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THE ALTERED VOLATILITY SPILLOVER SEQUENCE UNDER COVID-19: INDIAN SECTORAL INDICES IMPACT DEIBOLD YILMAZ INDEX

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ABSTRACT

The Industrial sectors have their unique place in the economic interlinkage. The sectoral valuation reflected by each sector indices shows how each sector responds to different events. The exogenous event Covid-19 impact has been differential due to the impact of lockdown and other Covid-19 appropriate restrictive measures. The present paper examines the change in the volatility spillover induced by Covid-19. The study uses daily sectoral indices data from India's oldest exchange, the Bombay Stock Exchange. Data from January 2010 to November 2020 has been split into four subgroups to find how COVID-19 has affected the volatility spillover using the Diebold and Yilmaz Index. Ranks have been assigned to find the change in the four periods' volatility to the volatility spillover's magnitude and direction. The impact of the COVID-19 is strong enough to change the volatility spillover, which followed a system. Capital Goods volatility increased three times. At the same time, the Auto sector becomes a volatility receiver instead of the net volatility dispenser, from 2.5% before COVID-19 to -3.39% after COVID-19 lockdown. Bankex remains unaffected by Covid-19.

INTRODUCTION

The COVID-19 seems to have impacted sectors like hospitality, manufacturing, and services industry almost immediately, followed by other sectors. Hence volatility transmission also should have followed the same sequence. A case in point is the Information technology sector. The shifting of “work from home” would have made no significant difference to this sector's volatility. However, our findings show a complete upsurge of the volatility sequencing.

COVID-19: The Contextual Background

COVID-19 is a rare event. It needs intense scrutiny, rightly termed a genuine exogenous shock (Ramelli & Wagner, 2020). Mainly so as the COVID-19 with 2.5 million deaths (March 1 2021) is next only to Spanish Flu in terms of fatality. The other pandemics and epidemics like 1957-58 H2N2, H3N2 1968, 2009-10 Swine Flu,2012 MERS, 2014-16 Ebola did not disrupt the globe as COVID-19 has. One common strand most researchers affirm today is how gargantuan COVID-19 is. Compared to COVID, the Spanish Flu killed nearly 50 million (Zimmer & Burke, 2009) worldwide, while around 20 million in India(Chandra & Kassens-Noor, 2014). The research on Spanish Flu is not new, neither for the finance field nor for medical sciences. Medical research has been active in the last decade, calling the Spanish flu virus the “mother of all pandemics”(Taubenberger & Morens, 2006). Much of such research extensively studied the COVID-19 type pandemic through the study of the Spanish Flu (Boëlle et al., 2011; Martini et al., 2019).

Baker et al. (2020) compared the financial markets under the present pandemic and other such epidemic effects. They confirm through their study that COVID-19 pandemic is most severe in its impact in the entire time frame from 1900 onwards. The impact of COVID-19 is almost double that of the Spanish Flu, as per Baker. More work hence is required to

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understand many aspects of such events. The essential objectives are interlinkage of volatility, global penetration, and the ripple effect to study the financial meltdowns.

As we move through the COVID-19 much research is being conducted to understand the financial markets' response to such black swan (Loginov & Heywood, 2020) events. What seems to be even more challenging is the economic recovery mechanism. Research studies on the impact of a pandemic, business cycles, financial crisis focus on the genesis and influence of channelization. However, the system for research to study volatility inflicted by COVID-19 creates its peculiar mechanism. On the one hand, we grapple with the battle to nurture back the economy to normal, while on the other hand, the COVID-19 does not seem to end. The present pandemic of COVID-19 is most intense in its impact. The spread of pandemic upsurge covering all the countries is another fact that the global community is coming to terms. The question now is whether this phase of uncertainty will end or whether COIVD 19 has become a more regular part of our lives. For the researchers, financial market and economic regulators, business managers, and fund managers, this phase of COVID-19, the battle of various vaccines and mutating viruses, is the test of time. Researches need to find insights into this COVID-19 pandemic.

Why Sector Level Study of Volatility?

The present study adds to the literature by opening the dimension of sector behaviour peculiar to COVID-19. The equity sector indices reflect the expected future earnings and valuation. The valuation differs across the sectors. The importance of the sectors as economic focal point has been changing dynamically as India moves from underdeveloped to developed economy. Over the years, the Indian economic structure has changed. Labour-intensive manufacturing has changed to a more service-based economy, changing the real wage to the rental price of capital ratio. The labour intensity has changed from 1.45 in the 1980s to 0.33 in the 2000s. (Economics & Series, 2014). The changing structure of the Indian economy itself needs regular assessment to assess the sector level data. With the COVID-19, a new window has opened to find how the sectors have behaved—especially the labour-intensive economic activities. COVID-19 has led to significant disruption for the factory workers. Nearly 600 million workers migrated internally in India due to COVID-19 (*Covid-19 fallout: How the pandemic displaced millions of migrants - News Makers News - Issue Date: January 11, 2021*, n.d.) Although the scenario before COVID-19 was not too good either. As per the MOC (Ministry of Commerce), 2019-20 had already seen a flat growth in the eight core industries (Coal, Crude Oil, Natural Gas, Refinery Products, Fertilizers, Steel, Cement, and Electricity)[2]. Sector level study need to be studied, with regards to how the lockdown has impacted certain sectors more than the others. How the sectors have transmitted the risk can be assessed.

Interest in sector-level associations and functionality has been a popular topic for research (Bahmani-Oskooee & Saha, 2019) . Narrowing to a more specific study of volatility spillover and connectedness, Gabauer et al. (2020) research is worth mentioning. Gabauer et al. (2020) has undertaken a more recent study to find the volatility spillover connectedness for Indian sectors. The unique relation supply demand relation sectors have many not necessarily transmit volatility in the order expected. Gabauer et al. (2020) consider the leading/lagging connectedness the driver of many critical growth-oriented decisions. Their study shows that this connectedness varied in India's previous crisis, mainly 2008, Inflation of 2011, national elections, and Demonetization of 2016. They tried to answer how this change occurred. The policy changes in particular between 2014-19 with the focus on “Making in India” and several initiatives to increase employment, regulate banking (the recent past has seen many mergers of Public sector banks) reflected in their study. Like the Ghatziantonion study, this paper tries to understand the system's volatility spillover connectedness the COVID-19. We use the Diebold and Yilmaz (2012) Index (DYI) with a volatility measure of Parkinson (Parkinson, 1980). The DYI can see the volatility spillover over different asset class portfolios and between the sectors. Their Index bypasses the controversial issues associated definition and existence of episodes of “contagion” or “herd behaviour” as per Diebold and Yilmaz.

The connectedness, by definition, is a linkage or relatedness of the components under study. The (Xiao & Huang, 2018) DYI is used by many authors. DYI has also led to more augmented methods like by Gabauer (2020); Antonakakis et al. (2018). Xiao and Huang compare and contrast the different methods used in measuring connectedness. Their study classifies the DYI based on different methods based on the volatility spillover and the system's contribution. They find the DYI 2012 appropriate when the whole system is the understudy for the volatility of the variable spillover connectedness and not merely the correlation. The direction of volatility spillover with pair-wise calculation makes the DYI intuitively superior to other methods. We can understand “which sector gives and receives the volatility spillover?”. More important feature of DYI 2012 methodology is to find the primary variable dispensing the highest volatility spillover and hence the variable which takes the central role in the system-wide volatility spillover connectedness.

