Contagious COVID 19: Leading to Hysteria in Indian Stock Markets and Sectoral Indices Performance

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ABSTRACT

The eruption of the novel corona virus in India has led to the outflow of panic due to high media coverage. This unparalleled broadcast of news has led to swift flow of information to investors and reactions can be assessed with increased volatility in financial markets. EGARCH (1,1) Model is applied to determine the relationship between the market returns of different industries along with the panic generated due to media coverage about the corona virus outbreak. Imposition of mobility control in terms of Lockdown has exerted the significant impact on stock market and sectoral indices returns. And depending on the nature of the business associated, different sectors have performed in a different way to this corona virus outburst. Even if returns are not affected directly then conditional volatility pervasiveness can easily be detected. So, the news burdened with panic and negative sentiment has definitely contributed to a prodigious level of volatility in the sectors professed to be most affected by the corona virus outbreak in India.

Key Terms: *Corona virus, COVID-19, Sectoral Indices Performance, EGARCH Model, Conditional Volatility, Panic Index, Nifty 50, Media Coverage*

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INTRODUCTION

The outbreak of Corona Virus (SARS-COV-2) popularly known as COVID-19 has its inception roots in Wuhan, China and has created a never seen before situation across the globe in all realms of life. To no one's astonishment, market capitalization of trillions of dollars has been gone away and it is too early to predict when and how this scenario is going to be changed.

The crisis ascended by this unexpected and new virus has shaken the global economies and stock markets are no exception to it. Numerous breathes have been claimed by this Covid-19 and it has dominated countries across the globe. Considerable fluctuations in financial markets have also been observed with different sectors countering to the disaster differently.

India has definitely curtailed the widespread of the pandemic as compared to other countries by taking various early policy measures but the economic impact cannot be ignored. Economic instability has major association with the periods which are highly volatile in nature. The lockdown decision taken by government to maintain social distancing and to dodge the outburst of virus in the country even when cases were not very high in number. This lockdown has reflected a huge economic loss to the country and have plunged the growth rates and GDP(Gross Domestic Product) to very low figures. India's GDP growth rate has plunged down to 3.1% for the current quarter Q4 of financial year (FY20) where as it was 4.1% for last quarter Q3 as compared to 5.7% for same quarter of last fiscal year. The overall FY20 GDP has declined to 4.2% from 6.1% of FY19, which is reported as lowest for past 11years. The unemployment rate has also witnessed quite a surge to 23.48 % in the month of April 2020 which is again quite a high from previous many years.

Now a days, there is instant flow of information across countries. Access to news about any event across globe is one of the major sources of information and it is observed that individuals are unable to evaluate the economic viability of the dispersed information. Literature supports that news plays a very important role in deciding trading strategies. There is significant portion of volatility in financial markets because of news announcements. (Ederington& Lee,1996; Barberis et al., 1998; Groß-Klußmann & Hautsch, 2011). Also, apart from traditional theories and models, there is an impact of some other factors like media coverage, any emergent situation prevailing in country or any health crisis which have effect on behaviour and psychology of the investor on market returns and stock prices.

The purpose of study stems from the ongoing pandemic situation where massive shocks are generated in financial markets. Present scenario, can be considered as an ideal environment to investigate the dynamics of unpredictability and extreme fluctuations in this time of financial crisis. The study aims to comprehensively evaluate the effect on market returns and volatility for the Indian Stock Market Index (Nifty 50) and different sectoral indices (Nifty Auto, Nifty Pharma, etc.) during this pandemic time from the investor's sentiment perspective. The study explores association of panic created among individuals due to media coverage of the pandemic and unseen volatility in market returns due to this negative global sentiment. Volatility profiling in different sectors of an economy is different depending on the nature of business it is associated with. The panic induced from media coverage makes financial markets more volatile. In finance literature, EGARCH models are extensively used in understanding the volatility of stock markets. The EGARCH model developed by (Nelson, 1991) is suggested as better fit for determining volatilities. The study is undertaken in the inception phase of the outbreak of the virus in the country India and can further be explored in upcoming times depending on the further blow-out of virus in the country. The current study can be extended to compare this with the volatility during more tranquil periods. The next section deliberates the literature associated and in further sections methodology and empirical results are discussed.

