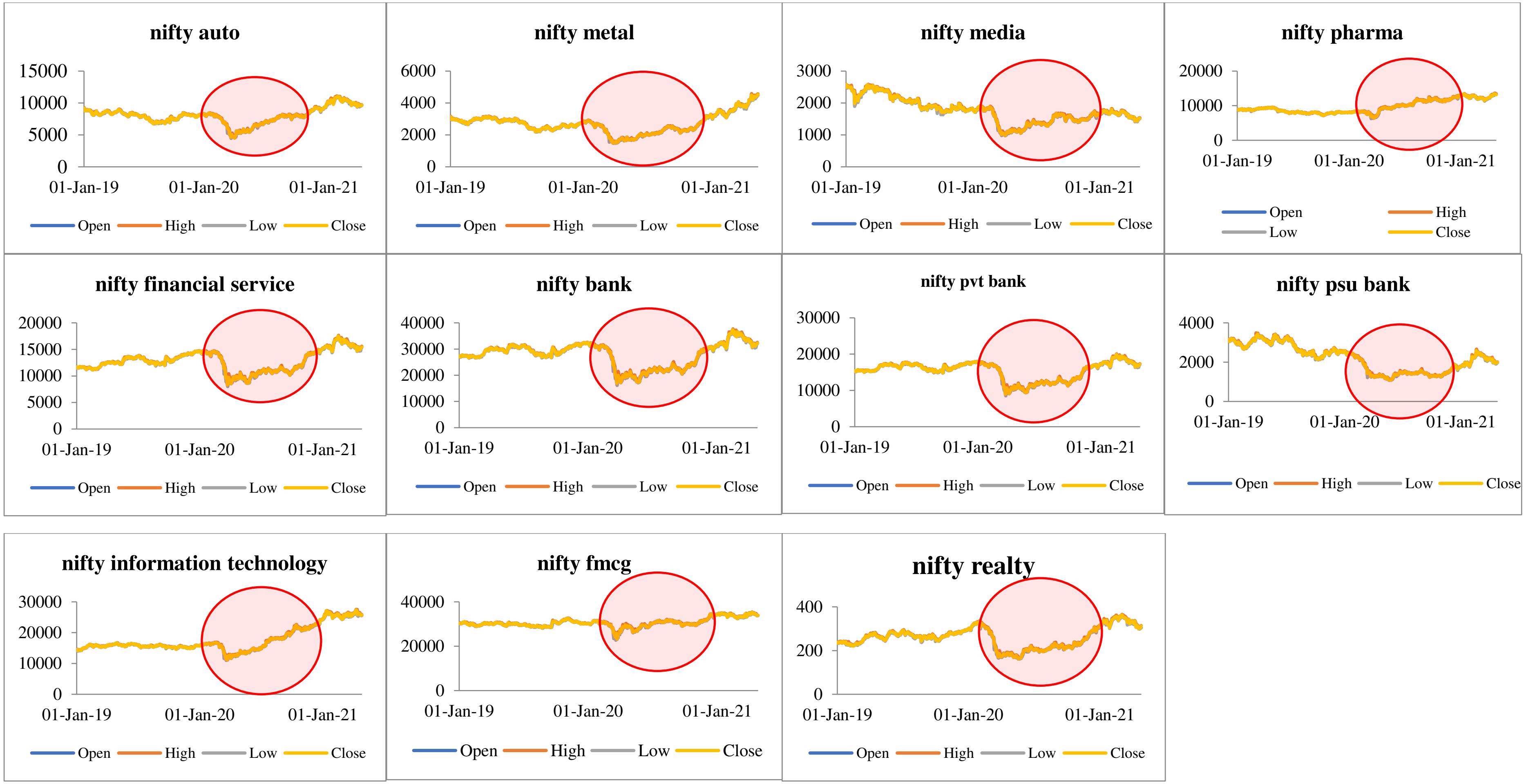
Source: Authors calculation based on Fiszeder et. al. (2019) using Eviews 12.

