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Interconnectedness and Risk Spillovers among Selected Indian Stocks During the COVID-19 Pandemic

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ABSTRACT

This paper examines the connectedness and spillovers of volatilities among ten selected BSE indexes during the COVID-19 pandemic. Daily data covering the periods from January 2015 to December 2020 has been utilized. We employed the "Diebold and Yilmaz" procedure to investigate directional and total volatility spillovers. The results reveal a significant overall pairwise connectedness of 56.8%, indicating a high degree of inter-stock dependency. Additionally, we computed an aggregate spillover index, and its graphical representation shows a substantial upsurge beginning at the end of 2019, eventually peaking on March 12, 2020. Finally, we divided the dataset into two samples: the period before and the period during the pandemic. The results confirm that COVID-19 has triggered a significant volatility spillover within the Indian market. The policy implications of these findings are also discussed.

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1. Introduction

The effects of COVID-19 have generated a high degree of uncertainties and enormous challenges for the global economy across the board, as well as serious consequences for the manufacturing activities and supply chain (Nguyen et al., 2021; Bello and Abdu, 2021; Si et al., 2021). When the crisis intensified, the stock market volatility increased at an unprecedented rate and subsequently spilled over across the markets. Recently, studies have found that the pandemic has triggered a significant risk spillover with varying effects across markets and over time (Aslam et al., 2021; Si et al., 2021). It has also caused massive disruptions to financial markets as well as an increase in the rate of risk-contagion, particularly in the countries with severe cases of pandemic Wang et al. (2020).

For example, the global stock market suffered a loss of approximately $6 trillion in just five trading days, from February 24, 2020, to February 28, 2020, as a result of the impact of the pandemic (Ozili and Arun, 2020). Since the COVID-19 outbreak, the SP-500 index has suffered a loss of up to 30% of its value and the increased uncertainties associated with the pandemic has also affected the returns and the values of the global stocks (Azimili, 2020).

The continued spread of the COVID-19 virus, as well as the administrative lockdown measures implemented by authorities to contain the trend, have seriously jeopardized almost every sector of the Indian economy. It halted the operations of many of India's largest manufacturing firms. Many businesses, except factories producing essential items, have also forced to remain closed until around March, 31st Amit (2020).

According to a report by the International Energy Agency (IEA, April 2020), by the first half of June 2020, the estimated total fuel demand would be 80% to 85% of what it was before the lockdown, and diesel demand was also expected to fall by 6%.

According to Bello and Abdu (2021) and Bora and Basistha (2021), COVID-19 has negatively affected the returns and triggered the volatility of the stocks. For instance, the report by FIRSTPOST has had it that on March 23, 2020, the Indian stock markets suffered their worst losses in history. The SENSEX dropped by 13.15% and the NSE NIFTY dropped by 12.98%. However, one day after a total 21-day lockdown was announced, the SENSEX revealed the additional value of US$62 billion for the stockholders which is its biggest gain in 11 years, (FIRSTPOST, 2020).

In the finance literature, event studies are mainly used to investigate the impact of unexpected events on the stock markets, businesses (both domestic and international), investors, and governments. Accordingly, several studies applied the event analysis to examine the upsurge of volatilities and changes in the stock market’s performance that are caused by COVID-19 (Bello and Abdu, 2021; Rao et al., 2021; Harjoto, et al., 2021). However, the abnormal returns generated by the events studies may not be purely due to the market’s response to the particular incident and this may lead to biased results (Si et al., 2021; Sitthipongpanich, 2011).

Several studies were conducted in trying to understand the behavior of stock markets during the pandemic period, which includes those that focus on the estimation of stock volatility and returns (Sharma, 2020; Wang et al., 2020a; Bora and Basistha, 2021) and those which are concerned with the stock returns reaction to information regarding the COVID-19 (Bello and Abdu, 2021; Harjoto et al., 2021; Rao et al., 2021). Others have gone further to examine the intensity of interconnectedness and risk spillover between various stock markets and indexes during the pandemic period (Wang et al., 2020b; Aslam at al., 2021; Ghorbel and Jeribi, 2021; Hung 2021a; Hung 2021b; Nguyen et al., 2021; Si et al., 2021; Behera and Mishra, 2022). The latter strand justified how multivariate VAR and dynamic conditional correlated (DCC) Garch approaches have gained traction in the literature courtesy of the works of Diebold and Yilmaz (2009; 2012; 2014) and Gabauer (2020).

This study seeks to examine how COVID-19 triggers the interconnectedness and risk spillovers among the ten selected BSE stock indexes in India using the DY approach. The DY approach has been widely used in various studies (Wu et al., 2019; Hu et al., 2020; Wang et al., 2020b; Aslam et al., 2021; Hung, 2021a: 2021b; Hung and Vo, 2021; Wu et al., 2021) as it is more effective in capturing precisely the level, patterns, and clustering of risk connectedness (Diebold and Yilmaz, 2014). Therefore, it would enable us to not only examine the connectedness and risk spillover among Indian stocks but also how they react to the changes at various times during COVID-19.

