Journal of Applied Economic Sciences
Volume XX, Spring, Issue 1(87), 2025

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

Susanta DATTA
https://orcid.org/0000-0001-6806-7760
Department of Economics, Seva Sadan's R. K. Talreja College of Arts, Science and Commerce
Affiliated to University of Mumbai[1], India
susanta.datta@ssrkt.edu.in and susantadatta2005@gmail.com

Neeraj HATEKAR
School of Development, Azim Premji University[2], India
neeraj.hatekar@gmail.com

Article's history:

Received 26th of December, 2025; Received in revised form 19th of January, 2025; Accepted 25th of January, 2025; Available online: 16th of February, 2025. Published as article in the Volume XX, Spring, Issue 1(87), 2025.

Copyright© 2025 The Author(s). This article is distributed under the terms of the license CC-BY 4.0., which permits any further distribution in any medium, provided the original work is properly cited.

Suggested citation:

Datta, S., & Hatekar, N. (2025). Range volatility spillover across Sectoral Stock Indices during COVID 19 pandemic: Evidence from Indian stock market. *Journal of Applied Economic Sciences*, Volume XX, Spring, 1(87), 79 – 100 https://doi.org/10.57017/jaes.v20.1(87).06

Abstract:

This study examines volatility spillover across sectoral stock indices in India, an emerging market economy, during the COVID-19 pandemic. Our research makes three key contributions: (a) incorporating range volatility measures to capture the pandemic's impact on stock market volatility, (b) providing a comparative assessment of volatility spillover across sectoral indices, and (c) identifying evidence of volatility spillover across different sectoral indices. Using daily historical open, high, low, and close price data for 11 NIFTY sectoral indices during first wave of pandemic; the findings reveal that open-to-close returns outperform close-to-close returns in forecasting sectoral stock indices, underscoring the importance of incorporating range-based volatility measures in forecasting models. Furthermore, the multivariate Range DCC model confirms significant volatility spillover across sectoral indices, highlighting the interconnectedness of Indian sectoral stock markets during crisis periods. The findings offer actionable insights for the Securities and Exchange Board of India (SEBI) to develop targeted, sectoral-level market surveillance strategies and robust risk management frameworks, ultimately enhancing the resilience of India's capital markets in post-pandemic scenarios.

Keywords: volatility, spillover, return, range, NIFTY, COVID 19.

JEL Classification: C58, C22, G17.

Introduction

The sudden outbreak of the COVID 19 pandemic has had a profound impact on the global economy, disrupting economic conditions and livelihoods worldwide (Baker et al., 2020). Empirical studies have shown significant economic effects resulting from the subsequent lockdowns (Padhan et al., 2021; Baldwin et al., 2020).

---

[1] Shivaji Chowk, Kalyan – Ambernath Road, Ulhasnagar III, District Thane, Maharashtra, India 421003
[2] Survey No 66, Burugunte Village, Bikkanahalli Main Road, Sarjapura, Bengaluru, India 562125

These studies can be categorized into three groups: (a) develop macroeconomic models (McKibbin et al., 2020), (b) assess the impact on income and wealth (Hanspal et al., 2020), and (c) examine the impact on the stock market (Xiaolin et al., 2020; Bohdan, 2020).

The stock market has been severely affected by the pandemic, with the World Health Organization (WHO) declaring COVID-19 a pandemic on March 11, 2020, following a global market crash on March 9, 2020[3]. Research on the pandemic's impact on the stock market has yielded valuable insights. The market's initial response to the pandemic was marked by extreme volatility, with little influence from country-specific factors (Capelle-Blancard et al., 2020). Government and central bank interventions have also played a crucial role in shaping market outcomes. Several studies have investigated the pandemic's impact on specific stock markets, including China (Xiaolin et al., 2020). These studies have found significant effects on industry and firm-level returns, as well as evidence of market overreactions. Other research has examined the pandemic's impact on stock markets across multiple countries, finding negative but short-term effects. Predictive models have also been used to examine the relationship between COVID-19 spread and stock market performance (Bohdan, 2020; Prabheesh et al. 2020a, 2020b).

The pandemic has significantly increased financial risks and adversely affected global financial markets (Padhan et al., 2021). Specifically, the pandemic has negatively impacted stock market returns and increased volatility spillover in stock returns. This study aims to investigate the daily historical open, high, low, and close (OHLC) prices of NIFTY sectoral indices to compare their forecasting performance and volatility spillover across different sectors during the pandemic. We also seek to identify the best-performing sector-specific model.

This article is organized into five distinct sections. Section 1 provides a comprehensive literature review, synthesizing existing research on stock returns volatility during the COVID-19 pandemic and range volatility. Section 2 outlines the motivation behind the study, highlighting the research gap and rationale for the investigation. The research design, data collection methods, and statistical techniques employed are detailed in Section 3. The results of the study are presented in Section 4, accompanied by relevant tables, figures, and graphs. Finally, last section provides a concise conclusion, summarizing the key findings, implications, and contributions of the study.

1. Literature Review

Stock Returns Volatility during COVID 19

Stock Market Reactions to COVID-19: The COVID - 19 pandemic has triggered significant reactions in stock markets worldwide. Haroon et al. (2020a) employed an asymmetric GARCH model to examine sentiment generation and equity volatility between the world and US markets. Their findings indicate that panic news contributes to volatility. Similarly, Haroon et al. (2020b) studied the impact of COVID-19 on 23 Emerging Market Economies (EMEs) using GARCH and panel regression models.

Research has also focused on volatility and financial contagion during the pandemic. Akhtaruzzaman et al. (2020) examined the occurrence of financial contagion among the world, China, and G7 countries using the VERMA DCC-GARCH and Diebold-Yilmaz models. Their findings indicate an increase in stock return correlation, suggesting a higher role of financial contagion. Corbet et al. (2020) investigated the contagion effect on the Chinese stock market and confirmed significant changes in volatility relationships during the pandemic.