Table 8. Comparison of DCC GARCH and DCC RGARCH separately for close-to-close return.

Sector	Close to close return							
	GARCH				RGARCH			
	Alpha(α)	Beta(β)	LR	AIC	Alpha(α)	Beta(β)	LR	AIC
Auto-Media	0.027	0.920***	66.460	-0.563	0.016	0.935***	65.933	-0.558
Auto-PSU	0.019	0.909***	52.196	-0.438	0.013	0.938***	51.617	-0.433
Auto-Realty	0.134***	0.711***	87.303	-0.745	0.109***	0.762***	84.924	-0.724
Bank-PSU	-0.015*	0.998***	124.724	-1.072	-0.017**	0.997***	125.619	-1.080
Bank-Realty	0.149*	0.678***	88.823	-0.758	0.053	0.903***	86.224	-0.736
Financial Services-PSU	0.002	0.902***	107.284	-0.920	-0.011	0.996***	108.485	-0.930
Financial Services-Realty	0.050*	0.914***	96.169	-0.822	0.042	0.920***	91.303	-0.780
FMCG-Pharma	0.053	0.793***	40.096	-0.333	0.039	0.801***	38.758	-0.321
FMCG -PSU	0.038	0.830***	29.439	-0.240	0.028	0.840***	26.681	-0.216
FMCG -Realty					0.029	0.860***	36.649	-0.303
IT-PSU	0.048**	0.926***	18.306	-0.142	0.036**	0.932***	15.394	-0.117
IT-Realty	0.091**	0.845***	21.974	-0.174	0.077**	0.864***	20.940	-0.165
Media-PSU	0.018	0.942***	56.389	-0.475	0.004	0.976***	54.450	-0.458
Media-Realty	0.019	0.902***	52.809	-0.444	0.008	0.924***	53.015	-0.446
Metal-PSU	0.035	0.910***	59.461	-0.502	0.037*	0.920***	61.405	-0.519
Metal-Realty	0.119	0.463	61.507	-0.520	0.054	0.688	62.210	-0.526
Pharma-PSU	0.093**	0.819***	16.435	-0.126	0.080**	0.827***	15.754	-0.120
Pharma_Realty	0.123**	0.707***	25.717	-0.207	0.117**	0.735***	26.814	-0.217
Pvt_Realty	0.179***	0.618***	86.592	-0.739	0.110	0.780***	83.676	-0.713
PSU_Realty	0.012	0.959***	63.280	-0.535	0.011	0.961***	62.886	-0.532
PSU_Pvt								