There are few existing COVID-19-based studies on Indian stocks (Bora and Basistha, 2021; Rao et al., 2021; Behera and Mishra, 2022) however, only Behera and Mishra, is somehow related to ours, albeit being slightly differed in terms of the techniques and the variables chosen. Another aspect in which our study differs from the above is its ability to follow the precedent established in the literature by dividing the data set into pre-and post-COVID-19 pandemic periods (Aslam et al., 2021; Bora and Basistha, 2021; Hung, 2021a; 2021b; Hung and Vo, 2021) to demonstrate explicitly how the effects tend to vary with the increase in pandemic's intensity and severity.

Consequently, the contribution of the paper is that we can trace not only the response of the stock market to the pandemic but also uncover the interrelationship between various BSE stock indexes during the period of the pandemic and the risk spillovers and contagion associated with it. We are also able to track the evolution of total spillovers over time.

2. Literature Review

The literature on stock markets during the recent pandemic period contains two major strands of studies, those that investigate the stock's volatility and returns and how they react to the COVID-19 pandemic. The various single equation techniques, such as panel models (Rao et al., 2021; Wang et al., 2020a), variance models (Bora and Basistha, 2021; Sharma, 2020), and event studies/abnormal returns (Bello and Abdu, 2021; Harjoto et al., 2021), have dominated this group. Accordingly, Bora and Basistha (2021) found the volatility to be higher during the covid-19 than before it. Similarly, Rao et al. (2021) found that it is the lockdown measures that significantly exacerbate the impact of COVID-19 on the stock market. Harjoto et al. (2021) suggest that US stocks have witnessed stronger positive abnormal returns than other emerging stocks covered in their study. These results have been supported by Bello and Abdu (2021) who used a similar method and suggested that COVID-19 has different effects on each region and that Northern and Southern American stocks have experienced the most negative returns. Emphasizing the variability of the effects of COVID-19, Sharma (2020) suggested that the commonality in volatility during the COVID-19 period is more prominent in the case of Singapore compared to the other four economies covered in his study.

The other strand has been dominated by the studies which adopt a multivariate VAR and dynamic conditional correlated (DCC) Garch as the frameworks (Wu et al., 2019; Hu et al., 2020; Wang et al., 2020a; Aslam et al., 2021; Ghorbel and Jeribi; 2021; Hung, 2021a: 2021b; Hung and Vo, 2021; Nguyen et al., 2021; Si et al., 2021; Wu et al., 2021; Behera and Mishra, 2022), and the focus has been mainly on the stock interconnectedness and how risk is being transferred among the various markets, as well as which market/stock has been a major source or distributor of the risk. These studies have been closely related to the earlier studies on the European sovereign debt crisis Samitas and Kampouris (2017a) and Aristeidis, S., & Elias, K. (2018). (2017b) as well as Bexit Samitas et al. (2020).

Additionally, the VAR and DCC approaches have also enabled the authors to identify not only the stock's contribution to the volatility spillover in the particular market or country but also the country that has been the main source of the spillover to the global or regional stock market. Wu et al. (2019) found that the industrial sector is the most significant contributor to volatility in the Chinese stock market. They also highlighted how the whole market is primarily affected by risks and changes in the industrial sector, and consequently how the entire market moves. Hu et al. (2020) revealed that the macroeconomic factors and geopolitical risks are more relevant to crude oil volatilities and the influence of macroeconomic factors on the realized volatility of commodities is varying time-varying. Behera and Mishra (2022) found that energy and oil are the main contributors to volatility, with natural gas of accounting for the smallest part of the volatility. Additionally, the commodity and natural gas sectors are net receivers. Si et al. (2021) on the other hand have reported the oil exploitation sector as the main recipient of volatility spillover from COVID-19 followed by the power and gas sectors.

According to Wu et al (2021) the dynamics of total systemic risk are mainly driven by the US stock market volatility and investors' sentiment in the financial market. Samitas et al. (2020) reveal the existence of the contagion hypothesis from the Eurozone to the sectors of major economies. In addition, Aristeidis and Elias (2018) have discovered the instant financial contagion which was due to the shock and increased uncertainty from the referendum results. Finally, Samitas and Kampouris (2017) unveil how Spain and Italy could significantly harm all the strong northern economies, while Greece's negative shocks are capable of co-moving the French index as France is revealed to be the most correlated country within the southern Eurozone.

Table 1 below summarizes the previous studies on the stock market, its returns, volatility, and interconnectedness in response to the COVID-19 pandemic.

Table 1. Empirical Studies on COVID-19 and Financial Markets.