LITERATURE REVIEW

Researchers agree that the present pandemic is comparable to the worst financial market meltdowns. The financial market downturn inflicted by COVID-19 is unparalleled in its magnitude, penetration, and severity. The Spanish Flu, which killed 50 million (*The Spanish Flu (1918-20): The global impact of the largest influenza pandemic in history - Our World in Data*, n.d.) People as compared to 2.5 million by COVID-19, had a much lesser impact on financial markets and economy. Baker and others find no other epidemic and pandemic having such intense effect on the economy and financial markets as COVID-19. They write in their white paper that the Spanish Flu impact was modest compared to COVID-19. (Baker et al., 2020a). Perhaps that brings under scrutiny the Governmental policies to check the COVID-19. Questions being asked such as “*Could the cost of battling COVID-19 have been much lesser*?”.(*Flatten the Coronavirus Curve at a Lower Cost - WSJ*,

[2] https://pib.gov.in/PressReleasePage.aspx?PRID=1601314 Ministry of Commerce and Industry India

n.d.)(Coibion et al., 2020). The lockdown, as a policy decision to check COVID-19, itself affected some sectors more than the others. Notably, the labour-intensive sectors were hit most by COVID-19 pandemic (Chaudhary et al., 2020). These measures containing the spread of Corona required immediate shut down of manufacturing and other such labour-intensive sectors. In India, the labour working in different manufacturing zones is spread across the country; labour to such sectors is predominantly served by the two most populous states of UP and Bihar. Most of these day workers had no other option but to migrate to their native place. The triggering ripple effects led to massive internal migration in India (more details given earlier in this article). These ripple effects should reflect in the financial market's valuation mechanism. Hence, volatility would follow a sequence linked to the supply chain system. Banks, the Power sector, Logistics are some sectors that continued functioning. Thereby immune to the lockdown but certainly affected by the social distancing and even spread of infection. Such differential sector level operations should reflect in the financial market information processing. There is a need to find the impact of financial markets and their sequence. Such asymmetric connections in sectors become vital for fund managers, regulators, and business managers.

The use of DYI is apt for such event as COVID-19, as discussed above. The method has been used by researchers in similar financial and economic crisis previously. Sehgal et al. (2015) using DYI find a change in the directional flow from the U.S. to Europe, varying as the stages of the 2008 crisis deepened. Accentuating the importance of connectedness measure even more, show how equity markets connectedness shows a robust geographical component, not found in the case for Bond markets. Their study reaffirms stronger international interlinkage in the "Great Financial crisis." Such volatility spillover connectedness has led to a series of studies that try to find the linkage among global institutions and markets. Khan and others' complex network method finds structural change through "node changes, clustering, and homogeneity" in the world market (Aslam et al., 2020). It is not surprising that in COIVD 19, the major banks' connectivity increased, and so did the spillover density. The author puts it more effectively using the word "unprecedented interconnectivity" in COVID-19 using DYI (Baumöhl et al., 2020).

Researchers define COVID-19 as a pure "exogenous factor." Unlike other crises such as political, economic, and financial, COVID-19 is an exact exogenous event to study the firm and industry interaction in such rare event. The infectious diseases earlier have been grossly underrated and slowly has crept into a more obscure event, as Ramelli and Wagner pointed out. Their paper quote "World Economic Forum's Global Risk Report (2020)" (Hall, 2020) listed the infectious disease as the tenth item in order of impact strength. In their paper, Ramelli and Wagner cite how the "disaster literature" can explain the complexity of such events and how they relate to their future use (Ramelli & Wagner, 2020). The researchers have been quick to provide useful benchmarks for the steps taken by different governments to check COVID-19. An example of such a study is by Carletti et al. (2020). They find a three-month lockdown to reduce the profit by 10% of yearly GDP. The most vulnerable are the small and mid-size organisations (Carletti et al., 2020).

The literature on COVID-19 can also be viewed as published initially at the beginning of the COVID-19. As WHO declared the pandemic, markets and governments acted. To this announcement by WHO, the researchers acted almost immediately. The researchers started publishing as early as March April 2020. Like Liu et al. (2020) published their work in April 2020. They effectively laid the composition for classifying the research of earlier similar studies on catastrophic events. Their study shows how more digitalised firms stood the test of the time to face COIVD 19 (Ding et al., 2020). Many such studies captured the data up to March 2020, publishing in July to September 2020. Some set of these studies compared the pandemic to other such crisis times.

However, COVID-19 pandemic differed from other such events in many ways. Firstly, the unique aspect of the COVID-19 is its almost simultaneous global onset. The studies measuring the impact of COIVD on markets use many methods to find the specific features relating to the COVID-19 pandemic. The epidemics like Ebola, SARS MERS, have been concentrated more in certain geographical regions but not COIVD 19. The panic and fear impact of the pandemics have been studied relatively well (Long et al., 2021). Their study shows that the pandemic's impact is more on the emerging economies than on the developed markets. The studies also related to the regions and economic classification based on development.

Albuquerque, Koskinen, Yang, and Zhang study and find that the companies high on the E.S. (environment and social) policies perform better than those with lower E.S. scores. They consider the COVID-19 pandemic to test the ESG (environment, social, and governance) theories (McWilliams & Siegel, 2001; Friedman, 1970) as opposed to the ESG) (Albuquerque et al., 2020).

Liu and others study the COVID-19 impact on the 21 leading stock markets to show how significant this pandemic is. They use the event study with the cumulative abnormal return. The event study using especially CAR (Cumulative abnormal return) remains the most preferred method used by the researchers to study COIVD 19. Liu and others published in June 2020 the short-term impact of the COVID-19. They also study the sectoral indices to find the impact of the COVID-19. Their study shows that pharmaceuticals, I.T. ware favored by the investors, while transport, lodging, and catering were negatively affected (Liu et al., 2020). The impact of COVID-19 is hence asymmetric.

In the economy, the sectoral distribution of the COVID-19 pandemic also attracted studies. Ten sectors are studied by Liew and Puah (2020). Liew and Puah (2020) find the OCIVD 19 effect on the Shanghai stock exchange and sectoral indices. They find that I.T. and Telecom were more immune to the COVID-19 effect.

Studies focusing on Indian markets and COIVD 19: The studies using the Indian NSE/BSE or primary markets found a substantial drop in the markets on January 20, 2020. H. Liu et al., (2020) based on abnormal and cumulative results returns. The volatility spillover based on market size shows considerable volatility from mid-cap to small-cap and primary Index of Bombay stock exchange. Trabelsi and others use Indian financial markets and Gold for portfolio optimisation during the COVID-19 times. Bora and Basistha study the COVID-19 effect on the Indian stock market using the GJH GARCH model. They find a significant effect of volatility on BSE. NSE was not affected with the same magnitude. This study, which takes the data from September 3 to July 10, 20020, finds that the upward trend started in their sample period (Bora, Debakshi, & Basistha, 2020).

Salisu et al. (2020) find that the emerging markets are affected more than the developed markets. They used 24 emerging markets and 21 (India as one of them) developed markets. Using out of sample and full sample data, they conclude that government policies have no effect on uncertainty from COVID-19. They used the Equity Market Volatility Infectious Disease Tracker (EVM).

Yousaf and Ali trace the high-frequency information transmission among the cryptocurrencies using VAR-DCC-GARCH (Yousaf & Ali, 2020). Their finding shows the unidirectional spillover from Ethereum to Bitcoin and Bitcoin to Litecoin.

The literature above has summarised the COVID-19 research, which sought to bring out different aspects of the COVID-19 on financial markets. The data used, methodology, statistical tools, graphs, and software. Put together, these studies point out the validity of finding more insights into such catastrophic events. Medical science and researchers have been pointing out the possibility of outbreak of events such as COVID-19. Had these forewarnings have been taken more seriously the COVID-19 could have been better tackled. On the ground level, the large internal migration of the labour in India and the loss of livelihood for the day worker is a massive hit to the "unfortunate bottom of the pyramid." The digitalised India quickly responded by giving relief packages (May 15 2020)of USD 260 billion (*India- Measures in response to COVID-19 - KPMG Global*, n.d.), saving the worker. The unemployment rate of 23.52% in (• *India: unemployment rate due to COVID-19 | Statista*, n.d.) April 2020 (which *now as of March 2021 is 6.53%)* had been severe, making them walk hundreds of kilometers. The present work finds this gap in understanding the volatility spillover under COVID-19 at the sector level.