ITERATURE REVIEW

Though the literature related to the virus is in emerging phase, the outbreak of novel coronavirus has attracted researchers from all the domains to scale its effect in their fields. There is not even a single life which remains untouched by the effect of the virus.To identify the financial and economic effect, various researchers, academicians and policy personnel's have undertaken studies on relative effect of increasing cases and deaths due to the virus on stock markets, currency exchange rates, GDPs of countries under influence, prices of various commodities like Oil, Gold, etc.(Corbet et al., 2020;Villarreal-samaniego, D. 2020).

China is the country which is considered responsible for the outbreak of the virus and its worldwide spread. A lot of interest has been developed by economists and researchers to identify the impact on Chinese Stock Markets. With strict measures of containment, China curtailed the outspread within the country but badly affected the production and economy. In order to quantify the pandemic effect on performance of Chinese Stock Markets (Liew & Puah, 2020) applied regression with EGARCH specification to analyse the performance of Chinese Stock Market represented by Composite Index of Shanghai Stock Exchange and its component sectoral indices. They introduced a lockdown dummy, cases of COVID-19, and a particular date dummy for 3th Feb 2020 (date of reopening after Chinese New Year holidays) in the regression analysis. There were certain sectors which were much affected due to this pandemic like IT, telecommunication services and healthcare whereas other sectors like energy and financial sectors have not shown a greater impact for the outbreak of the pandemic.

The interlinkage and interdependence of global financial markets, has led to flow of crisis from one country to another. And high cross correlation is witnessed in the stock markets. The another country which has been majorly affected after China is US (United States of America) (Onali, 2020) identified that there is presence of conditional heteroskedasticity for US Stock markets with the increase in number of cases and number of deaths due to COVID 19. Data for almost one year has been collected for 7 countries which has daily deaths of more than 1000 people and includes US, China, Italy, Spain, UK, Iran, France. Stock market returns of US (S&P 500 and Dow Jones are not directly affected and only persistence of conditional heteroskedasticity is positive except for China cases. GARCH(1,1) modelling is used to identify this impact whereas VAR model identified the negative impact of France and Italy's reported death's on US Market returns (Dow Jones) and VIX has positive effect of the ongoing crisis. Similarly, (Baig et al., 2020) identified the association of COVID-19 cases and deaths with increase in volatility and illiquidity in the US equity markets. Contribution of restrictions imposed and lockdown to decreased mobility leading towards decline in liquidity of markets is studied with the help of OLS regression. (Zhang et al., 2020) identified that due to outbreak, significant loses are suffered by investors during this duration of pandemic outbreak.

Various studies over a period of time has been conducted to identify the relationship of stock market movements to any global announcement or any situation which has a macroeconomic impact. Studies related to effect on market returns in relation to natural disasters, disease prone crisis, and terrorist attacks, are conducted in limited number. Literature has not reported so strong impact of outbreak of any infectious disease to this extent on the market volatilities. (Baker et al., 2020) used automated and human readings of articles from newspapers to quantify the importance and role of news in relation to outbreak of infectious disease. Various major infectious diseases from past like SARS, Ebola were taken into consideration to gauge the market movements related to developments of pandemic. The market volatility is very minutely associated, but in case of Covid-19 news it has been a major driver of movements in US Stock Markets. (Tetlock, 2007) iterated that news related to infectious diseases can cause alarm and influences investors sentiments. (Haroon & Rizvi, 2020) discovered that the unparalleled coverage of news regarding the virus has heightened the volatility in the ambiguous stock markets.

DATA & METHODOLOGY

This study is an attempt to determine the returns and volatility of Indian Stock Market Index Nifty 50 and other Nifty Sectoral Indices during the outbreak of this novel corona virus. The sectoral indices by Nifty represents the benchmark data for the given industry or sector which allows investors to track the stock markets for that particular industry. Nifty 50 is a flagship index which comprises of 50 stocks of the index from 12 different sectors. Nifty sectoral index is a gauge of companies falling under the one particular sector. Like Nifty Auto reflects the performance and behaviour of automobile sector and comprises of 15 stocks that are listed on National Stock Exchange (NSE). Now a days, artificial intelligence also plays an important role in determining investor sentiments. So, Indexes like Panic Index, Sentiment Index and Media Coverage Index from Ravenpack Finance has been taken as representative variables to discover the news related sentiment effect on returns of the market index as wells as these sectoral indices. The association of these indexes with Covid-19 cases and deaths has been detected by running the regression equation and EGARCH (1,1) model is developed to gauge the returns and model volatility of financial markets. A lockdown dummy is introduced for the lockdown period to instrument the effect of mobility control.