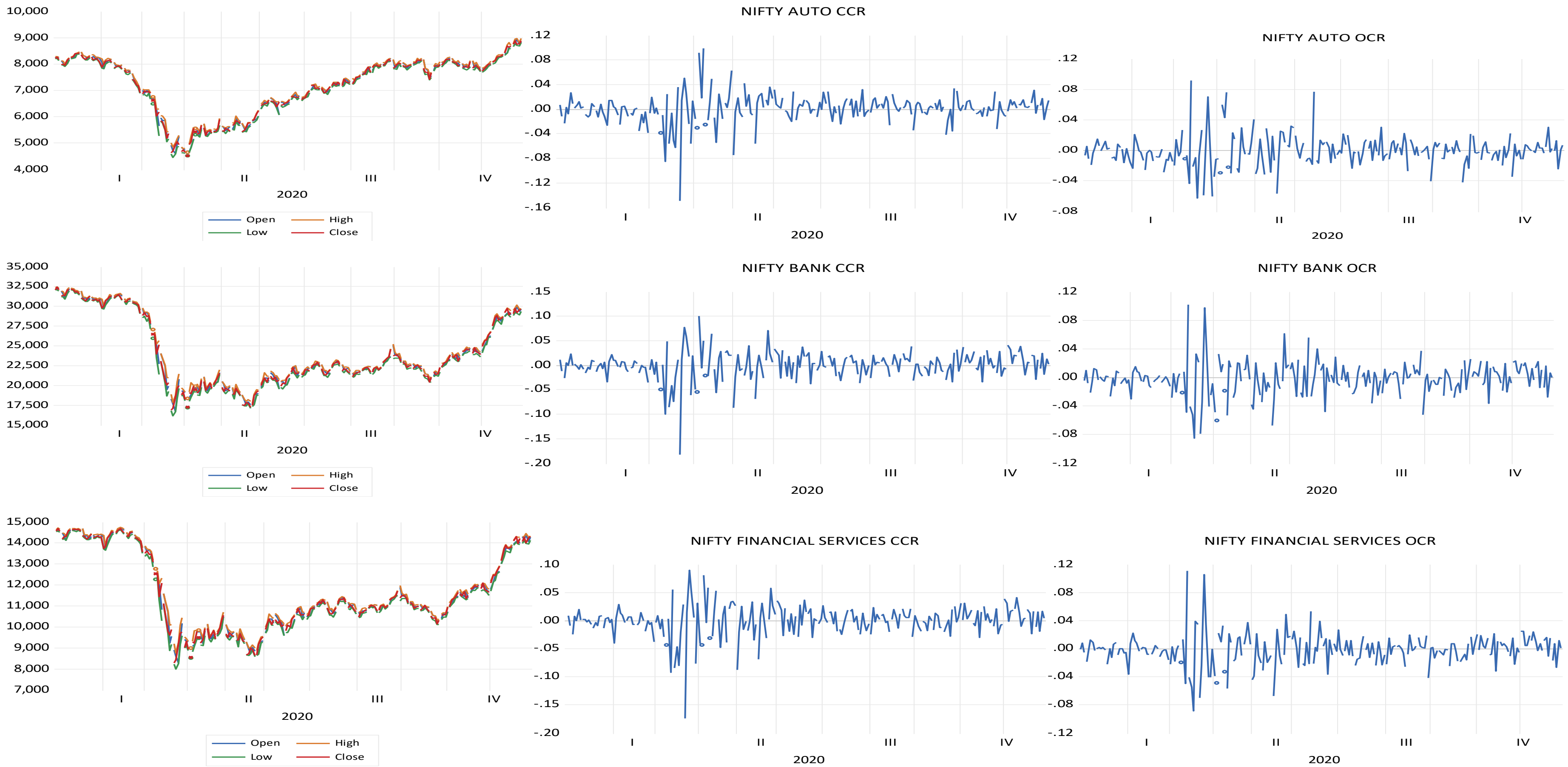
Source: Authors calculation based on Fiszeder et. al. (2019) using Eviews 12.

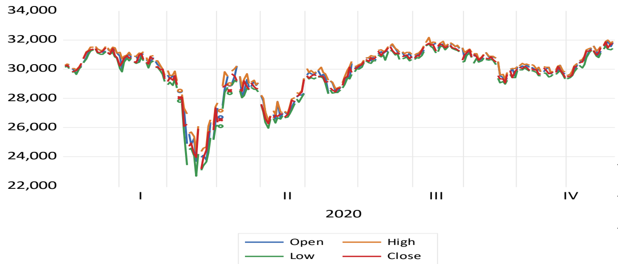
Figure 1. Identification of study time period for first wave outbreak of COVID 19 and its recovery phases across different sectors.