DATA AND METHODOLOGY

Model Used

The use of the volatility spillover and connectedness approach by Diebold and Yilmaz can give an insight into the mechanism of volatility spillover. The past data of the financial market would show a system of connectedness based on historical data. The upheaval brought by COVID-19 in the economy and markets should follow the same system of connectedness. The out-of-sample data would affirm such a system. The data set before the COVID-19 can be seen as a benchmark to compare the CORONA period as out of sample data for comparison. Although many researchers have used connectedness and volatility spillover, no such study uses this methodology to compare the sub-periods post and previous to the COVID-19. The primary motivation for using the Diebold and Yilmaz Index and other derivations of their method by researchers is presented under.

In their paper *"Better to give than receive: Predictive directional measurement of volatility spillover,"* (Diebold & Yilmaz, 2012) extends their Index further. D.Y. spillover index is an output of variance decomposition with *N*-variable vector autoregression. Familiar terrain for researchers. The primary focus of the *D.Y.* is on the total spillover in a somewhat simplified *VAR* model. The Cholesky factor orthogonal drives the potential order-dependent results. As directional spillover is measured in a generalised *VAR* framework, it eliminates the dependency on ordering results.

An *N*-variable VAR (*p*) (covariance stationery) $x_t = \sum_{i=1}^{p} \emptyset_i \, x_{t-i} + \varepsilon_i$. The identically distributed disturbance vector is represented by $\varepsilon_i(0, \sum)$. The *NxN* coefficient matrices A_i obeys the recursion $A_i = \emptyset_1 A_{i-1} + \emptyset_2 A_{i-2} + \cdots \emptyset_p A_{i-p}$, with A_0 an *NxN* identity matrix and $A_i = 0$ for $i<0$.

The dynamics of the system build on the moving average coefficients. An important part is the "system shocks." These system shocks segregate in various components based on variance decomposition. Such as variance decomposition impulse response. The variance decompositions make the fractions of H-step ahead error variance in forecasting X_j, $\forall j \neq i$, for each *i*.

While the VAR innovations are contemporaneously correlated, calculating variance decompositions requires orthogonal innovations. Cholesky factorisation achieves orthogonality as the identification method. Variance decomposition depends on the variable orders act. DIY solves this by using VAR generalised framework.

Here, the generalised approach allows correlated shocks and explains the past observed error distribution. This is done instead of orthogonalising the shocks. This way, the total contribution to the variance of forecast error (Row sum of the variance decomposition table) may not be equal to unity. Such exploratory power allows correlated shocks.

The fraction of the H-step ahead error variance in forecasting is forecasting, is "own variance shares" for x_i due to shocks to x_i, for $i=1,2,\ldots,$ and cross variance shares, or spillovers, to be the fractions of the *H*-step ahead error variances in forecasting x_i, due to shocks to x_j, for $i,j=1,2\ldots, N$, such that $i \neq j$.

The expression denoting KPPS *H*-step ahead forecast error variance decomposition $\theta_{ij}^{g}(H)$, for H = 1,2…, we have

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (\acute{e}_i A_h \Sigma e_j)^{\wedge}2}{\sum_{h=0}^{H-1} (\acute{e}_i A_h \Sigma e_i)} \qquad (1)$$

Here the Variance matrix for error vector ε, is $\sum$. The standard deviation of the error term for the i^{th} equation is σ_{ij}. Whereas e_j is the selection vector with one as the i^{th} element and zero otherwise. As expressed earlier $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$, variance decomposition table each element in a row is not equal to one. For calculating the spillover index, and utilising the information through variance decomposition matrix, normalising each entry of the variance decomposition matrix by the sum, can be expressed as

$$\tilde{\theta}_{ij}^{g}\,(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \qquad (2)$$

By construct $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\,(H) = 1$ and $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}\,(H) = N$.

The total spillover volatility index is constructed by variance decomposition volatility contribution from the KPPS.

$$\tilde{\theta}_{ij}^{g} = \frac{\sum_{i,j=1,i\neq 1}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} \text{ x } 100 = \frac{\sum_{i,j=1,i\neq 1}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} \text{ x } 100 \qquad (3)$$

The spillover of volatility shocks across variables contributes to the total forecast error variance estimated by the total spillover index. Spillover of volatility contributed by variables in analysis to the total forecast error variance is measured by the total spillover index.

More meaningful information is provided by the direction of the spillovers across variables. The generalised VAR approach enables us to provide this informative part. Much information can be extracted from the total volatility spillover index, and directional spillovers complete the total picture of volatility movement. The directional volatility spillovers through normalised elements of the general variance decomposition matrix hey can be expressed as

$$S_{i}^{g}(H) = \frac{\sum_{j=1,j\neq 1}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} \text{ x } 100 \qquad (4)$$

Measures B.I. directional volatility spillovers by variable *i* from all other variables j. This is generalised impulse responses, and variance decompositions are invariant to the ordering of variables

$$S_{i}^{g}(H) = \frac{\sum_{j=1,j\neq 1}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H)} \qquad (5)$$

Net spillovers from variable *i* to all other variables *j* are expressed as

$$S_{i}^{g}(H) = S_{i}^{g}(H) - S_{j}^{g}(H) \qquad (6)$$

To find the net volatility spillover, we can calculate the difference between gross volatility shocks received and gross volatility shock transmitted from all other variables.

The pair-wise variable i to j for volatility spillover is the difference between gross volatility shocks transmitted from variable i to j and that transmitted from j to i. Net pair-wise spillover, in addition to the net volatility spillover, make the interpretation much more effortless. Expressed as:

$$S_{ij}^{g}(H) = \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{k=1}^{N}\tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{k=1}^{N}\tilde{\theta}_{jk}^{g}(H)} \text{ x } 100 \qquad (7)$$

Data

The data used is daily for the ten sectors and primary Index "Sensex." All the indices are from India's oldest and most popular Index, the "Bombay Stock Exchange." The time taken is from January 4 2010, up to November 2020. (*The limitation of the time period has been the data availability, which for some of the Index starts from the date given)*. Like Diebold and Yilmaz for volatility Parkinson method has been used. Parkinson, (1980) volatility measure requires low and high Index values during the day for each Index. For some of the indexes, this data was not available (daily "High" and "Low") for the period earlier to January 2010. Hence, such indexes were left out of the calculation.

Analysis Methodology

The analysis seeks to find and explain the volatility spillover peculiar to COVID-19. For this reason, Diebold and Yilmaz Index (referred hereafter as DYI) is used.

The following sectors from BSE (Bombay Stock Exchange) are included; Automobile (Auto), Banks (Bankex), BSE (Sensex, the primary Index of BSE), Capital Good (CAP), Consumer goods (CD), Metal (Metal), Oil and Gas, Power, Reality, Technology (TECH).

The (DYI) Diebold Yilmaz Index output provides total volatility spillover within the model and each sector associated with other sectors. The advantage of DYI is that it shows which sector is more or less volatile than other sectors with a directional flow of volatility. This is shown in each DYI by the row named as CTO and column as FROM. The column and row "From" "CTO" (contribution to others) give the volatility spillover received by each sector from the other sectors and disseminated to other sectors, respectively. The net volatility spillover row shows if the sector is the net receiver or provider of volatility spillover. Diagonal in each DYI model gives each sector's volatility spillover.

The data from January 4 2010, to November 14 2020, is split into four parts.

(i) Daily volatility from January 4, 2010, to November 14 2020, referred as S1
(ii) Daily volatility from January 4, 2010, to January 31 2019, referred as S2
(iii) Daily volatility from February 4 2019, to December 31 2019 (221 days) as Pre COVID-19
(iv) Daily volatility from January 1, 2020, to November 14 2020 (221 days) as during COVID-19

The above period group S1 constitutes the entire sample. The other three samples become the “In sample” subsets. The three-period groups, S2, Pre and During COVID-19, becomes the separate “Out of sample” sets. The time set S2, Pre COVID-19, and COVID-19 should have approximately the same volatility profile.