Author(s) and Year	Sample Country	Technique	Objective	Findings
Bora and Basistha (2021)	India	Garch-Model	To study the impact of COVID-19 on the volatility of stock prices	Indian stock market experienced higher volatility and higher returns during the pandemic than before.
Wang et al. (2020a)	China	fixed-effects model	To investigate how COVID-19 affects the insurance markets	The pandemic has a significant negative impact on property and personal insurance
Bello and Abdu (2021)	Global	Event-study and panel regression	The impact of COVID-19 on the global stock market	COVID-19 has different effects on each region. Northern and Southern American stocks have experienced the most negative returns
Rao et al. (2021)	India	Panel regression and event analysis	To assess the effect of COVID-19 on Indian capital market	The lockdown measures have a significant impact on the stock market
Harjoto et al. (2021)	Global	Event analysis	To study the stock market's reactions to the shock and the stimulus	The US stock market witnessed strong positive abnormal returns from the April 9, 2020 event compared to emerging Markets in developed and developing countries
Sharma (2020)	Asia	Garch-Model	To examine whether COVID-19 changed the commonality in volatility within the Asian region	The commonality in volatility during the COVID-19 period is more prominent in the case of Singapore compared to the other four economies.
Ghorbel and Jeribi (2021)	G7	Markov-Switching-GARCH	To investigate the association and volatility between the energy index, crude oil, gas prices, and financial assets volatilities and examine the dynamic correlation and volatility spillover	For the high regime, the results indicate a high level of dynamic correlation between energy assets and stock indexes which proves the existence of the contagion effect of COVID-19.
Wang et al. (2020b)	International	Diebold and Yil-maz	To investigate the dynamic changes in volatility spillovers across several major international financial markets.	The COVID-19 pandemic has caused massive shocks to international financial markets, particularly in countries with severe pandemics, and that the pandemic has resulted in increased financial market spillovers.
Aslam et al. (2021)	Europe	Diebold and Yil-maz	To examine the dir-ectional volatility spillover between European countries during the COVID-19 pandemic	The existence of important information about European stock market interdependence during COVID-19 has been revealed by the study
Nguyen et al. (2021)	U.S and China	Correlation, VAR-Granger causality analyses and GARCH	To examine contagion effects emanating from the U.S and China stock markets	There are significant contagion effects from the stock markets of the United States and China during the COVID-19 pandemic period.
Si et al. (2021)	China	high-dimensional and time-varying factor-augmented VAR model	To quantify the impact of COVID-19 on the Chinese the energy industry and to depict the pandemic's risk transmission path to diverse energy sectors	The volatility spillover of the COVID-19 is not only the highest but also lasts the longest for the oil exploitation sector, followed by the power and gas sectors.
Wu et al (2021)	top 20 global energy companies	Diebold and Yilmaz (2014)	To examine the risk, conn-expectedness by means of a Value-at-Risk (VaR) measure	The results show that dynamics of total systemic risk are mainly driven by the US stock market volatility and investors' sentiment in the financial market over the full sample.
Hung (2021a)	international	Diebold and Yilmaz (2012) and the wavelet coherence model	To analyse the spillover effects and time-frequency connectedness between crude oil prices and agricultural commodity markets, and assess whether the time-varying return spillover index unveiled the intensity and direction of transmission during the Covid-19 outbreak	When compared to the pre-COVID-19 period, the return spillover is more visible during the COVID-19 crisis.
Hung and Vo (2021)	US	Diebold and Yilmaz (2012) and the wavelet coherence	To study the spillover effects and time-frequency connected-ness between S&P 500, crude oil prices, and gold asset	Return transmissions are more visible during the COVID-19 crisis compared to the pre-COVID-19 period, and there exist significant dependent patterns about information spillovers among observed stocks.

Table 1.

Author(s) and Year	Sample Country	Technique	Objective	Findings
Hung (2021b)	US	M-GARCH and Diebold and Yilmaz, (2012)	To examine the financial interconnectedness of the Gulf Cooperation Council countries between 2008 and 2019 using mean and volatility spillovers across stock markets	The average return equicorrelation among GCC stock markets is positive, even though it is found to be very time-varying within a specific period.
Hu et al. (2020)	US	Diebold and Yilmaz's (2014)	To study how these macro factors contribute to the volatility fluctuations in commodity markets.	Macroeconomic factors and geopolitical risks are more relevant to crude oil volatilities. Macro influence on the realized volatility of commodities is time-varying.
Wu et al. (2019)	China	Simple correlation and Diebold and Yilmaz's (2014)	To look into the systemic contagion and connectedness across the Chinese stock market.	Based on both methods, it is found that the industrial sector is the most significant sector in China's stock market. The whole system is primarily affected by risks and changes in the industrial sector, and therefore it determines how the entire market moves.
Behera and Mishra (2022)	India	DCC-GARCH and Nonlinear Granger causality approach	To investigate the interconnectedness and non-linearity between the Indian currency and energy futures indexes.	According to the findings, energy and oil are the main contributors to volatility, with natural gas accounts for the smallest part of the volatility. Secondly, they suggest that the energy future is the net shock transmitter. Additionally, the commodity and natural gas sectors are net receivers. The study also discovers a nonlinear causal relationship between COF and ER.
Samitas et al. (2020)	major developed and emerging stock markets	Asymmetric Dynamic Conditional Correlation (ADCC) and the copula functions	To study the spread of the Subprime Crisis and the European Sovereign Debt Crisis from Eurozone countries to the real economy	The empirical results reveal the existence of the contagion hypothesis from the Eurozone to the sectors of major economies for a larger sample period. In addition, it also provides significant information on the link between the market indices and the policy uncertainty indexes.
Aristeidis and Elias (2018).	Eurozone, European Union, Europe, BRICS, North and South America, Africa and Asia.	time-varying copulas; regime-switching models	To investigate the effects of contagion during the shock period of Brexit on cross-country indices	The results showed instant financial contagion due to the shock and increased uncertainty from the referendum results; the shock and uncertainty were very limited
Samitas and Kampouris (2017)	the southern and northern parts of the Eurozone	dynamic conditional correlation model and the BEKK model	To investigate the volatility spillover effects from the southern to the northern part of the Eurozone during the sovereign debt crisis.	Spain and Italy can significantly damage all strong northern economies, while Greece's negative shocks are capable of co-moving the French index. Finally, France is the most correlated country within the southern Eurozone.