Traditional volatility models, such as GARCH, have been widely used to examine volatility during the pandemic. However, these models have limitations, as they fail to utilize the information contained in the daily price range. Range volatility models offer a more comprehensive approach to measuring volatility, as they capture the full information contained in the price range (Datta et al. 2024).

[3] Banerjee, S. & Chauhan, A. (2020, September 10-12). Financial Markets during the Pandemics and New Finance in The Post Covid Era, [S3IL - KEYNOTE ADDRESS III], EconTR2020@Eskişehir, International Conference on Economics, Eskişehir Osmangazi University, Eskişehir, Turkey. https://econtr.org/

Range Volatility

The concept of range-based volatility measures has been explored in various studies since the 1980s. Parkinson (1980) developed a range-based volatility measure that was more efficient than classical return-based estimators. Garman et al. (1980) and Wiggins (1991) also contributed to the development of range-based volatility models. Rogers et al. (1991) and Andersen et al. (1997) further extended these models. In the 2000s, researchers continued to refine range-based volatility models. Yang et al. (2000) and Alizadeh et al. (2002) developed new range-based volatility measures. Brandt et al. (2006) and Chou et al. (2015) further contributed to the literature on range-based volatility models. Recent studies have provided empirical evidence on the effectiveness of range-based volatility models. Molnar (2012, 2016) derived the properties of range-based estimators and suggested a simple way to improve the GARCH model using the intraday range. The study found 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. Datta (2019) and Datta et al. (2024) also found that using high/low range data can acquire more efficient results than return data based on close prices.

Multivariate volatility models, such as the Dynamic Conditional Correlation (DCC) model, have been used to explain how covariance changes over time. Engle (2002) introduced the DCC model, which is based on closing prices. However, Fiszeder et al. (2019) incorporated high and low prices into the DCC framework and found that the range-based DCC model outperforms the return-based DCC model across various asset classes.

Motivation

This study bridges several existing literature gaps by investigating the impact of COVID-19 on Indian sectoral stock indices, which have been largely overlooked in favour of developed markets and aggregate stock market indices. Existing research has also relied on traditional volatility models, neglecting the benefits of range volatility models, and has neglected the importance of volatility spillover across sectoral indices during the pandemic. By addressing these gaps, this study provides a comprehensive understanding of the impact of COVID-19 on Indian sectoral stock indices, specifically addressing the gap in literature on COVID-19's impact on financial markets in emerging markets like India. This study makes three key contributions: (a) incorporating range volatility as an alternative measure, (b) comparing spillover in price and volatility between return-based and range-based models using optimal lag length, and (c) identifying evidence of volatility spillover across Indian sectoral indices.

2. Research Methodology

Data

The unit of analysis for this study consists of daily Open-High-Low-Close (OHLC) historical price data of 11 NIFTY sectoral indices: Auto, Bank, FMCG, Financial Services, Information Technology (IT), Metal, Media, Pharma, PSU Bank, Private Bank, and Realty. Secondary data was sourced from the National Stock Exchange (NSE) India website. The study period, spanning January 1, 2020, to November 30, 2020, captures the first phase of the COVID-19 pandemic, as depicted in Figure 1 (Appendix).

Methodology

This study employed a quantitative research approach to examine the impact of COVID-19 on Indian sectoral stock indices. Daily Open-High-Low-Close (OHLC) historical price data of 11 NIFTY sectoral indices. Both close-to-close and open-to-close returns were calculated and visualized graphically alongside OHLC prices for all sectoral indices. Descriptive statistics, including mean, median, maximum, minimum, standard deviation, skewness, and kurtosis, were estimated for 229 close-to-close return observations and 230 open-to-close return observations.

To ensure the reliability of the results, diagnostic tests were conducted, including the Jarque-Bera (JB) normality test, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests, and autocorrelation tests using the Portmanteau Q statistic and Ljung-Box squared Q statistic. Stability checks were also performed using the UDmax and WDmax tests based on the Bai-Perron (1998, 2003) method.

The optimal lag length for each sectoral stock index was determined by considering the minimum Akaike Information Criterion (AIC) value among 10 lags. The study then verified that the models satisfied three conditions: (a) no linear autocorrelation in the error term, (b) linear autocorrelation in the squared error term, and (c) rejection of the null hypothesis of zero autoregressive conditional heteroskedasticity (ARCH) effect using the ARCH Lagrange Multiplier (LM) test for the optimal lag length.

GARCH (1, 1) Model Specification

This study employs Engle (1982) and Bollerslev (1986) to estimate the volatility of Indian sectoral stock indices. The GARCH (1,1) model is specified as follows:

- Mean Equation: The mean equation is modelled as an Autoregressive (AR) process of order p*, using close-to-close returns:

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

where $\varepsilon_t \sim N(0, h_t)$ and p* is the optimal lag length selected based on the Akaike Information Criterion (AIC).