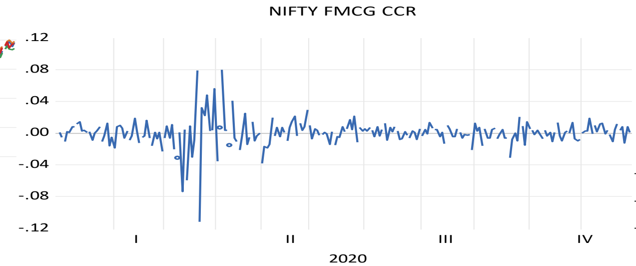


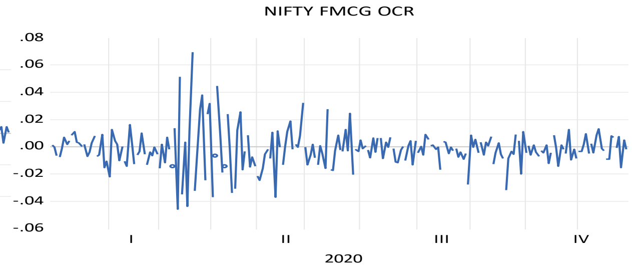
Source: Nifty (Sector wise) historical price data, January 2019 – April 2021, National Stock Exchange (NSE)

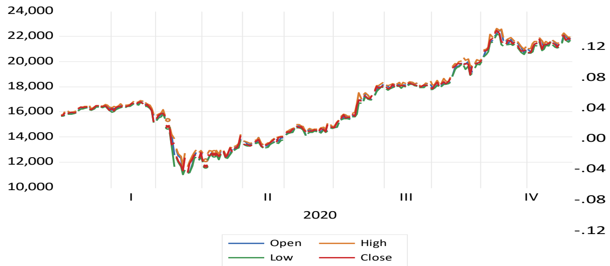
Figure 2. Graphical plot of OHLC price, close-to-close return and open-to-close return of 11 NIFTY stock indices.

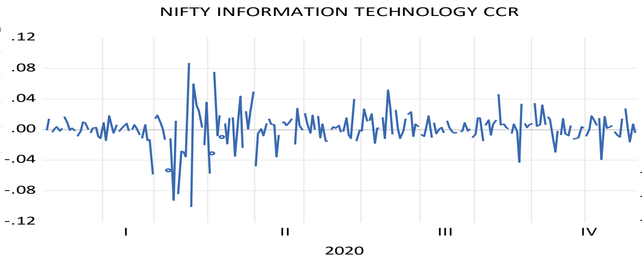



34,000
32,000
30,000
28,000
26,000
24,000
22,000
I
II
III
IV
2020
Open
High
Low
Close


NIFTY FMCG CCR
.12
.08
.04
.00
-.04
-.08
-.12
I
II
III
IV
2020


NIFTY FMCG OCR
.08
.06
.04
.02
.00
-.02
-.04
-.06
I
II
III
IV
2020


24,000
22,000
20,000
18,000
16,000
14,000
12,000
10,000
I
II
III
IV
2020
Open
High
Low
Close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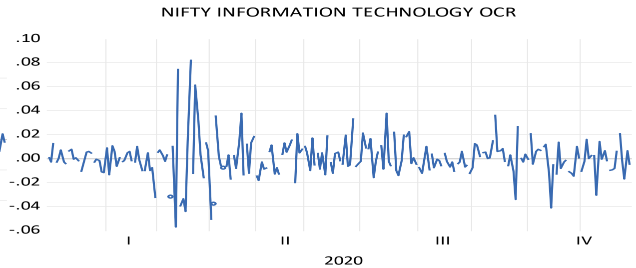
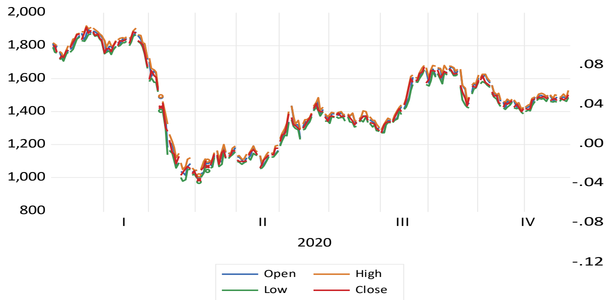
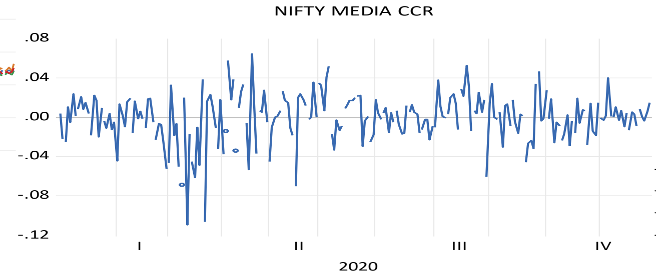
.08
.04
.00
-.04
-.08
-.12
I
II
III
IV
2020