From Table 1, it is observed those studies focusing on Indian stocks are limited and mostly devoted to the use of single-equation models (Bora and Basistha, 2021; Rao et al., 2021), except Behera and Mishra (2022) which applies a VAR framework. However, despite having a similar objective to ours, the authors used a different set of stock indexes.

3.1 Data and Methodology

In this study, we have collected the daily observations on 11 stocks from the Bombay Stock Exchange (BSE)'s website (www.bseindia.com) for the five-year five-year periods i.e., January 2015 to December 2020, the indexes include Auto, Bankex, Energy, Fast Moving Consumer Goods (FMCG), Health Care (Hcare), IT, Manufacturing, Oil & Gas, Realty and Telecom. The study used tools such as descriptive statistics, the Generalised Autoregressive Conditional Heteroskdasticity Model (GARCH (1,1), and the Diebold and Yilmaz (2014) henceforth DY approach. Thus, the daily log return for each index is calculated as follows:

$$Rt = ln\left(Pt - Pt - 1\right) \tag{1}$$

Based on the returns obtained from model (1) we estimate the blow GARCH (1,1) model:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

Where ε_{t-i}^2 is the previous time squared error from the given mean equation, σ_{t-j}^2 is the previous conditional variance and ω, α_i and β_i are the coefficients.

The remainder of the analysis is carried out using the multivariate vector autoregressive (VAR) model.

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \varepsilon_i \tag{3}$$

Where ϕ_i = matrix of coefficients and $\varepsilon_i \sim ii(0, \Sigma)$

The moving average presentation of the above VAR (p) process is given by:

$$x_t = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t-1} \tag{4}$$

Our main focus is on the proportion of the realized shocks to the returns of a particular stock that resulted from its own shocks or shocks to the other indexes during the COVID-19 pandemic.

This can be achieved using the forecast error variance decomposition; thus, the model (4) above can be rewritten as:

$x_{t+n} = \mu + \sum_{i=0}^{\infty} \phi_i \varepsilon_{t+n-i}$ Such that x_{t+n} is the nth step ahead forecast x_t and $\phi_0 \varepsilon_{t-1+n}$ is the nth step ahead forecast error

Following the DY, we employ the GVD technique of Koop et al. (1996) and Pesaran and Shin (1998) henceforth KPPS to determine the ratio of the forecast error variance decomposition FEVD of variable i as a result of shocks from variable j. The advantage of KPPS is that it generates variance decompositions that are insensitive to the ordering.

3.2 Variance share

This is used to analyse the proportion of the nth step ahead of FEVD in forecasting the risk of a particular stock index, which is due to its own shocks and shocks from other indexes.

$$\vartheta_{ij}^{k}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i^I A_h \sum e_j)^2}{\sum (e_i^I A_h \sum A_h^I e_i)} \tag{5}$$

Whereas σ_{ij} is the SD of ε_j from j^{th} equations; $\sum$ is the ε s' matrix of covariance; and e_i is the Vector of selection matrix with values of ones at ith elements and zeroes otherwise. $\vartheta_{ij}^{k}(H)$ is the NXN GVD-matrix.