- Conditional Variance Equation: The conditional variance equation for the GARCH (1,1) model, using both close-to-close and open-to-close returns, is specified as:

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

- Necessary and Sufficient Conditions: The necessary and sufficient conditions for the GARCH (1,1) model to be well-defined and to ensure the positivity of the conditional variance are:

(a) $\beta_o > 0$; $\beta_i \geq 0$ and $\beta_j \geq 0$

(b) $(\beta_i + \beta_j) < 1$ for all *i* and *j*

Range GARCH (1, 1) Model Specification

This study employs the Range GARCH (1,1) or RGARCH (1,1) model, as proposed by Molnar (2012) and Molnar (2016), to estimate the volatility of Indian sectoral stock indices. The RGARCH (1,1) model incorporates exogenous volatility proxies, specifically range volatility proxies, to capture the volatility dynamics of the sectoral indices. Three range volatility proxies are employed in this study: (i) Parkinson (1980) volatility proxy, (ii) Garman and Klass (1980) volatility proxy, and (iii) Rogers and Satchell (1991) volatility proxy. These proxies are calculated as follows:

(i) Parkinson (1980) volatility proxy: $\sigma^2_{Park} = (\ln H_t - \ln L_t)/4\ln 2$

(ii) Garman and Klass (1980) volatility proxy: $\sigma^2_{GK} = 0.5[\ln(H_t/L_t)]^2 - [2\ln 2 - 1]\,[\ln(C_t/O_t)]^2$

(iii) Rogers and Satchell (1991) volatility proxy: $\sigma^2_{RS} = (1/N)\ \sum \ln(H_t/O_t)\ [\ln(H_t/O_t) - \ln(C_t/O_t)] + \ln(L_t/O_t)[\ln(L_t/O_t) - \ln(C_t/O_t)]$

The RGARCH (1,1) model is specified as follows:

Mean Equation:

$$Y_t = \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_{p^*} Y_{t-p^*} + \varepsilon_t \qquad (3)$$

where $\varepsilon_t \sim N(0, h_t)$ and p* is the optimal lag length selected based on the Akaike Information Criterion (AIC).

Conditional Variance Equation:

(i) RGARCH (1,1) using Parkinson (1980): $h_t = \beta_0 + \beta_i\sigma^2_{Park,t-1} + \beta_j h^2_{t-1}$ (4)

(ii) RGARCH (1,1) using Garman and Klass (1980): $h_t = \beta_0 + \beta_i\sigma^2_{GK,t-1} + \beta_j h^2_{t-1}$ (5)

(iii) RGARCH (1,1) using Rogers and Satchell (1991): $h_t = \beta_0 + \beta_i\sigma^2_{RS,t-1} + \beta_j h^2_{t-1}$ (6)

Necessary and Sufficient Conditions: The necessary and sufficient conditions for the RGARCH (1,1) model to be well-defined and to ensure the positivity of the conditional variance are:

(a) $\beta_0 > 0$; $\beta_i \geq 0$ and $\beta_j \geq 0$

(b) $(\beta_i + \beta_j) < 1$ for all i & j

Comparison of RGARCH (1,1) and Standard GARCH (1,1) Models: The relative performance of the RGARCH (1,1) model is assessed by comparing the estimated coefficients βi and βj with those obtained from the standard GARCH (1,1) model. Specifically, it is examined whether the incorporation of range-based volatility proxies in the RGARCH (1,1) model leads to an increase in the coefficient βi and a decrease in the coefficient βj, relative to the standard GARCH (1,1) model.

In sample estimation and out of sample forecasting

Approximately 72% of the sample, corresponding to 167 observations from January 2020 to August 2020, is utilized for in-sample estimation, where the in-sample estimates and out-of-sample forecasting performance of two GARCH (1,1) and three RGARCH (1,1) models are estimated and compared. The necessary conditions for the GARCH (1,1) and RGARCH (1,1) models are verified, and the estimated parameter values, probability of rejection, and information criteria values are reported. A comparative analysis is conducted to examine the coefficient βi and βj dynamics. The remaining 28% of the sample, corresponding to the last 63 observations from September 2020 to November 2020, is used for out-of-sample forecasting, where dynamic forecasting is carried out, and the Root Mean Squares Error (RMSE) and Mean Absolute Error (MAE) are reported to identify the best-performing model.

Multivariate Volatility Model: DCC GARCH and DCC RGARCH

This study employs multivariate volatility models to estimate pair-wise dynamic conditional correlations between two NIFTY sectoral indices. Separate analyses are conducted for close-to-close returns and open-to-close returns, using both DCC GARCH and DCC RGARCH models. The DCC GARCH model is estimated using close-to-close returns, whereas the DCC RGARCH model incorporates open-to-close returns and fluctuations in the high and low-price range.

The models estimate both alpha (α) and beta (β) coefficients, following a moving average (MA) and autoregressive (AR) structure, respectively. The significance of these coefficients is examined to determine the presence of dynamic conditional correlations (DCC) between the sectoral indices. This analysis enables us to investigate whether external shocks in one sector are transmitted to another sector through the error term, thereby assessing the interconnectedness of the Indian sectoral stock markets.

3. Empirical Findings

Figure 2 (see Appendix) presents the daily movements of Open-High-Low-Close (OHLC) prices, along with close-to-close returns and open-to-close returns, for 11 NIFTY sectoral indices. A pronounced decline in the OHLC price range was observed around the declaration of the first lockdown, attributed to unprecedented uncertainty in the market. However, a gradual recovery in the price range was noted, indicating a quicker recovery than previous crises.

Descriptive statistics and diagnostic test results for close-to-close returns and open-to-close returns are presented in Table 2 and Table 3 (see Appendix), respectively. The results indicate that 8 out of 11 sectoral indices exhibited positive close-to-close returns, while 10 out of 11 indices exhibited negative open-to-close returns. The median, maximum, minimum, and standard deviation values were as expected. The close-to-close return series followed a negatively skewed distribution, while the open-to-close return series followed a positively skewed distribution, except for Private Bank. Both return series exhibited leptokurtic distributions, confirming non-normality due to fat-tailed financial data. The Jarque-Bera test for normality confirmed non-normality for both return series of all 11 indices at a 1% level of significance. The Augmented Dickey-Fuller test and Phillips-Perron test for stationarity rejected the null hypothesis of non-stationarity at a 1% level of significance for all 11 indices and both return series. The UDmax and WDmax tests were conducted to ensure stability conditions. The results showed that certain sectors exhibited significant test statistics, indicating structural breaks. However, due to the limited sample size, sub-sample basis estimates were not feasible.