The DYI are assigned ranks. The reasons are as follows:-
DYI is calculated for each of the four periods. As these volatilities are in percentage, each sector role in volatility is known, making a comparison across four periods easy. For example, the Auto sector column “From” shows the volatility from other sectors. For the total period under study (which includes the COVID-19 period), volatility received by the Auto sector is 68.32%. This increases to 82.29% during the COVID-19. However, this shows the quantum jump in volatility due to COVID-19. It does not show if the Auto sector has become more or less volatile in the crisis than other sectors. The 13.97% increase in the Auto sector can be similar for all the sectors if all sectors receive the same exogenous impact. If we rank each sector for the volatility being received and transmitted, we can also know if a particular sector has become more or less volatile relative to other sectors.

For this reason, the assigned ranks are summarised in Table 10. The rank of the Auto sector remains the fifth largest volatility receiver in all the three periods baring 221 days period before COVID-19, whereas it was the seventh-largest volatile receiver. It thereby becomes clear that Auto volatility reduced before the COVID-19 sub-sample of the period. Hence the percentage change in the volatility needs to be seen in comparison to the entire batch of sectors in comparison.

Another dimension added by ranking is the relative increase or decrease of volatility as “receiver” or “transmitter”. The Auto sector volatility ranks as the receiver is maintained at 5^{th} rank even in COVID-19 time, but the volatility transmission becomes seventh from sixth rank pre COVID-19. The transmission of volatility is reduced. This position is also seen in the column “Net”, which shows Auto sector transmit -3.39% volatility but reduces the overall rank to the seventh-highest transmitter.

Plan of Analysis

The descriptive statistics for the entire sample data of S1 is based on returns. Daily variance is used using the high and low prices of each sector used by Diebold and Yilmaz. The Parkinson (Parkinson, 1980) method is used for the DYI.
For sector *i* on the day *t* we have
$\widetilde{\sigma_{it}^2} = 0.361\left[ln(P_{it}^{max}) - ln\left(P_{it}^{min}\right)\right]^2$ where P_{it}^{max} is the high and P_{it}^{min} is the low in the market *i* on day *t*

Table 1. Discriptive Statistics for all the ten sectors and primary index

Table 1	Auto	Bank	CAP	CD	Metal	OG	Power	PSU	Reality	BSE	Tech
Mean	0.04%	0.06%	0.02%	0.08%	-0.01%	0.02%	-0.01%	-0.02%	-0.01%	0.04%	0.05%
Standard Error	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Median	0.10%	0.10%	0.00%	0.10%	0.00%	0.00%	0.00%	0.00%	0.10%	0.10%	0.10%
Standard Deviation	1.40%	1.60%	1.50%	1.40%	1.70%	1.40%	1.30%	1.30%	2.00%	1.10%	1.20%
Sample Variance	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Kurtosis	821.30%	894.30%	656.30%	546.20%	289.60%	857.50%	439.10%	654.00%	204.10%	1395.60%	761.70%
Skewness	-16.10%	-34.20%	-25.00%	-29.50%	-12.60%	-56.00%	-35.70%	-34.60%	-29.70%	-75.90%	-44.30%
Range	23.60%	27.50%	23.70%	20.30%	20.70%	21.70%	18.60%	19.90%	19.70%	22.10%	17.90%
Date for Min Return	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20	23-Mar-20
Minimum	-13.40%	-16.80%	-14.90%	-11.70%	-11.90%	-12.70%	-8.40%	-10.90%	-10.90%	-13.20%	-9.60%
Maximum	10.30%	10.70%	8.80%	8.60%	8.80%	9.10%	10.20%	9.00%	8.80%	9.00%	8.40%
Sum	1.1629	1.5093	0.4137	2.1737	-0.2144	0.4866	-0.3138	-0.4061	-0.1426	1.0731	1.3097
Count	2698	2698	2698	2698	2698	2698	2698	2698	2698	2698	2698

The descriptive statistics sectors are based on returns for the total period S1 (table 1). This shows that the worst day of Indian financial markets occurred on March 23 2020. The highest fall is recorded for the Bank & Capital Goods sector with -16.8% and -14.9%. The least single-day fall was in the Power sector. The highest mean returns for the whole sample period are given by Consumer durable on a daily basis. The highest and the lowest standard deviance is shown by reality and Metal with 2% and 1.7%. The skewness, a measure of asymmetry threshold, is negative for all the sectors. Hence, the sectors' return is longer to the left side of the distribution than to the right. As the universal indices for markets in general, the high kurtosis is heavy-tailed.(“Coefficient of Skewness,” 2008)

ANALYSIS

Total Volatility Spillover

Figure 1 compares the total sample size with the other three sets of the sample for the "Total volatility spillover." The sample consisting of the entire sample which also includes (blue colour) the COVID-19 volatility spillover. The volatility spillover reaches 82.5% during the COVID-19. Earlier to the COVID-19 period, the sample period of 2010-18 (figure 1) with the highest touching 78% compared to COVID-19 at 82.5%. Most of the earlier periods in the two graphs show how the total system volatility spillover ranges between 67% to 77%. The upsurge of the volatility spillover hence becomes very clear. For the sample period of 221 days pre COVID-19, Figure 4, the volatility spillover's highest point is 68.9% (approx.), while after Covid Figure 5 shows 81.8% volatility