3.3 Directional spillover

It is used to assess pairwise volatility spillover from stock j to all i and vice versa (see equations 6 and 7 respectively)

$$C_{i \leftrightarrow j}(H) = \tilde{\vartheta}_{ij}^{g}(H) = \frac{\vartheta_{ij}^{g}(H)}{\sum_{j=1}^{N} \vartheta_{ij}^{g}(H)} \tag{6}$$

$$C_{i \leftrightarrow j}(H) = \tilde{\vartheta}_{ij}^{g}(H) = \frac{\vartheta_{ji}^{g}(H)}{\sum_{j=1}^{N} \vartheta_{ji}^{g}(H)} \tag{7}$$

3.4 Total Directional Spillovers from index-i to all or from all indexes to i, i.e., Contributions to Others (CTO) and Contributions from Others (CFO)

This measures the percentage of volatility shocks from other stock indexes in the total FEVD for index i and vice versa, see equation (8) and (9) respectively.

$$C_{i\leftarrow .}(H) = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{n} \tilde{\vartheta}_{j}^{g}(H)} *100 = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\vartheta}_{ij}^{g}(H)}{N} *100 \quad (8)$$

$$C_{.\leftarrow i}(H) = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{n} \tilde{\vartheta}_{j}^{g}(H)} *100 = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\vartheta}_{ij}^{g}(H)}{N} *100 \quad (9)$$

3.5 Total and Net Volatility Spillovers

The total or gross spillover index (10) takes into account the share of volatility spillovers on all observed indexes to total FEVD.

$$C(H) = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{n} \tilde{\vartheta}_{j}^{g}(H)} *100 = \frac{\sum_{j=1, j\neq i}^{n} \tilde{\vartheta}_{ij}^{g}(H)}{N} *100 \quad (10)$$

The index's net volatility spillover is defined as the difference between total volatility shocks disseminated to others and total volatility shocks received from all other indexes within markets.

$$C_i(H) = C_{.\leftarrow i}(H) - C_{i\leftarrow .}(H) \quad (11)$$

4. Results Presentation and Discussions

This section begins with the preliminary analysis of the stock indexes used in this study which include: Auto returns, Bankex returns, Energy returns, FMCG, Hcare, IT, Manufacturing, Oil & Gas, Realty, and Telecom. Table 2 reveals that the mean returns value is lower than the standard deviation for all the stocks during the sample periods which indicates that risk is higher than the returns and the probability values associated with the Jaque-Bera statistics of all stocks indicate that the returns are normally distributed.

Table 2. Descriptive Statistics

BSE Index	Mean	SD	Skewness	Kurtosis	JB	Probability
Auto	0.034	0.597	-0.041	2.931	0.595	0.866
Bankex	0.037	0.393	-0.039	3.064	0.342	0.940
Energy	0.040	0.301	-0.034	2.992	0.070	0.989
Fast Moving Consumer Goods	0.011	0.159	-0.045	2.889	3.383	0.566
Health Care	0.034	0.345	-0.065	2.943	0.838	0.669
IT	0.043	0.474	-0.039	2.998	0.273	0.891
Manufacturing	0.013	0.203	0.009	2.931	0.375	0.844
Oil & Gas	0.041	0.289	-0.011	2.991	0.075	0.998
Realty	0.046	0.301	0.042	2.912	0.824	0.824
Telecom	0.048	0.345	-0.047	2.956	0.567	0.910

We examined the conditional volatilities of all stocks using the GARCH (1,1). Its plots are reported in Figure 1. From the figure, it is seen that all the indexes have exhibited higher volatility clustering beginning from March 2020 (Bello and Abdu, 2021; Bora and Basistha, 2021 have also stated similar results). This means that the severity of COVID-19's effects on Indian stocks began when the administrative lockdown was declared. This trend has been observed across all the stocks.

In Tables 3, 4, and 5, we reported the estimated "input–output" breakdowns of the total volatility spillover index. Its ijth's entries define the calculated shares of the market i's spillover from shocks to market j. It should be noted that these results are based on the GVAR of order 2 and generalized variance decompositions (GVD) for 10-day-ahead FEVD. The sums of the off-diagonal columns (excluding the diagonal terms) describe the "contributions to others (CTO)" of spillovers which indicate how much volatility each stock market index brings to the system. Similarly, the sum of the off-diagonal row (again, excluding the diagonal terms) describes the level of volatility received by each stock index from the system (CFO contribution from others). Finally, the net contribution from (NC), represents net volatility spillovers.