NIFTY INFORMATION TECHNOLOGY OCR
.10
.08
.06
.04
.02
.00
-.02
-.04
-.06
I
II
III
IV
2020


2,000
1,800
1,600
1,400
1,200
1,000
800
I
II
III
IV
2020
Open
High
Low
Close


NIFTY MEDIA CCR
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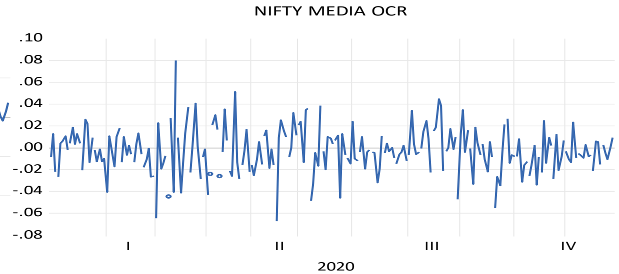
.04
.00
-.04
-.08
-.12
I
II
III
IV
2020


NIFTY MEDIA OCR
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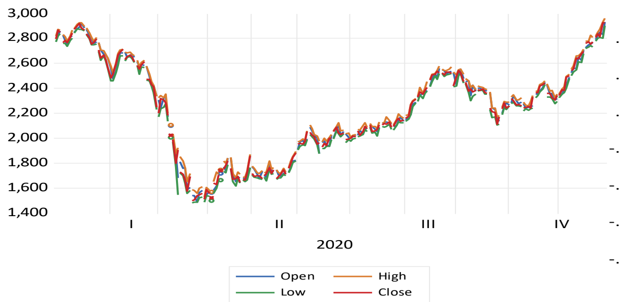
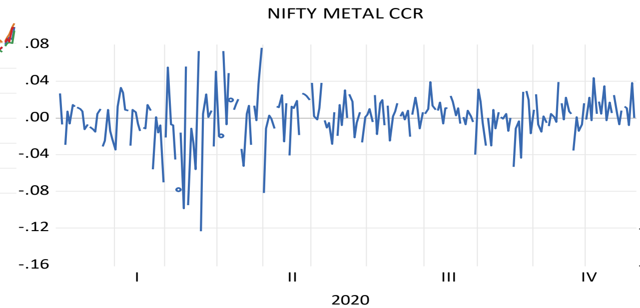
.08
.06
.04
.02
.00
-.02
-.04
-.06
-.08
I
II
III
IV
2020


3,000
2,800
2,600
2,400
2,200
2,000
1,800
1,600
1,400
I
II
III
IV
2020
Open
High
Low
Close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.04
.00
-.04
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-.12
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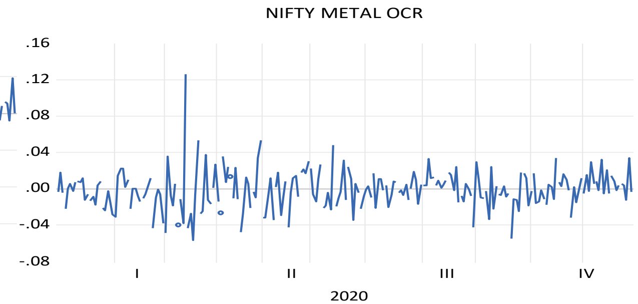
I
II
III
IV
2020