The daily data of closing prices of Indian Stock Market Index NIFTY 50 along with other 11 Sectoral Indices namely NIFTY Auto, NIFTY Bank, NIFTY Pvt. Bank, NIFTY PSU Bank, NIFTY Metal, NIFTY FMCG, NIFTY Pharma, NIFTY IT, NIFTY Realty, NIFTY Financial Services, NIFTY Media has been collected for the period beginning from 31st January 2020 (when first case of Coronavirus was detected in Kerala, India) till 15th May 2020 from the NSE website. Daily returns are calculated for all the Indices by taking log of the daily closing prices and subtracting it with the previous day closing price of the same index.

$$\text{Return}_{(i,t)} = \log(P_{i,t}) - \log(P_{i,t-1}).$$

To identify the effect of increasing daily cases of Coronavirus and daily deaths of Coronavirus patients on volatility and returns in Indian Stock Market Index and other sectoral Indices, the data for daily cases and deaths for the same period (31st Jan to 15th May 2020) has been collected from the website of statista. com. Recent studies of (Haroon & Rizvi, 2020; Baig et al., 2020 & Rogone et al., 2020) have utilized various Indexes like Sentiment Index, Panic index, Media Coverage Index and many others from Ravenpack Finance for the purpose of conducting research. These indexes help in understanding the sentiment originated from news and its association with stock market volatility. The details and visual representation of data collected from these is represented in Figure 2, 3 and 4.

Natural logarithms(log) of all values of covid-19 cases and deaths and all of the above mentioned indexes(Panic index, sentiment index and media coverage index) are taken for the calculations. Unit root test ADF (Augmented Dickey Fuller Test) is conducted to check the stationarity of the calculated returns and log series of variables and indexes and data is utilised at first level difference where all the series were stationary. Throughout the Sentiment Index data is negative, so for log calculations absolute values are considered.

The ARCH family models are used for prediction and forecasting purposes. Also, these can be used to model the present volatility pertaining in the markets. Engle (1982), developed ARCH Model, which undertakes the changing variance into account for the time series data. Bollerslev (1986), elaborated ARCH Model and developed GARCH Model which introduced conditional variance equation. In 1991, Nelson to overcome the limitations of GARCH Model further proposed a model known as EGARCH Model which is capable of capturing the asymmetric effect on the variance caused by positive and negative market news.

Here in the study, first of all OLS Regression is run to determine the relatedness of these 3 Indexes (Panic Index, Sentiment Index and Media Coverage Index) to the reported cases and related deaths of COVID-19. The equations for the same is:

$$\textit{Panic Index}(\ln)_t = \alpha_0 + \alpha_1 (\ln \textit{Cases})_t + \varepsilon_t \quad 1(a)$$

$$\textit{Panic Index}(\ln)_t = \alpha_0 + \alpha_1 (\ln \textit{Deaths})_t + \varepsilon_t \quad 1(b)$$, where

Panic Index is taken as dependent variable and independent variables are total cases and total deaths reported respectively in equation 1(a) and 1(b). All values are taken in log form for the basic assumption of stationary of the data.

Similarly, equations for other two indexes are:

$\textit{Sentiment Index}(ln)_t = \alpha_0 + \alpha_1\ (ln\ Cases)_t + \varepsilon_t 2\ (a)$

$\textit{Sentiment Index}(ln)_t = \alpha_0 + \alpha_1\ (ln\ Deaths)_t + \varepsilon_t 2\ (b),$

$\textit{Media Coverage Index}(ln)_t = \alpha_0 + \alpha_1\ (ln\ Cases)_t + \varepsilon_t\ 3\ (a)$

$\textit{Media Coverage Index}(ln)_t = \alpha_0 + \alpha_1\ (ln\ Deaths)_t + \varepsilon_t\ 3\ (b)$

After identifying the relationship among them, these indexes are primarily used to model the EGARCH(1,1) equation to estimate the returns of various sectoral indices, and volatility persisting in markets. For this purpose, both mean and variance equation are taken into consideration. Also, lockdown dummy (LD) from the date of beginning of first lockdown i.e. 22nd March 2020 has been introduced to identify the effect of mobility control, economic loss and panic associated with it. For observations from the date of lockdown 22nd March 2020, LD has taken value as 1 till end of the study period i.e. 15th May 2020 and otherwise the value of LD is 0.