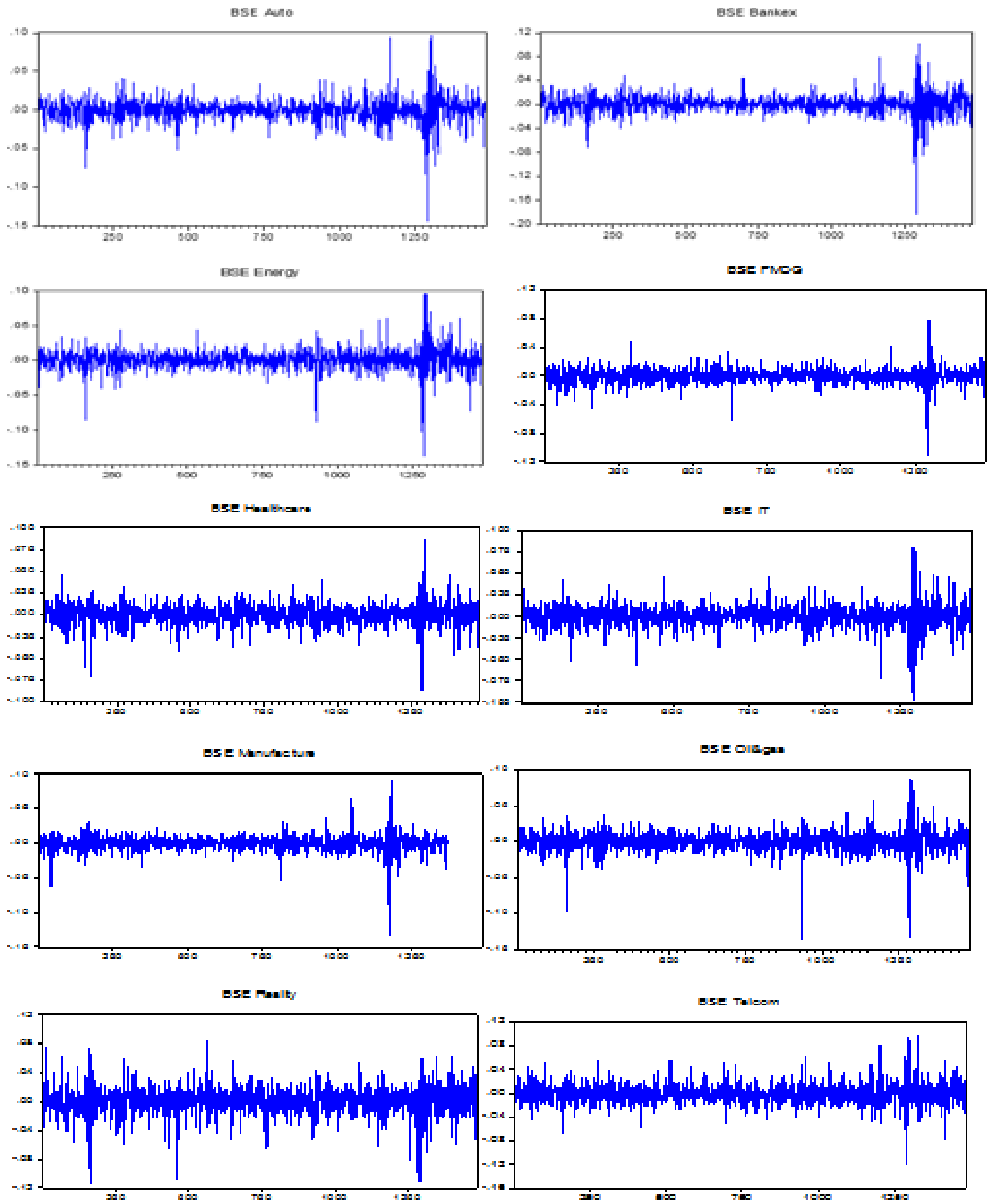

Figure 1: Garch plots of the 10 selected stocks. *Sources: Authors' computations using dataset collected from www.bseindia.com for the period January 2015 to December 2020*

Table 3. Spillover connectedness (Full Sample)

Stock indexess	auto	bankex	energy	FMCG	hcare	it	manufacturing	Oil&gas	reality	telecome	CFO
Auto	31.3	12.7	8.4	9.9	7.3	2.4	0.2	11.2	11.1	5.5	68.7
Bankex	14.9	29.3	9.4	9.8	5.6	3.8	0.2	11.0	11.5	4.5	70.7
Energy	8.7	8.7	32.0	9.8	5.4	2.4	0.3	22.6	6.2	4.0	68.0
FMCG	11.3	9.9	8.5	37.7	6.8	3.5	0.5	9.6	8.0	4.1	62.3
Hcare	11.0	8.1	6.7	9.1	38.2	3.5	0.2	7.4	9.8	5.8	61.8
IT	6.0	6.7	7.6	7.9	5.9	55.3	0.1	3.8	4.5	2.1	44.7
Manufacturing	0.1	0.0	0.4	0.6	0.1	0.4	98.0	0.1	0.2	0.0	2.0
Oil&gas	11.5	10.3	20.4	9.0	5.5	1.9	0.2	29.9	7.5	3.8	70.1
Reality	14.3	13.5	7.9	8.2	7.5	1.8	0.0	10.4	30.2	6.2	69.8
Telecome	8.4	6.0	6.7	5.3	7.0	1.2	0.4	6.1	8.9	49.8	50.2
CTO	86.2	75.8	76.1	69.1	51.0	21.0	2.2	82.1	68.0	36.0	568.1
CIO	117.6	105.1	108.1	107.4	89.3	76.3	100.2	112.1	98.1	85.8	**56.8%**
NC	17.5	5.1	8.1	7.4	-10.8	-23.7	0.2	12	-1.9	-14.2	

Note: CFO means contribution from others, CTO means a contribution to others, CIO means a contribution to others plus self, NC is the net-contribution and FMCG is the Fast Moving Consumer Goods.