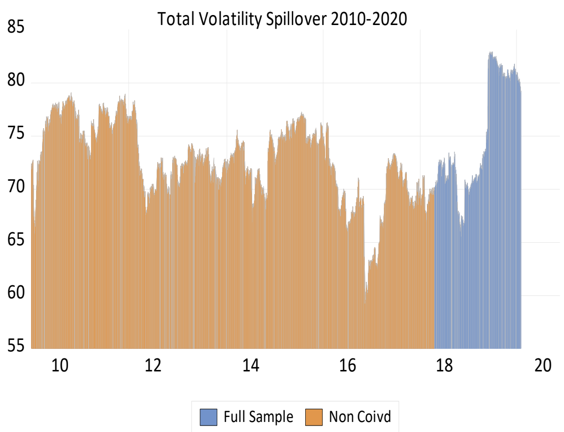

Figure 1. Total Volatility spillover 2010-2020

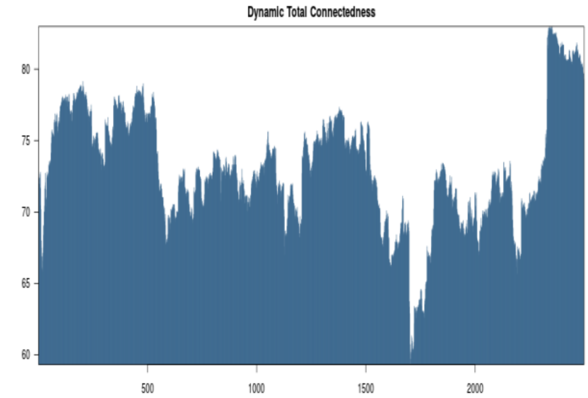

Figure 2. Dynamic Total Connectedness Full Sample S1

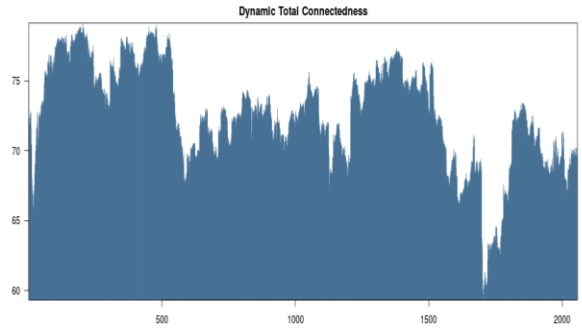

Figure 3. 2010-18 Dynamic Total Connectedness S2

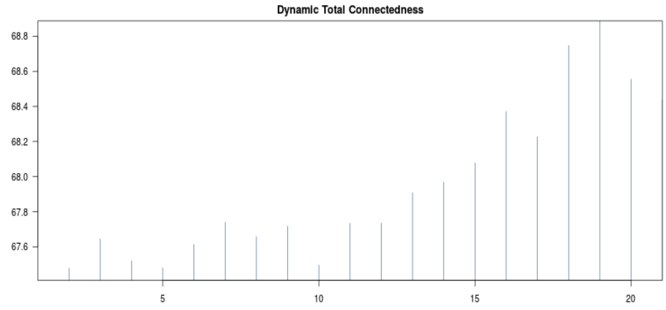

Figure 4. Pre COVID-19 Dynamic Total Connectedness

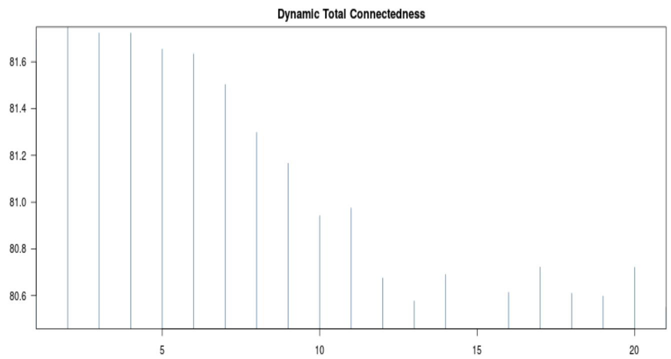

Figure 5. COVID-19 Dynamic Total Connectedness

The Total Connectedness

The total volatility spillover, the Composite Index of various directional volatility spillovers, appears in the lowermost right corner of each index table. If one looks at Pre and during COVID-19 and the full sample (S1) index table, we can note that Total volatility spillover is 67.7%, 81.24%and 72.6%.This shows that the Covid-19 pandemic turbulence adds a 27% increase in volatility.

Table 2. Data S1

Table 2	Auto	Bankex	CAP	CD	Metal	OilGas	Power	PSU	Reality	BSE	Tech
Mean	-9.476	-9.355	-9.296	-9.087	-8.902	-9.373	-9.48	-9.599	-8.565	-10.073	-9.742
Variance	0.936	1.105	0.934	0.84	0.808	0.818	0.9	0.949	0.893	0.991	0.823
Skewness	0.365***	0.392***	0.380***	0.447***	0.253***	0.471***	0.332***	0.372***	0.271***	0.487***	0.450***
0	0	0	0	0	0	0	0	0	0	0	
Kurtosis	0.443***	0.347***	0.333***	0.425***	0.233**	1.081***	0.543***	0.439***	0.202**	0.771***	0.777***
0	-0.001	-0.002	0	-0.022	0	0	0	-0.042	0	0	
JB	82.128***	82.816***	77.315***	110.128**	34.935***	231.362**	*82.824***	84.061***	37.557***	173.719**	158.944***
0	0	0	0	0	0	0	0	0	0	0	
ERS	-8.022***	-2.952***	-2.335**	-5.475***	-8.616***	-5.953***	-2.473**	-4.842***	-3.212***	-7.030***	-3.492***
0	-0.003	-0.02	0	0	0	-0.013	0	-0.001	0	0	
Q(20)	2807.845*	4104.888*	*2086.891*	*1787.858*	1885.059*	*1826.328*	*2103.494*	2104.510*	1133.040*	*3768.076*	1707.907**

0	0	0	0	0	0	0	0	0	0	0	
Q2(20)	2190.766*	3312.629*	*1721.525*	*1589.049*	1354.105*	*1274.887*	*1770.456*	1518.099*	888.473**	*3023.454*	1274.023**
0	0	0	0	0	0	0	0	0	0	0	
LM(20)	306.420**	425.344**	*230.745**	*238.739**	254.348**	*236.133**	*270.231**	273.705**	146.375**	*431.797**	202.161***
0	0	0	0	0	0	0	0	0	0	0	
Auto	1	0.651	0.588	0.476	0.584	0.55	0.578	0.599	0.533	0.725	0.478
Bankex	0.651	1	0.638	0.484	0.549	0.54	0.59	0.659	0.546	0.816	0.486
CAP	0.588	0.638	1	0.477	0.533	0.536	0.662	0.63	0.561	0.649	0.416
CD	0.476	0.484	0.477	1	0.425	0.434	0.453	0.464	0.488	0.508	0.369
Metal	0.584	0.549	0.533	0.425	1	0.555	0.612	0.674	0.526	0.591	0.443
OilGas	0.55	0.54	0.536	0.434	0.555	1	0.583	0.719	0.507	0.639	0.469
Power	0.578	0.59	0.662	0.453	0.612	0.583	1	0.746	0.57	0.604	0.435
PSU	0.599	0.659	0.63	0.464	0.674	0.719	0.746	1	0.579	0.643	0.445
Reality	0.533	0.546	0.561	0.488	0.526	0.507	0.57	0.579	1	0.552	0.393
BSE	0.725	0.816	0.649	0.508	0.591	0.639	0.604	0.643	0.552	1	0.607
Tech	0.478	0.486	0.416	0.369	0.443	0.469	0.435	0.445	0.393	0.607	1

Table 3. Data S2

Table 3	Auto	Bankex	CAP	CD	Metal	OilGas	Power	PSU	Reality	BSE	Tech
Mean	-9.571	-9.429	-9.31	-9.065	-8.983	-9.423	-9.542	-9.689	-8.568	-10.127	-9.801
Variance	0.836	0.978	0.901	0.789	0.757	0.756	0.871	0.875	0.877	0.898	0.748
Skewness	0.169***	0.211***	0.237***	0.374***	0.184***	0.294***	0.266***	0.282***	0.203***	0.227***	0.220***
Kurtosis	-0.132	-0.205**	-0.058	0.165	0.005	0.677***	0.268**	0.09	0.112	-0.149	-0.047
-0.192	-0.031	-0.617	-0.118	-0.901	0	-0.017	-0.361	-0.267	-0.136	-0.694	
JB	12.418***	20.774***	21.498***	55.265***	12.807***	75.627***	33.353***	30.648***	16.658***	21.525***	18.438***
ERS	-7.896***	-2.853***	-2.100**	-5.160***	-8.338***	-5.333***	-2.352**	-4.947***	-2.966***	-6.579***	-3.240***
Q(20)	1398.319*	2235.424*	1493.624**	1058.597**	1029.662*	1011.197**	1366.441**	1140.460*	726.933***	2347.848**	780.619***
Q2(20)	1283.337*	2077.128*	*1298.618*	*1005.396*	780.192**	*794.434**	*1214.136*	882.724**	*610.523**	*2173.183*	728.878***
LM(20)	191.234**	311.336**	*185.397**	*166.934**	160.068**	*162.585**	*193.686**	184.902**	*98.927***	335.616**	117.595***
Auto	1	0.627	0.577	0.463	0.541	0.5	0.563	0.558	0.534	0.711	0.439
Bankex	0.627	1	0.639	0.463	0.52	0.496	0.584	0.639	0.533	0.794	0.419
CAP	0.577	0.639	1	0.435	0.516	0.497	0.67	0.614	0.548	0.624	0.381
CD	0.463	0.463	0.435	1	0.419	0.396	0.445	0.463	0.466	0.47	0.331
Metal	0.541	0.52	0.516	0.419	1	0.518	0.599	0.648	0.532	0.558	0.406
OilGas	0.5	0.496	0.497	0.396	0.518	1	0.555	0.684	0.481	0.593	0.426
Power	0.563	0.584	0.67	0.445	0.599	0.555	1	0.735	0.577	0.588	0.404
PSU	0.558	0.639	0.614	0.463	0.648	0.684	0.735	1	0.581	0.604	0.397
Reality	0.534	0.533	0.548	0.466	0.532	0.481	0.577	0.581	1	0.528	0.366
BSE	0.711	0.794	0.624	0.47	0.558	0.593	0.588	0.604	0.528	1	0.567
Tech	0.439	0.419	0.381	0.331	0.406	0.426	0.404	0.397	0.366	0.567	1