Table 4 (see Appendix) presents the optimal lag length for each sectoral index, satisfying the necessary conditions for GARCH and RGARCH models. Table 5 presents the estimated coefficients, level of significance, and information criterion values for the 5 estimated models. The results showed that the RGARCH model with the Parkinson (1980) volatility proxy outperformed the other models. The estimated coefficients βi and βj were significant at a 1% level of significance, and the value of βi increased while βj decreased for all NIFTY indices. These findings are consistent with the results of Molnar (2016). Table 6 presents the dynamic forecasting of volatility using five models, along with the corresponding Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values.

This study examines the dynamic conditional correlations between 11 NIFTY sectoral indices using the DCC GARCH and DCC RGARCH models. Following the rule of thumb, if both α and β coefficients are insignificant, it suggests the absence of dynamic conditional correlations. Conversely, if at least one coefficient is significant, it confirms the presence of dynamic conditional correlations. Table 7 and Table 8 (see Appendix) present the estimated coefficients for the DCC GARCH and DCC RGARCH models using open-to-close returns and close-to-close returns, respectively. Due to numerical optimization issues, only 34 pairs of open-to-close returns and 21 pairs of close-to-close returns were estimated.

The results indicate that, except for a few pairs, the β coefficient is significant at the 1% level for both DCC GARCH and DCC RGARCH models. Specifically, for open-to-close returns, 31 out of 34 pairs exhibit significant β coefficients (Table 7). Similarly, for close-to-close returns, 19 out of 21 pairs exhibit significant β coefficients (Table 8). These findings suggest the presence of dynamic conditional correlations between the NIFTY sectoral indices.

Conclusion

This study undertakes a comprehensive examination of the volatility spillover effects across Indian sectoral stock indices during the COVID-19 pandemic. The empirical findings reveal that the RGARCH (1,1) model, utilizing the Parkinson (1980) volatility proxy, exhibits superior performance in capturing the true intraday fluctuations during the pandemic. Furthermore, the results indicate that employing open-to-close returns, rather than close-to-close returns, yields improved forecasting performance for all selected sectoral stock indices.

Empirical findings have significant implications for market regulators and investors. The results suggest that sectoral-level market surveillance strategies can be more effective in capturing the underlying volatility regime across sectors during a pandemic. Moreover, the findings of this study can also inform the development of more effective risk management strategies and market surveillance systems.

This study contributes to the existing literature on volatility spillover effects, suggesting that these effects are more pronounced during periods of high market uncertainty, such as during the COVID-19 pandemic. The results also underscore the importance of utilizing range-based volatility models, such as the RGARCH model, in capturing the true intraday fluctuations in financial markets. Overall, this study provides new insights into the volatility spillover effects across Indian sectoral stock indices during the COVID-19 pandemic, with significant implications for market regulators, investors, and researchers.

While this study provides valuable insights into the volatility spillover effects across Indian sectoral stock indices during the COVID-19 pandemic, it also acknowledges several limitations and avenues for future research. Future studies can build upon this research by exploring the volatility spillover effects across other emerging markets and incorporating other macroeconomic and financial variables into the analysis. Additionally, further research can examine the impact of other global events on the volatility spillover effects across sectoral stock indices.

Credit Authorship Contribution Statement

The corresponding author takes full responsibility for this research paper, encompassing all aspects of the project, including conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, software, supervision, validation, visualization, and writing under the guidance and overall supervision of the second author. This includes originating the research idea, collecting, and analysing data, overseeing the project timeline and resources, and composing and revising the manuscript for publication. Errors are the authors' responsibility.

Acknowledgments/Funding

The authors express their gratitude to the researchers who provided valuable feedback during the online Second SEBI NISM Research Conference, held on February 25-26, 2021. Special thanks are also extended to Prof. Peter Molnar, Prof. Marcin Faldzinski, and Dr. Srikanta Kundu for their insightful comments and contributions to the research. The authors declare that they have not received any financial grants or funding to carry out this research from any public, commercial, or not-for-profit sectors. However, the first author received an editorial grant from RITHA enabling the publication of this article. The authors acknowledge the generous support of the Eviews sales team and the Gauss sales team, who provided free licenses to facilitate the research.

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2020). Financial contagion during COVID–19 crisis. *Finance Research Letter*. http://dx.doi.org/10.1016/j.frl.2020.101604

Alizadeh, S., Brandt, M. W., & Diebold, F. X. (2002). Range-based estimation of stochastic volatility models. *Journal of Finance,* 57, 1047−1091. https://doi.org/10.1111/1540-6261.00454

Andersen, T. & Bollerslev, T. (1997). Heterogeneous information arrivals and return volatility dynamics: uncovering the long run-in high frequency returns. *Journal of Finance*, 52, 975−1005. https://doi.org/10.1111/j.1540-6261.1997.tb02722.x

Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 47-78. https://doi.org/10.2307/2998540

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1-22. https://doi.org/10.1002/jae.659

Baker, S. R., Bloom, N., Davis, S. J., Kost, K. J., Sammon, M. C. & Viratyosin, T. (2020). The unprecedented stock market impact of COVID-19. *National Bureau of Economic Research Working Paper* (26945). https://www.nber.org/papers/w26945

Baldwin, R. & Weder di Mauro, B. (eds) (2020). Mitigating the COVID Economic Crisis: Act Fast and Do Whatever It Takes, CEPR Press, Paris & London. https://cepr.org/publications/books-and-reports/mitigating-covid-economic-crisis-act-fast-and-do-whatever-it-takes