NIFTY METAL OCR
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.12
.08
.04
.00
-.04
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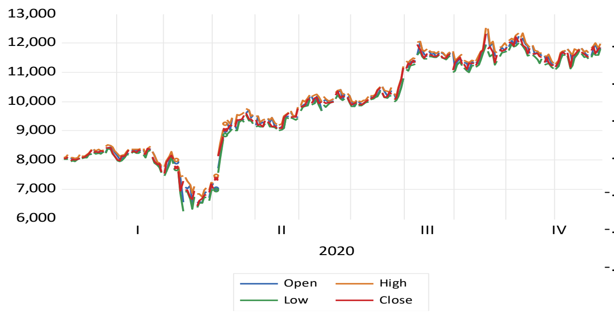
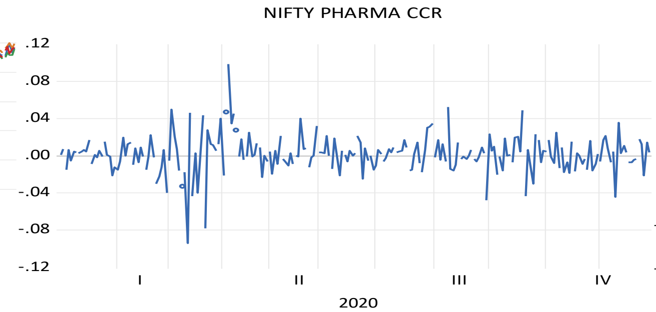
I
II
III
IV
2020


13,000
12,000
11,000
10,000
9,000
8,000
7,000
6,000
I
II
III
IV
2020
Open
High
Low
Close


NIFTY PHARMA CCR
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.08
.04
.00
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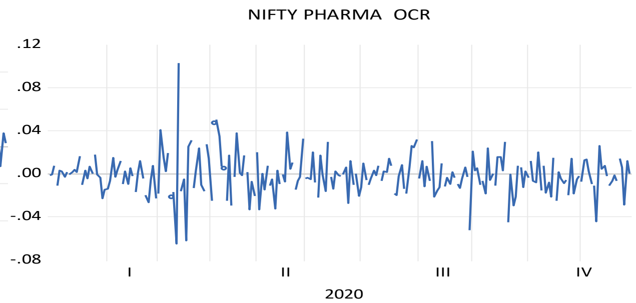
-.08
-.12
I
II
III
IV
2020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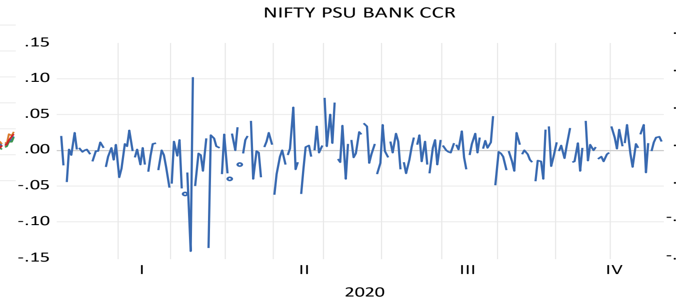
.12
.08
.04
.00
-.04
-.08
I
II
III
IV
2020


2,600
2,400
2,200
2,000
1,800
1,600
1,400
1,200
1,000
I
II
III
IV
2020
Open
High
Low
Close


NIFTY PSU BANK CCR
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.10
.05
.00
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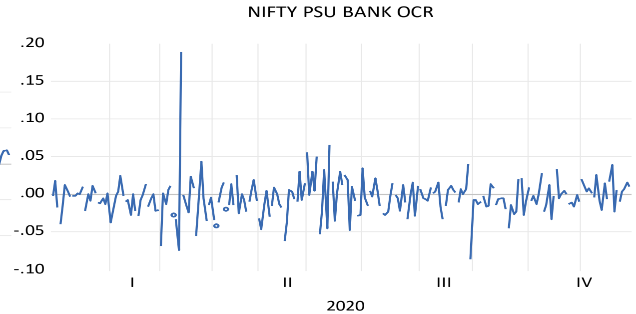
-.10
-.15
I
II
III
IV
2020