Table 4. Data Pre - COVID-19

Table 4	Auto	Bankex	CAP	CD	Metal	OilGas	Power	PSU	Reality	BSE	Tech
Mean	-9.261	-9.575	-9.426	-9.514	-8.673	-9.358	-9.49	-9.391	-8.843	-10.214	-9.801
Variance	0.858	0.941	0.782	0.727	0.671	0.697	0.657	0.771	0.669	0.735	0.584
Skewness	0.434***	0.259	0.514***	0.414**	-0.102	0.350**	0.082	0.232	0.197	0.383**	0.423**
Kurtosis	0.457	0.736**	0.829**	1.250***	-0.154	0.483	-0.168	0.298	0.446	1.044**	0.677*
JB	8.861**	7.464**	16.055***	20.692***	0.605	6.651**	0.506	2.802	3.259	15.424***	10.800***
ERS	-1.991**	-2.219**	-3.085***	-2.052**	-1.298	-1.664*	-0.697	-2.713***	-2.304**	-2.367**	-2.565**
Q(20)	150.01	192.65	76.788*	61.664*	70.390*	49.371*	76.333*	71.481*	51.421*	63.596*	18.901*
Q2(20)	129.28	179.59	73.303*	67.099*	58.150*	46.590*	77.409*	70.058*	42.314*	56.189*	16.606*
LM(20)	35.265***	31.601***	22.115***	17.969**	25.254***	15.465	27.585**	17.466**	11.102	16.367*	15.924*
Auto	1	0.545	0.498	0.416	0.542	0.555	0.413	0.555	0.402	0.594	0.241
Bankex	0.545	1	0.519	0.397	0.5	0.5	0.378	0.607	0.499	0.805	0.339
Cap	0.498	0.519	1	0.517	0.464	0.561	0.557	0.62	0.475	0.621	0.257
CD	0.416	0.397	0.517	1	0.316	0.397	0.38	0.383	0.391	0.449	0.246
Metal	0.542	0.5	0.464	0.316	1	0.464	0.45	0.556	0.406	0.509	0.217
OilGas	0.555	0.5	0.561	0.397	0.464	1	0.578	0.774	0.475	0.605	0.214
Power	0.413	0.378	0.557	0.38	0.45	0.578	1	0.688	0.434	0.494	0.213
PSU	0.555	0.607	0.62	0.383	0.556	0.774	0.688	1	0.539	0.653	0.245
Reality	0.402	0.499	0.475	0.391	0.406	0.475	0.434	0.539	1	0.491	0.227
BSE	0.594	0.805	0.621	0.449	0.509	0.605	0.494	0.653	0.491	1	0.386
Tech	0.241	0.339	0.257	0.246	0.217	0.214	0.213	0.245	0.227	0.386	1

Table 5. Data Post – COVID-19

Table 5	Auto	Bankex	CAP	CD	Metal	OilGas	Power	PSU	Reality	BSE	Tech
Mean	-9.261	-9.575	-9.426	-9.514	-8.673	-9.358	-9.49	-9.391	-8.843	-10.214	-9.801
Variance	0.858	0.941	0.782	0.727	0.671	0.697	0.657	0.771	0.669	0.735	0.584
Skewness	0.434***	0.259	0.514***	0.414**	-0.102	0.350**	0.082	0.232	0.197	0.383**	0.423**
Kurtosis	0.457	0.736**	0.829**	1.250***	-0.154	0.483	-0.168	0.298	0.446	1.044**	0.677*
JB	8.861**	7.464**	16.055***	20.692***	0.605	6.651**	0.506	2.802	3.259	15.424***	10.800***
ERS	-1.991**	-2.219**	-3.085***	-2.052**	-1.298	-1.664*	-0.697	-2.713***	-2.304**	-2.367**	-2.565**
Q(20)	150.01	192.65	76.788*	61.664*	70.390*	49.371*	76.333*	71.481*	51.421*	63.596*	18.901*
Q2(20)	129.28	179.59	73.303*	67.099*	58.150*	46.590*	77.409*	70.058*	42.314*	56.189*	16.606*
LM(20)	35.265***	31.601***	22.115***	17.969**	25.254***	15.465	27.585***	17.466**	11.102	16.367*	15.924*
Auto	1	0.545	0.498	0.416	0.542	0.555	0.413	0.555	0.402	0.594	0.241
Bankex	0.545	1	0.519	0.397	0.5	0.5	0.378	0.607	0.499	0.805	0.339
CAP	0.498	0.519	1	0.517	0.464	0.561	0.557	0.62	0.475	0.621	0.257
CD	0.416	0.397	0.517	1	0.316	0.397	0.38	0.383	0.391	0.449	0.246
Metal	0.542	0.5	0.464	0.316	1	0.464	0.45	0.556	0.406	0.509	0.217
OilGas	0.555	0.5	0.561	0.397	0.464	1	0.578	0.774	0.475	0.605	0.214
Power	0.413	0.378	0.557	0.38	0.45	0.578	1	0.688	0.434	0.494	0.213
PSU	0.555	0.607	0.62	0.383	0.556	0.774	0.688	1	0.539	0.653	0.245
Reality	0.402	0.499	0.475	0.391	0.406	0.475	0.434	0.539	1	0.491	0.227
BSE	0.594	0.805	0.621	0.449	0.509	0.605	0.494	0.653	0.491	1	0.386
Tech	0.241	0.339	0.257	0.246	0.217	0.214	0.213	0.245	0.227	0.386	1

NET Spillover

The column and row (off-diagonal) summation presents "CTO" and "From" directional spillovers. The net spillover gives the direction of volatility spillover. The row total, which is the direction from others to the sectors volatility spillover, is a collection of volatility spillover from each sector contribution. When each sector row sum is subtracted from the column total, we get the net flow of volatility spillover. A positive sign means that the sector is the net provider of the volatility spillover. While negative net volatility spillover would mean that sector is the receiver of volatility spillover.

Diebold and Yilmaz Index of Volatility spillover

The model's volatility spillover within the model (table 6 & 7) increases from71.29% to 72.59% when we compare the entire sample, and partial sample denoted as S1 and S2 (out of sample and in the sample, respectively). This 1.3% increase in the volatility spillover is substantial, especially if we see that the comparative smaller data set of 221 days has caused this increased volatility spillover. What is noteworthy is that Pre Covid-19 is much calmer comparatively. The volatility spillover is 67.72% for the S2 data set. The graph of DTC (figure 2) also shows the lowermost volatility spillover drops to touch 60%. This does not happen with any other time frame under the study.