Bohdan, M. P. (2020). Regression Approach for Modelling COVID-19 Spread and its Impact on Stock Market. https://doi.org/10.48550/arXiv.2004.01489

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Brandt, M. & Jones, C. (2006) Volatility Forecasting with Range-Based EGARCH Models. *Journal of Business and Economic Statistics*, 24, 470-486. http://dx.doi.org/10.1198/073500106000000206

Capelle-Blancard, G. & Desroziers, A. (2020). The Stock Market Is not the Economy? Insights from the COVID-19 Crisis (June 16, 2020). CEPR Covid Economics. https://ssrn.com/abstract=3638208 or http://dx.doi.org/10.2139/ssrn.3638208

Chou, R. Y., Chou, H., & Liu, N. (2015). Range volatility: A review of models and empirical studies. In C. F. Lee & J. C. Lee (Eds.), *Handbook of Financial Econometrics and Statistics* (pp. 2029–2050). Springer New York. https://doi.org/10.1007/978-1-4614-7750-1_74

Corbet, S., Larkin, C., & Lucey, B. (2020). The contagion effects of the covid-19 pandemic: Evidence from gold and cryptocurrencies. *Finance Research Letter*. http://dx.doi.org/10.1016/j.frl.2020.101554

Datta, S. (2019). Range Volatility in Commodity Future Price Index: Evidences from Indian Multi Commodity Exchange. *International Journal of Advance and Innovative Research*, Volume 6, Issue 2 (XIV). https://www.researchgate.net/publication/334362099

Datta, S. & Hatekar, N. (2024). Modelling range volatility in currency bid - ask spreads: Implications for financial resilience and sustainable development in emerging market economies. *Journal of Global Sustainability and Development*, Volume I, Issue 1, 27 – 40. https://doi.org/10.57017/jgsd.v1.i1

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50, 987-1007. https://doi.org/10.2307/1912773

Engle, R. F. (2002) Dynamic Conditional Correlation: A Simple Class of Multivariate GARCH Models. *Journal of Business and Economic Statistics*, 20, 339-350. http://dx.doi.org/10.1198/073500102288618487

Fiszeder P., Fałdziński, M. & Molnár, P. (2019). Range-based DCC models for covariance and value-at-risk forecasting. *Journal of Empirical Finance*, Volume 54, 58- 76. https://doi.org/10.1016/j.jempfin.2019.08.004

Garman, M. B., & Klass, M. J. (1980). On the Estimation of Security Price Volatilities from Historical Data. *The Journal of Business,* 53(1), 67–78. http://www.jstor.org/stable/2352358

Hanspal, T. Weber, A. & Wohlfart, J. (2020). Income and Wealth Shocks and Expectations during the COVID-19 Pandemic. CESifo Working Paper, No. 8244, Center for Economic Studies and Ifo Institute (CESifo), Munich. https://hdl.handle.net/10419/216640

Haroon, O. & Rizvi, S. A. R. (2020a). COVID-19: Media coverage and financial markets behavior - A sectoral inquiry. *Journal of Behavioral and Experimental Finance*, Volume 27, 100343. http://dx.doi.org/10.1016/j.jbef.2020.100343

Haroon, O. & Rizvi, S. A. R. (2020b). Flatten the curve and stock market liquidity–an inquiry into emerging economies. *Emerging Market Finance Trade*, 56(10), 2151–2161. http://dx.doi.org/10.1080/1540496X.2020.1784716

McKibbin, Warwick J. & Fernando, R. (2020). The Global Macroeconomic Impacts of COVID-19: Seven Scenarios. CAMA Working Paper No. 19/2020. http://dx.doi.org/10.2139/ssrn.3547729

Molnár, P. (2012). Properties of Range-Based Volatility Estimators. *International Review of Financial Analysis*, Volume 23, 20-29, https://ssrn.com/abstract=2691435

Molnar, P. (2016). High-low range in GARCH models of stock return volatility. *Applied Economics*, 48(51), 4977-4991. https://doi.org/10.1080/00036846.2016.1170929

Padhan, R. & Prabheesh, K. P. (2021). The Economics of COVID 19 pandemic: A Survey. *Economic Analysis and Policy*, 70, 220–237. https://doi.org/10.1016/j.eap.2021.02.012

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business*, 53, 61–65. https://www.jstor.org/stable/2352357

Prabheesh, K. P., Garg, B., & Padhan, R. (2020a). Time-varying dependence between stock markets and oil prices during COVID-19: The case of net oil-exporting countries. *Economics Bulletin*, 40(3), 2408–2418, http://www.accessecon.com/Pubs/EB/2020/Volume40/EB-20-V40-I3-P210.pdf

Prabheesh, K. P., Padhan, R., & Garg, B. (2020b). COVID-19 and the oil price–stock market nexus: Evidence from net oil-importing countries*. Energy Research Letters*, 1(2). http://dx.doi.org/10.46557/001c.13745

Rogers, L. C. & Satchell, S. E. (1991) Estimating Variance from High, Low and Closing Prices. *The Annals of Applied Probability*, 1, 504-512. https://doi.org/10.1214/aoap/1177005835

Wiggins, J. (1991). Empirical tests of the bias and efficiency of the extreme-value variance estimator for common stocks. *Journal of Business*, 64, 417-432. https://ideas.repec.org/a/ucp/jnlbus/v64y1991i3p417-32.html

Xiaolin, H. & Zhigang, Q. (2020). How does China's stock market react to the announcement of the COVID-19 pandemic lockdown? *Economic and Political Studies.* https://doi.org/10.1080/20954816.2020.1780695

Yang, D. & Zhang, Q. (2000). Drift-independent volatility estimation based on high, low, open, and closing Prices. *Journal of Business,* 73, 477-491. http://dx.doi.org/10.1086/209650

APPENDIX

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

Note: ***; ** and * represents level of significance at 1%, 5% and 10%.; 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.