Conditional Mean Equation,

$Return_t = \alpha_0 + \alpha_1 LD + \alpha_2 MCI + \alpha_3 PI + \alpha_4 SI + \varepsilon_t$ *where,*

$Return_t$ is the return of Indian Stock Market Index Nifty 50 and other sectoral indices like Nifty Auto, Nifty pharma, Nifty Bank, etc, all 11 sectoral indices mentioned above.

α takes values from 0 to 4 , the coefficients of the parameters to be estimated,

LD, is lockdown dummy, MCI, is Media Coverage Index, PI, is Panic Index

SI, is Sentiment Index, and

ε_t is the error term

Conditional Variance Equation,

$Log(\sigma^2 t) = \beta_0 + \beta_1 (|\varepsilon_t\text{-}1| / \sigma_t\text{-}1) + \beta_2 (\varepsilon_t\text{-}1 / \sigma_t\text{-}1) + \beta_3 log\sigma^2 t\text{-}1 + \beta_4 LD,$ *where*

$Log(\sigma^2 t)$, is the log (Garch),

β takes values from 0 to 4, the coefficients of parameters,

$|\varepsilon_t\text{-}1| / \sigma_t\text{-}1$, is the absolute residual (-1) divided by square root of Garch (-1),

$\varepsilon_t\text{-}1 / \sigma_t\text{-}1$, is the Arch effect measuring the leverage effect which defines the absorption of good and bad developments in the market,

$log\sigma^2_{t-1}$, is the Garch effect measuring the perseverance of volatility in the markets.

LD, is lock-down dummy taken as variance regressor.

EMPIRICAL ANALYSIS & RESULTS

The above figure represents the percentage change in the daily closing prices of the benchmark Index considered under study for the period 31st January 2020 -15th May 2020. With a concern about economic consequences, market began to react to the news and information in very initial stage only. A major movement can be witnessed in the month of March where in the shock started flowing in the form of news from the other countries. The announcement of pandemic by WHO also played its role in market fluctuations. The elevated anxiety because of the announcement of the lockdown and increase in panic has clearly demonstrated panic effect of mobility control on market prices and returns.