From Table 3, Auto has contributed the most to the spillovers of the Bankex and Reality. In fact, it is the leading contributor of volatility spillovers in the whole network, followed by Oil & Gas, Energy, and Bankex respectively. On the other hand, Bankex, Oil & Gas, Reality, and Energy are the top recipients of spillovers from others respectively. Manufacturing is by far the least recipient industry, followed by IT and Telecom. At the same time, Manufacturing and IT have provided the least contribution to the system's volatility spillovers.

Bankex is the most important source of the volatility witnessed by Auto and Reality. The Oil & Gas received a large percentage of their external spillovers from Energy and at the same time contributed the most to Energy's external spillovers. It also contributes significant risk spillovers to the Auto and Bantex industries.

The last row of the table (3) reports the net spillover for each index; those with positive values are net contributors, while those with negative values are net receivers of risk spillovers. The Auto industry and Oil & Gas are the largest net contributors to the risk spillovers, followed by Energy, FMCG, and Bankex respectively. IT is the major net recipient, followed closely by Telecommunications. Reality is the least net receiver of spillovers, while Manufacturing is the least contributor to spillovers. The table has also revealed the significant pairwise connectedness of 56.8%. This indicates the existence of strong inter-stock spillovers in the market. Other studies also found higher and more persistent spillovers using different stock markets during COVID 19 (Wang et al.; 2020b; Aslam et al., 2021; Ghorbel and Jeribi, 2021; Hung and Vo, 2021; Nguyen et al.; 2021; Si et al., 2021).

Figure 2, provides information on the historical evolution of the aggregate spillover index. The index did not start rising significantly until the end of 2019 reaching its peak (63.9%) on March 12, 2020. The studies by Aslam et al. (2021) and Wang et al. (2020b) have reported the same result.

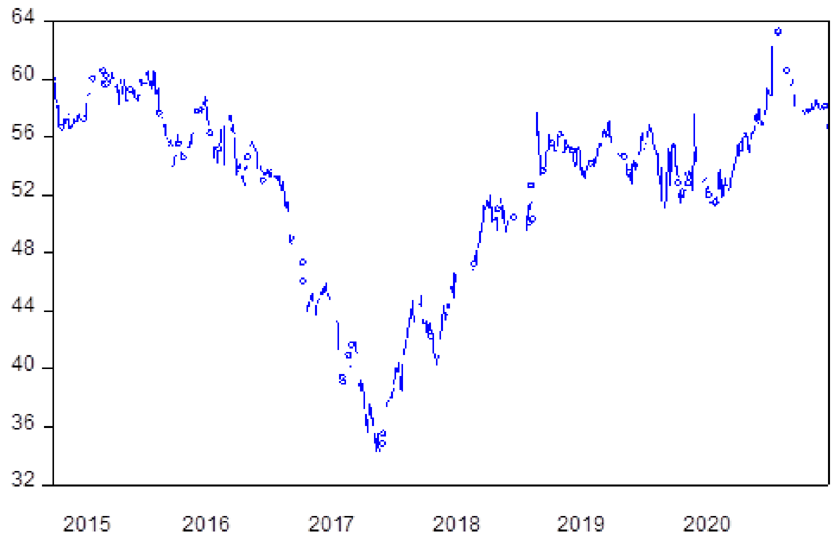

Figure 2. Total Spillover index

This has clearly shown that, despite the increasing interconnectivity among stocks due to COVID-19, the stronger connectedness is only visible in March 2020 which corresponds to the period when the lockdown measure was adopted by the authorities. However, this rise in the dynamics of the aggregate index has been reduced to (57%) in the month of June 2020 (see also Si et al., 2021). Likewise, at that period, there was a slight relaxation in the administrative lockdown.

Given the negligible role played by Manufacturing stock, by both contributing and receiving the least of the volatilities in the network which might be in connection with the fact that more values were found missing in the series, we dropped it from the analysis and subsequently divided the sample into two. The period from the beginning to 2/12/2010 and the period from 2/12/2019 to the end of the sample. These groups have been estimated separately and the results are reported in tables (4) and (5) respectively.

According to table (4), only IT and Telecom have received the least amount of systemic spillovers from the other sectors. The Auto industry has contributed the most to the spillovers of the system and also received the highest net spillovers from the system. This is followed by the Bankex. The overall value of the volatility spillover indicates that, on average, only 58.7% of the volatility of FEVD across the stocks was due to the spillovers during the pre-pandemic period.