Source: Authors calculation based on NIFTY sectoral stock indices

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

Note: ***; ** and * represents level of significance at 1%, 5% and 10%.; 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.

Source: Authors calculation based on NIFTY sectoral stock indices

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)

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(.), Q2(.) 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.

Source: Authors calculation based on NIFTY sectoral stock indices

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

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.

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

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 & Klass (1980)		RGARCH (1,1) using Roger & 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

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.

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

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

Note: ***; ** and * represents level of significance at 1%, 5% and 10%.

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

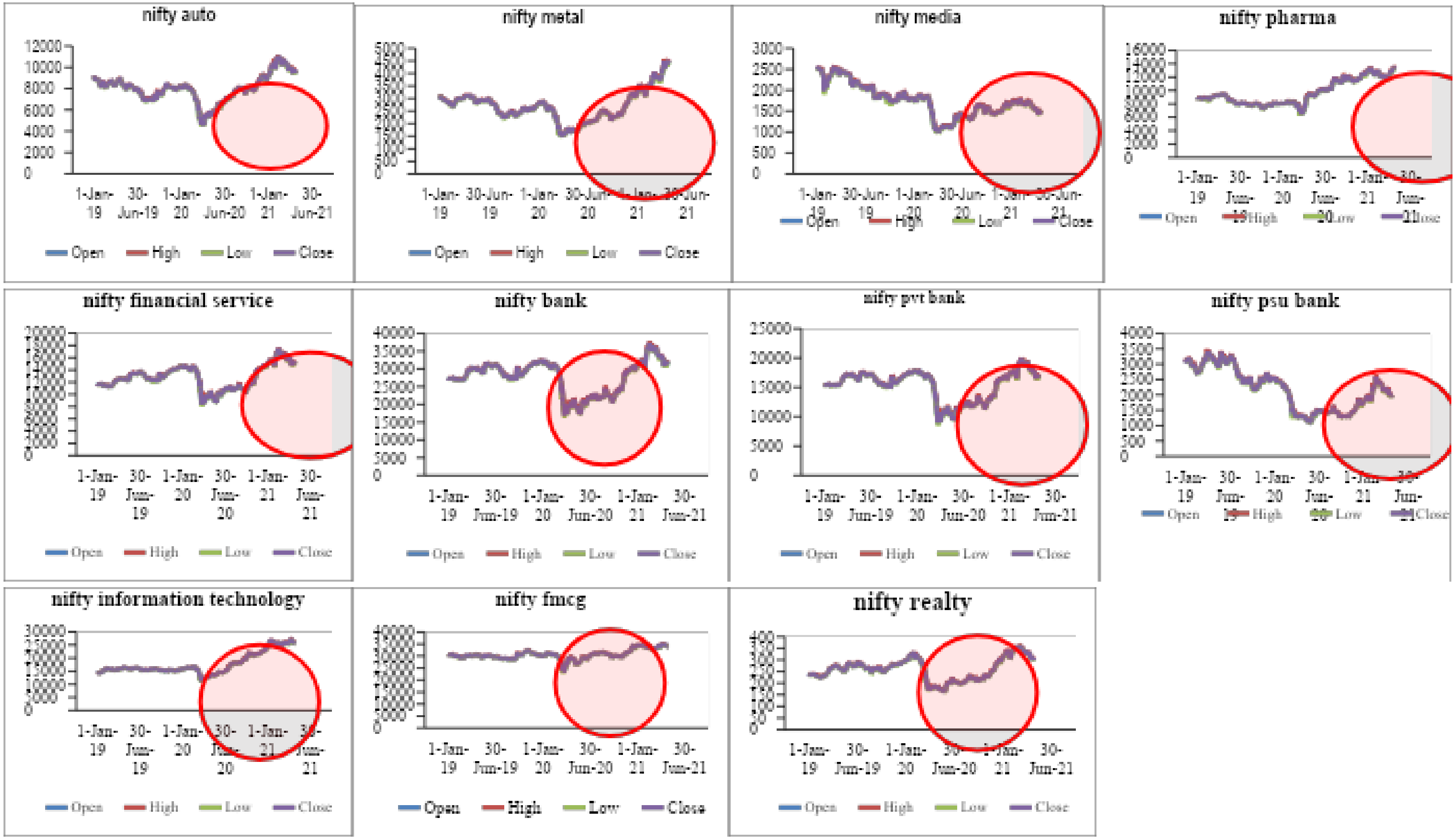
Table 8: Comparison of DCC GARCH and DCC RGARCH separately for close-to-close return.

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								

Note: ***; ** and * represents level of significance at 1%, 5% and 10%.