Table 6. S1 VOLATILITY SPILLOVER Connectedness Diebold and Yilmaz Index

Table 6	**Auto**	**Bankex**	**CAP**	**CD**	**Metal**	**OilGas**	**Power**	**PSU**	**Reality**	**BSE**	**Tech**	**FROM**
Auto	25.319	9.565	7.364	4.91	7.092	6.477	7.871	8.611	5.786	12.953	4.051	74.681
Bankex	8.469	24.719	8.309	4.666	5.602	5.769	7.752	9.805	5.641	15.359	3.908	75.281
CAP	7.598	9.228	26.073	4.867	5.754	6.43	10.747	9.548	6.865	10.023	2.867	73.927
CD	6.277	7.397	6.755	36.521	4.83	6.376	6.604	6.981	6.984	8.152	3.123	63.479
Metal	8.025	7.315	6.603	4.317	26.488	7.346	9.139	11.706	6.182	9.036	3.844	73.512
OilGas	6.658	6.587	6.427	4.415	6.702	27.514	8.181	13.264	5.446	10.223	4.581	72.486
Power	7.074	7.431	9.556	4.467	7.578	7.55	25.281	12.91	6.771	8.29	3.093	74.719
PSU	6.962	9.101	7.717	4.365	8.425	10.789	11.686	22.767	6.201	8.801	3.184	77.233
Reality	6.806	7.571	7.752	6.329	6.65	6.883	8.664	9.109	28.714	8.325	3.196	71.286
BSE	9.921	13.45	7.965	4.866	6.149	7.762	7.503	8.567	5.024	22.502	6.29	77.498
Tech	6.471	7.439	4.795	4.006	5.834	6.656	6.037	6.355	4.107	12.479	35.821	64.179
CTO	74.261	85.086	73.243	47.208	64.617	72.039	84.185	96.856	59.006	103.642	38.137	798.28
CTI	99.58	109.805	99.316	83.73	91.105	99.553	109.465	119.624	87.72	126.144	73.958	TCI
Net SPO	-0.42	9.81	-0.68	-16.27	-8.9	-0.45	9.47	19.62	-12.28	26.14	-26.04	72.571

Table 7. S2 VOLATILITY SPILLOVER Connectedness Diebold and Yilmaz Index

Table 7	**Auto**	**Bankex**	**CAP**	**CD**	**Metal**	**OilGas**	**Power**	**PSU**	**Reality**	**BSE**	**Tech**	**FROM**
Auto	25.579	9.323	7.95	5.297	6.536	5.784	8.048	8.031	6.595	13.085	3.771	74.421
Bankex	8.226	25.052	9.193	4.88	5.599	5.182	7.931	9.814	5.927	15.1	3.096	74.948
CAP	7.598	9.893	26.56	4.168	5.603	5.9	11.231	9.521	7.077	9.747	2.704	73.44
CD	6.31	7.639	6.125	38.343	5.025	5.465	6.63	7.396	7.019	7.47	2.579	61.657
Metal	7.273	7.235	6.901	4.703	26.936	7.016	9.276	11.184	6.801	8.996	3.679	73.064
OilGas	6.052	6.53	6.228	4.299	6.416	29.699	7.982	13.095	5.523	9.896	4.279	70.301
Power	6.947	7.716	10.089	4.556	7.311	7.252	24.931	12.586	7.119	8.391	3.103	75.069
PSU	6.364	9.313	7.92	4.754	7.995	10.515	11.777	23.236	6.606	8.618	2.902	76.764
Reality	6.948	7.423	7.913	6.167	6.876	6.494	8.988	9.324	28.964	7.926	2.977	71.036
BSE	9.988	13.351	8.259	4.766	6.218	7.161	7.713	8.301	5.176	23.15	5.916	76.85
Tech	6.156	6.325	4.886	4.031	5.795	6.185	5.902	5.765	4.253	12.175	38.529	61.471
CTO	71.861	84.748	75.464	47.622	63.374	66.954	85.478	95.016	62.095	101.404	35.006	789.022
CTI	97.44	109.8	102.024	85.964	90.31	96.653	110.408	118.253	91.059	124.554	73.535	TCI
Net SPO	-2.56	9.8	2.02	-14.04	-9.69	-3.35	10.41	18.25	-8.94	24.55	-26.47	71.729

Table 8. Pre-COVID-19 VOLATILITY SPILLOVER Connectedness Diebold and Yilmaz Index

Table 8	Auto	Bankex	CAP	CD	Metal	OilGas	Power	PSU	Reality	BSE	Tech	FROM
Auto	31.678	9.748	6.941	5.204	9.368	8.943	4.75	8.251	3.901	10.113	1.105	68.322
Bankex	7.78	28.692	6.784	3.451	6.758	7.394	4.156	10.419	5.778	16.931	1.857	71.308
CAP	7.497	7.264	27.545	7.165	6.365	8.114	8.992	10.196	6.204	9.796	0.861	72.455
CD	6.889	6.57	9.684	40.039	3.95	6.705	5.924	6.107	5.048	7.602	1.481	59.961
Metal	9.274	8.817	7.273	3.579	33.78	6.592	6.492	9.877	5.171	8.481	0.663	66.22
OilGas	8.412	6.477	7.762	4.311	5.577	26.091	9.245	15.747	6.694	9.166	0.519	73.909
Power	5.97	4.159	9.469	4.069	6.211	10.732	30.675	14.704	6.081	7.145	0.784	69.325
PSU	7.265	8.894	8.5	3.43	7.244	13.648	10.997	23.46	6.339	9.358	0.863	76.54
Reality	5.102	9.606	6.915	5.085	5.582	7.167	7.089	10.467	34.518	7.687	0.783	65.482
BSE	8.357	15.876	8.317	4.322	6.543	8.957	6.181	10.309	5.103	23.45	2.585	76.55
Tech	4.295	7.059	4.763	4.637	4.714	2.111	2.993	3.629	3.205	7.401	55.191	44.809
CTO	70.841	84.469	76.408	45.254	62.314	80.363	66.819	99.705	53.525	93.682	11.501	744.881
CIO	102.518	113.161	103.952	85.293	96.093	106.454	97.494	123.165	88.043	117.132	66.693	TCI
Net SPO	2.518	13.161	3.952	-14.707	-3.907	6.454	-2.506	23.165	-11.957	17.132	-33.307	67.716

Table 9. Post-COVID-19 VOLATILITY SPILLOVER Connectedness Diebold and Yilmaz Index

Table 9	Auto	Bankex	CAP	CD	Metal	OilGas	Power	PSU	Reality	BSE	Tech	FROM
Auto	17.731	9.225	9.687	8.004	7.042	8.752	6.055	8.09	4.815	12.176	8.422	82.269
Bankex	7.368	19.278	9.722	6.946	5.228	8.163	5.198	8.207	4.67	15.057	10.162	80.722
CAP	8.6	8.796	18.661	7.725	6.928	8.5	6.292	9.657	5.461	11.806	7.575	81.339
CD	8.882	8.593	9.318	17.659	6.673	8.599	5.63	8.196	5.752	11.249	9.449	82.341
Metal	8.382	6.479	9.219	6.624	17.781	9.281	7.292	10.7	4.697	10.98	8.566	82.219
OilGas	7.857	7.388	9.351	6.422	7.313	16.613	6.596	11.666	5.312	12.056	9.427	83.387
Power	7.763	6.133	9.677	5.989	7.212	8.712	21.133	12.978	5.378	9.086	5.94	78.867
PSU	7.147	7.197	10.307	6.162	8.401	11.404	9.103	16.925	5.351	10.794	7.211	83.075
Reality	7.642	8.311	10.007	6.889	5.301	8.285	6.235	7.826	20.972	10.657	7.874	79.028
BSE	8.833	11.879	9.668	7.311	6.491	9.626	5.722	8.969	4.789	16.452	10.26	83.548
Tech	6.397	10.252	8.59	6.407	4.787	9.568	5.186	7.941	4.327	13.444	23.1	76.9
CTO	78.871	84.252	95.545	68.479	65.375	90.889	63.309	94.23	50.552	117.304	84.886	893.694
CTI	96.602	103.531	114.207	86.139	83.155	107.502	84.443	111.155	71.524	133.756	107.986	TCI
Net SPO	-3.398	3.531	14.207	-13.861	-16.845	7.502	-15.557	11.155	-28.476	33.756	7.986	81.245

The major jolt of COVID-19 sets rolling a very volatile period, but the lockdown announcement beginning with significant uncertainty shows how volatility spillover touches an all-time high of 81.25% within the model (table 9).

The S1, S2, and Pre Covid data set should adhere to the volatility spillover sequence built on historical data. An out-of-sample data should confirm the concurrence of the robustness, which is the post-COVID-19 data set. Hence, it can show if the volatility spillover remains the same or changes. The S2 Pre Covid-19 are identical, showing the similarity in the volatility spillover profile within these two data sets.