NIFTY PSU BANK OCR
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.10
.05
.00
-.05
-.10
I
II
III
IV
2020


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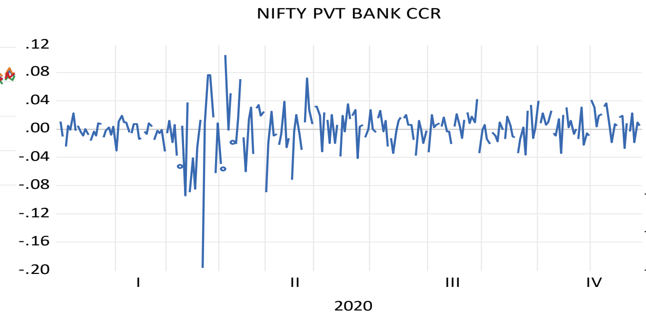
18,000
16,000
14,000
12,000
10,000
8,000
I
II
III
IV
2020
Open
High
Low
Close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.04
.00
-.04
-.08
-.12
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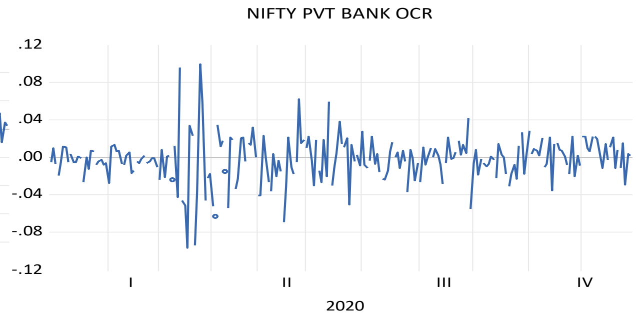
I
II
III
IV
2020


NIFTY PVT BANK OCR
.12
.08
.04
.00
-.04
-.08
-.12
I
II
III
IV
2020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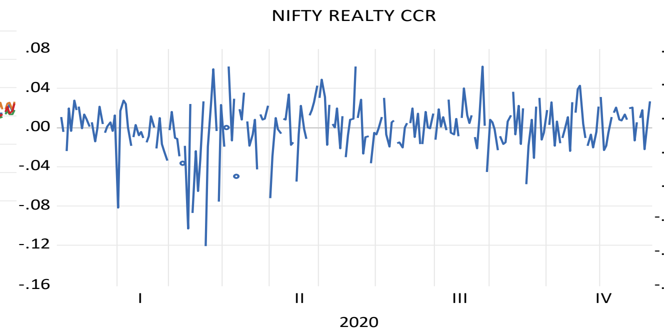
325
300
275
250
225
200
175
150
I
II
III
IV
2020
Open
High
Low
Close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.00
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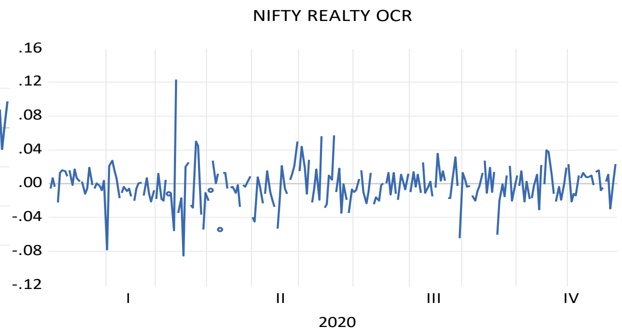
I
II
III
IV
2020


NIFTY REALTY OCR
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I
II
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