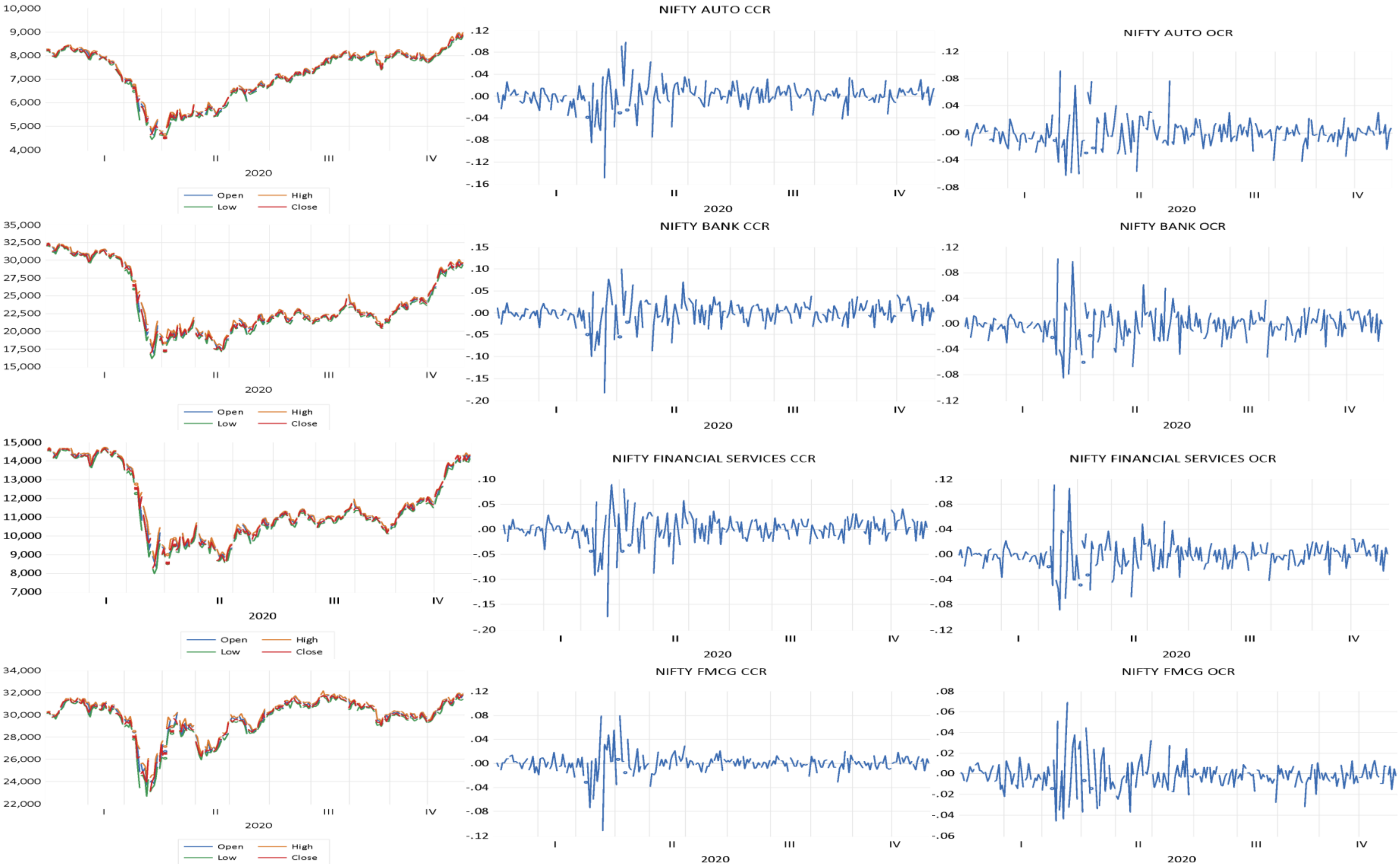
Source: Authors calculation based on Fiszeder et. al. (2019) using Eviews 12.

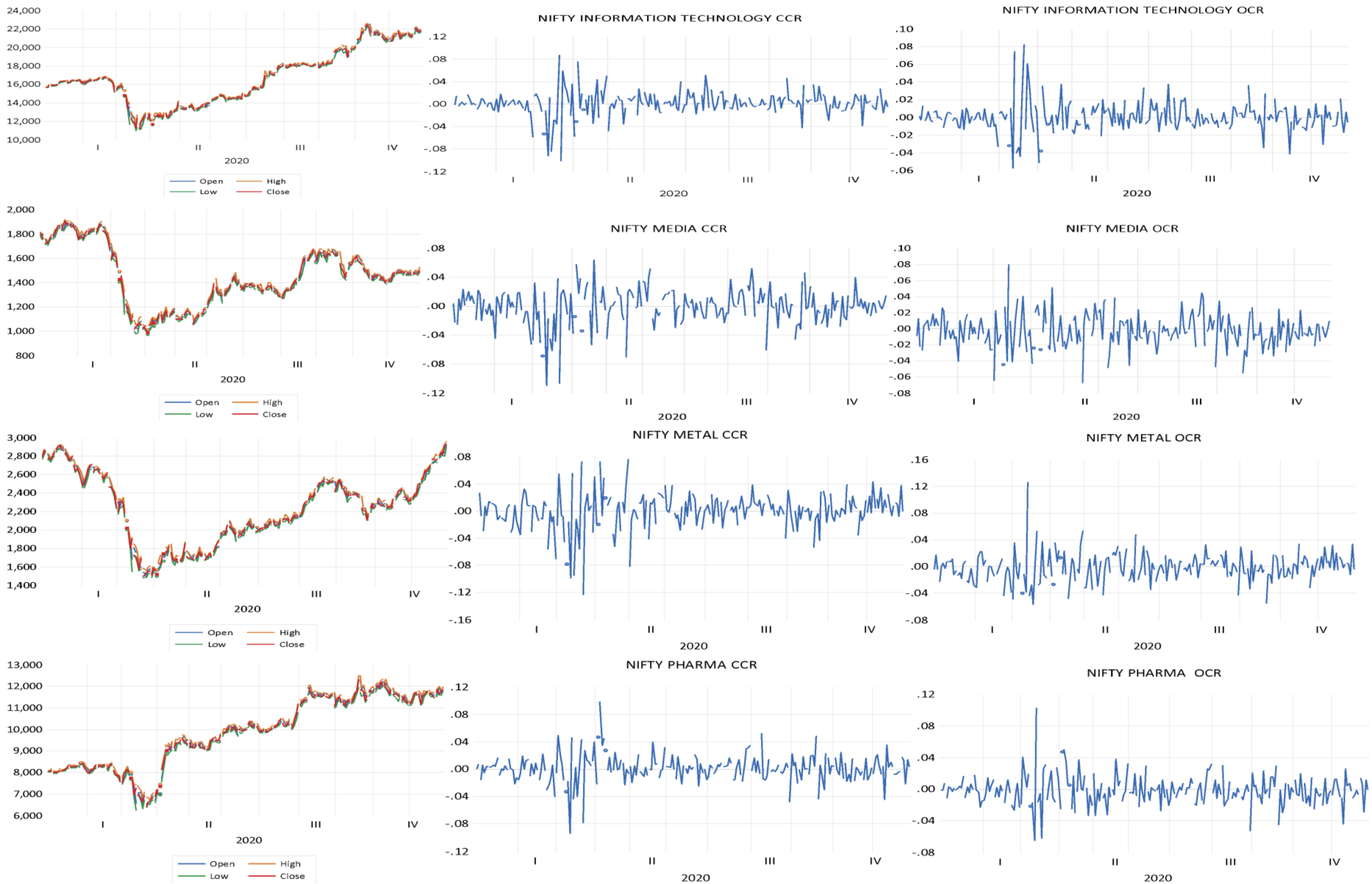
Figure 1: Identification of study time period for first wave outbreak of COVID 19 and its recovery phases across different sectors.