The sectors receiving the volatility spillover are ranked for better comparison. The rankings can show the sequencing of the volatility spillover changes or not. Does the COVID-19 upsurge the volatility spillover or not is hence answered.

The section named "CTO," the first part of table 10 (summarized from table 6 to 9), shows the sector-wise volatility spillover transmission to other sectors. The number in each column shows how much volatility spillover has been induced by that sector. In this part of table 10, we can compare the S2 and Pre-COVID-19 periods. Out of eleven sectors, five (45% of total), the ranking as volatility spillover dispenser remains the same. These sectors are Capital Goods, Auto, Metal, Consumer and Technology, ranking 5, 6, 8, 10 and 11.

Table 10 shows the “FROM.” This column shows the volatility spillover received by each sector from others. Out of eleven sectors, four maintain their ranking as the volatility spillover receivers. These sectors are BSE, PUS, Consumer, and Technology, with ranks of 1,2,10, and 11. (36% of all the sectors). The out of sample confirms the validity of the significant volatility spillover movement within the model.

The Net Spillover adds the directional explanation to the volatility spillover. The positive sign shows the variable as the transmitter of the volatility spillover, while the negative sign shows that the variable is the receiver of the volatility spillover. This section shows that 36% of the sectors maintain their ranking as either receivers or dispensers of the volatility spillover. Capital Goods remain the volatility transmitter with value of 2, increasing marginally to 3.9%. The consumer sector maintains its position with a negative sign volatility spillover of -14.0% to -14.7%. Technology increases from -26.46 to -33.30 while it maintains its overall ranking of the eleventh position. A noteworthy change is only in the Auto sector, which changes from negative to positive but maintains its sixth position.

Has the COVID-19 altered the volatility spillover sequence?

The fourth data set of Post should have the exact nature as the S2, Pre COVID-19 data set to answer the question. Change in the ranking of one position up or down can be seen in the data sets S2 and Pre. Those sectors changing with position one rank down or up can be ignored, as the DYI table of (table 10) in the S2 and Pre COVID-19. When we compare the Post or COVID-19 period with the Pre, we see a significant upsurge in the ranking sequence change. In the "CTO" section, we can see that seven sectors change their ranking by two to as many as six positions. The pattern is also seen in the "FROM" section, where six sectors show similar rank movement patterns. The "Net" volatility spillover section shows the change in eight sectors.

Table 10. The Ranking Based on the VOLATILITY SPILLOVER Tables

Table 10	Volatility Spillover Values %				Ranks of Volatility Spillover			
To	**S1**	**S2**	**PreCOVID**	**PostCOVID**	**S1**	**S2**	**PreCOVID**	**PostCOVID**
Auto	74.261	71.861	70.841	78.871	5	6	6	7
Bankex	85.086	84.748	84.469	84.252	3	4	3	6
BSE	103.642	101.404	93.682	117.304	1	1	2	1
CAP	73.243	75.464	76.408	95.545	6	5	5	2
CD	47.208	47.622	45.254	68.479	10	10	10	8
Metal	64.617	63.374	62.314	65.375	8	8	8	9
OilGas	72.039	66.954	80.363	90.889	7	7	4	4
Power	84.185	85.478	66.819	63.309	4	3	7	10
PSU	96.856	95.016	99.705	94.23	2	2	1	3
Reality	59.006	62.095	53.525	50.552	9	9	9	11
Tech	38.137	35.006	11.501	84.886	11	11	11	5

From	S1	S2	PreCOVID	PostCOVID	S1	S2	PreCOVID	PostCOVID
Auto	74.681	74.421	68.322	82.269	5	5	7	5
Bankex	75.281	74.948	71.308	80.722	3	4	5	8
BSE	77.498	76.85	76.55	83.548	1	1	1	1
CAP	73.927	73.44	72.455	81.339	6	6	4	7
CD	63.479	61.657	59.961	82.341	11	10	10	4
Metal	73.512	73.064	66.22	82.219	7	7	8	6
OilGas	72.486	70.301	73.909	83.387	8	9	3	2
Power	74.719	75.069	69.325	78.867	4	3	6	10
PSU	77.233	76.764	76.54	83.075	2	2	2	3
Reality	71.286	71.036	65.482	79.028	9	8	9	9
Tech	64.179	61.471	44.809	76.9	10	11	11	11
NET	**S1**	**S2**	**PreCOVID**	**PostCOVID**	**S1**	**S2**	**PreCOVID**	**PostCOVID**
Auto	-0.42	-2.56	2.518	-3.398	5	6	6	7
Bankex	9.81	9.8	13.161	3.531	3	4	3	6
BSE	26.14	24.554	17.132	33.756	1	1	2	1
CAP	-0.68	2.024	3.952	14.207	7	5	5	2
CD	-16.27	-14.036	-14.707	-13.861	10	10	10	8
Metal	-8.9	-9.69	-3.907	-16.845	8	9	8	10
OilGas	-0.45	-3.347	6.454	7.502	6	7	4	5
Power	9.47	10.408	-2.506	-15.557	4	3	7	9
PSU	19.62	18.253	23.165	11.155	2	2	1	3
Reality	-12.28	-8.941	-11.957	-28.476	9	8	9	11
Tech	-26.04	-26.465	-33.307	7.986	11	11	11	4
Model	72.571	71.729	67.716	81.245	NA	NA	NA	NA

The significant changes take place in the ranking of Technology. The I.T. sector is more immune to the market portfolio (primary Index) and the right candidate for portfolio optimisation. Here the COVID-19 alters the position. Technology becomes the transmitter of the volatility spillover—sign changes to positive. However, the change is not significant enough when we look within sample S1 and compare it with S2. The past performance of the sector volatility spillover reduces the volatility spillover from -26.46 to -26.04.

BSE as the primary market index doubles its volatility spillover transmission. 17.13 to 33.75. Nevertheless, the ranking changes from two to one.

Other observations: Bankex shows a significant volatility spillover reduction. Capital Goods increased volatility spillover 3.6 times from 3.9 to 14.20. Metal increases the volatility spillover by almost four times. Power volatility spillover increases by 6.2 times from -2.5 to -15.5. PSU reduces the volatility spillover from 23.11 to 11.15. Consumer goods show resilience by maintaining the status of net volatility spillover receiver.

What is essential is to witness the peculiarity of the COVID-19 volatility spillover mechanism. The lockdown announcement leads to the closure of manufacturing sectors sending a rippling effect on the ancillaries and the supply chain. The bankex shows very robust resistance to the COVID-19. This can be because of the digitalisation motivated by *Demonetization*. The event of Demonetization had prepared India by a significant shift of retail banking to a digital platform. The episode of COVID-19 has shown bankex as the most robust investment vehicle.

CONCLUSION

The analysis shed some critical implications of the nature of the COVID-19 pandemic. The data set of 221 days stands out in its COVID-19 effect implications. For some time, it seemed that in India, the situation had rolled back to pre COVID-19. The financial markets rebounded. The gross change in the sector volatility spillover shows the uniqueness of the shock which hit the financial markets in 2020. Factories are operational for the entire four shifts. However, as seen above, the volatility moved in a more differentiated manner. As the second wave of COVID-19 sets in, this volatility behaviour can help the fund managers, regulators, and business managers to forecast and understand how the volatility will unfold.

The lessons must be learned how digitisation in India had been a significant mark of help in helping the displaced labour force through online relief transfer into their account by the Indian government. The "*Demonetisation,"* which was grossly criticised earlier by many, forced the digital payment to an extent. As seen through the bank index "Bankex", digitalisation has been the least to dispense the volatility. Technology has changed its profile from a volatility receiver to a volatility spiller. The sector based on foreign clientele needs to relook at the risk factors. The work change from the office to home should have made the sector's response resilient, yet it performed the opposite. The takeaway for the PSU and the Power sector is that they need to reassess the risk mitigation strategies under such COVID-19 type shocks.

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