Table 4. Spillover connectedness B4 the COVID-19

Stocks	auto	bankex	energy	FMCG	hcare	IT	Oil&gas	reality	telecome	CFO
auto	33.5	13.9	7.9	11.3	6.1	1.7	9.0	10.5	6.0	66.5
Bankex	15.3	35.4	7.7	11.6	5.6	2.2	7.7	8.7	5.8	64.6
Energy	10.8	8.6	34.3	7.6	3.6	2.0	23.2	5.5	4.5	65.7
FMCG	13.2	11.7	7.4	41.0	4.7	2.9	6.5	8.3	4.2	59.0
Hcare	12.1	12.8	5.5	6.7	38.5	4.2	5.0	9.6	5.4	61.4
IT	4.9	3.8	4.2	5.3	3.9	71.9	0.6	3.3	2.0	28.1
Oil&gas	12.4	9.8	26.1	6.4	3.8	0.8	30.8	6.3	3.7	69.2
Reality	13.4	11.5	6.9	10.2	7.8	1.0	8.3	33.5	7.5	66.5
telecome	8.4	6.9	5.3	6.2	6.2	0.7	4.7	9.0	52.6	47.4
CTO	90.5	79.1	71.0	65.3	41.6	15.5	65.0	61.4	39.1	528.4
CIO	124.0	114.5	105.3	106.3	80.1	87.4	95.8	94.8	91.7	**900**
NC	24	14.5	5.3	6.3	-19.8	-12.6	-4.2	-5.1	-8.3	**58.7%**

Table 5 shows the static connectedness of the stock market during the pandemic period. All the stocks have received a substantial amount of volatility from the market system as none of them has received less than 50% of its overall standardized spillovers from the network. In the same vein, all the stocks passed a significant amount of the spillovers to the rest. The highest net contributor of the volatility is Auto followed by the Bankex. The largest net recipients of the volatility are the Hcare and IT.

Table 5. Spillover connectedness during the COVID-19

Stocks	auto	bankex	energy	fmcg	Hcare	IT	Oil & gas	reality	telecom	CFO
auto	20.5	11.6	7.0	13.8	8.6	9.3	14.9	8.9	5.4	79.5
Bankex	14.1	23.1	4.5	13.7	4.6	11.1	13.5	11.6	3.9	76.9
Energy	11.4	6.3	26.4	13.4	7.9	9.1	18.9	3.0	3.5	73.6
Fmcg	9.2	7.1	3.9	31.4	7.9	9.1	18.9	3.0	3.5	73.6
Hcare	7.9	2.9	3.6	18.6	31.8	14.3	9.4	5.8	5.7	68.2
IT	9.4	6.4	5.9	13.0	12.1	35.8	9.2	5.5	2.6	64.2
Oil&gas	12.9	10.5	9.5	17.3	7.3	8.4	20.8	7.2	6.1	79.2
Reality	15.1	11.0	4.1	14.0	6.8	10.0	14.4	20.6	4.0	79.4
telecome	7.9	6.3	3.9	11.9	9.5	7.0	11.2	7.0	35.3	64.7
CTO	88.1	62.2	42.5	115.7	68.2	80.6	103.6	56.2	37.3	654.4
CIO	108.6	85.2	68.9	147.0	100.0	116.4	124.5	76.8	72.6	900
NC	8.6	-14.7	-31.1	42.1	0	16.4	24.4	-23.2	-27.4	**72.7%**

According to the results, 72.7% of volatility during the pandemic is as a result of the spillovers which is significantly higher than the above results of the pre-pandemic and the entire samples. The studies by Aslam et al. (2021) and Hung (2021a) also reported a high degree of connectedness among the sampled stocks using the same period.

5. Conclusion

The paper adopts the Deibold and Yilmaz (2014) approach to examine the connectedness and volatility spillover across the ten selected BSE indexes in India during the COVID-19 pandemic.

The preliminary descriptive statistics revealed that the mean value of the returns is lower than the standard deviation for all the stocks for the given sample period. Using the GARCH (1,1) model we have found evidence of the high degree of volatility clustering across the stocks in the month of March, 2020.

The directional and total volatility spillovers were also examined. The results reported that Auto stock is the leading contributor to the volatility spillovers in the whole network. Bankex is the top recipient of spillovers from other stocks. The net spillovers indicate that the Auto industry and Oil & Gas are the largest net contributors to the risk spillover and IT is the major net recipient. The results have also shown the significant pairwise connectedness which indicates the existence of strong inter-stock dependency in the BSE market. We have also generated the total dynamic spillover index and its graphical illustration indicates that the index did not rise significantly until the end of 2019 and it eventually reached its peak on March 12, 2020. This clearly showed that, despite the increased interconnectivity among stocks due to COVID-19, the stronger contagion was only visible during the period when the lockdown policy was being declared by the authorities. These findings have an important implication for both authorities and prospector investors in the regulation of the stock market, it will also help them to understand the fact that specific regulatory measures should be applied to different stock types in order to achieve the optimal regulatory effects. In addition, they should focus on stocks that contribute the most to the risk transmissions so as to accurately assess how it is likely to respond to certain government policies at any given time. Finally, it will provide a guide to the prospective investors on how to appropriately diversify their assets' holding according to the nature of information spillovers between target stocks so as to mitigate the risk of their investment.

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