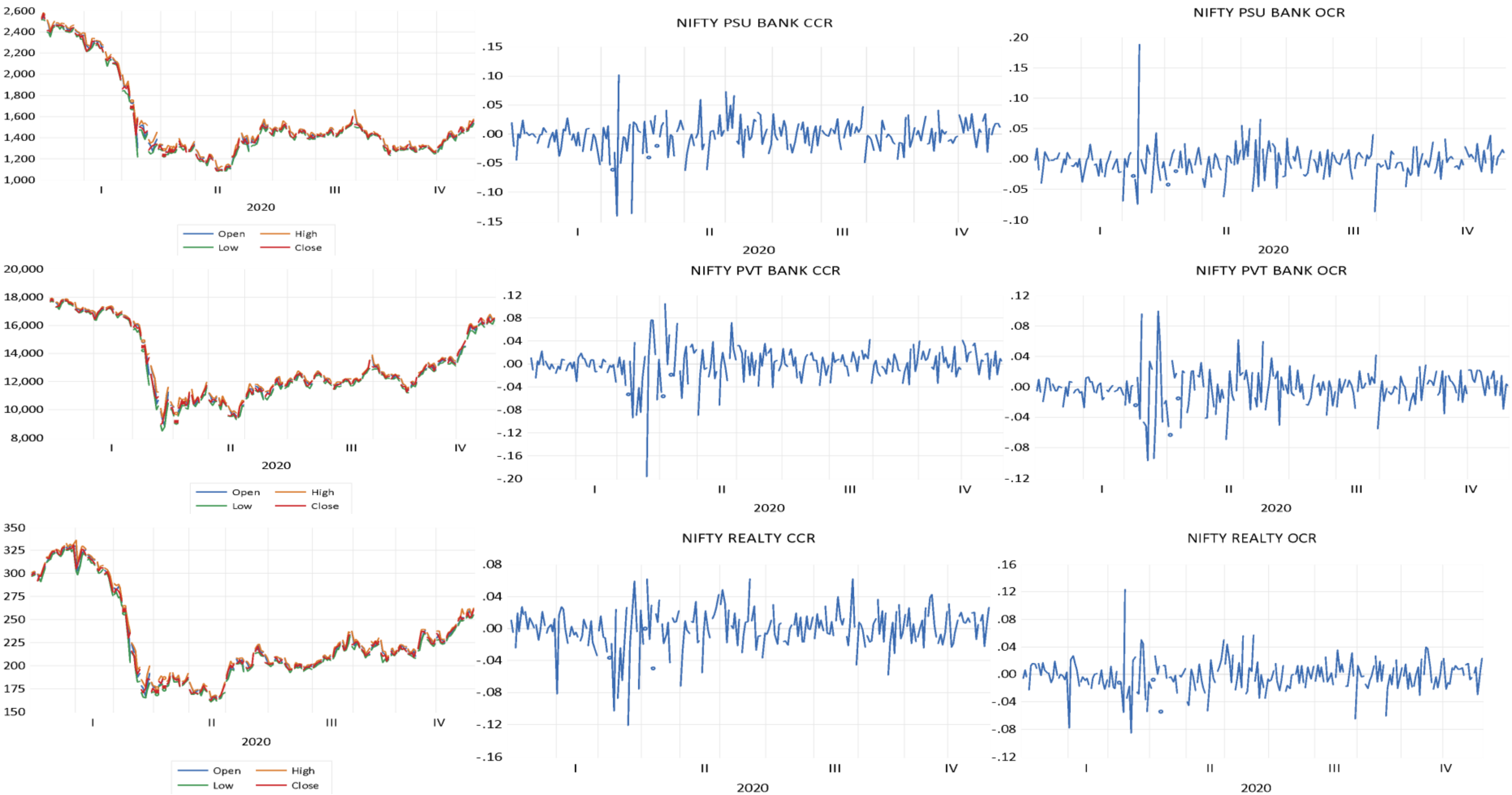
Source: Nifty (Sector wise) historical price data, January 2019 – April 2021, National Stock Exchange (NSE)

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





NIFTY INFORMATION TECHNOLOGY CCR
NIFTY INFORMATION TECHNOLOGY OCR
NIFTY MEDIA CCR
NIFTY MEDIA OCR
NIFTY METAL CCR
NIFTY METAL OCR
NIFTY PHARMA CCR
NIFTY PHARMA OCR
Open
High
Low
Close
2020
I
II
III
IV



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