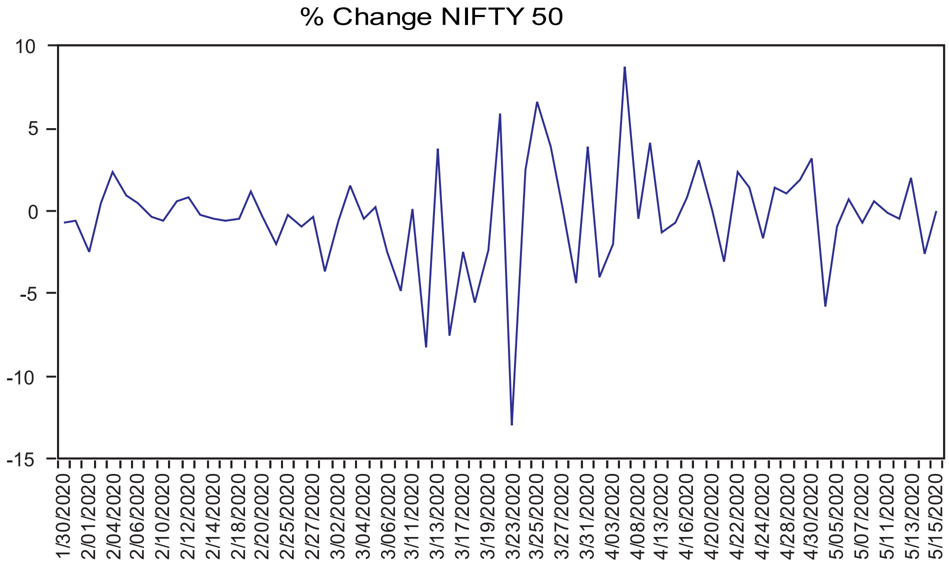

Figure 1 : Percentage Change in Nifty 50

Source: Author's own compilation with E-views

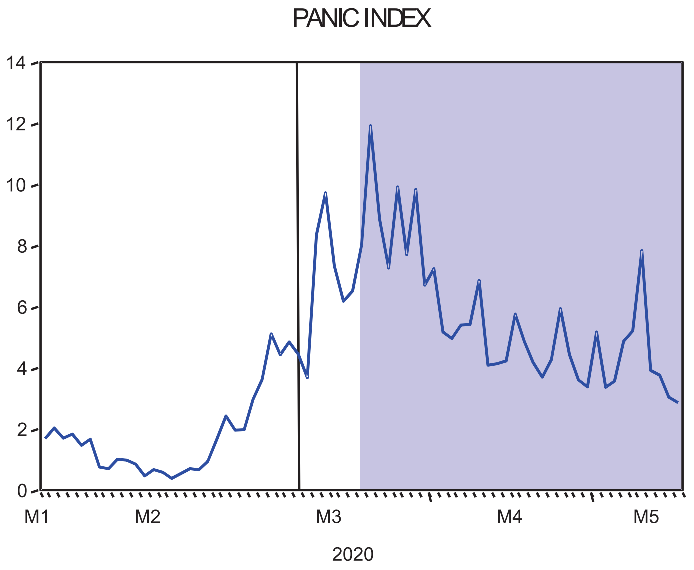

Figure 2 : PANIC INDEX

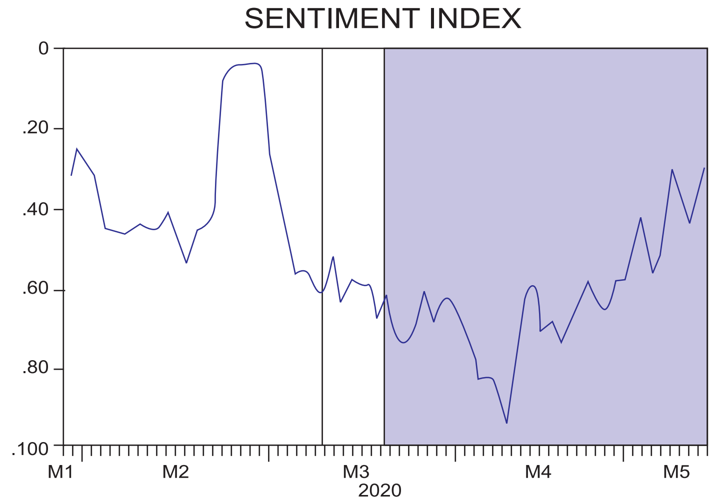

Figure 3 : SENTIMENT INDEX

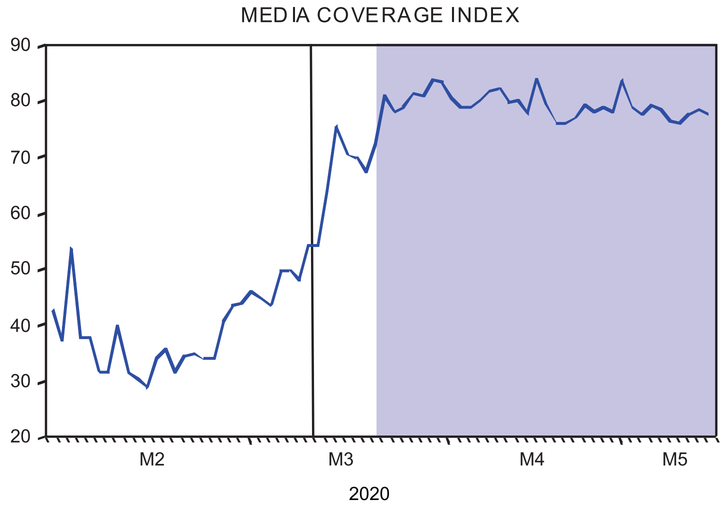

Figure 4 : MEDIA COVERAGE INDEX

Source: Author's own compilation with E-views

The Coronavirus Panic Index by Ravenpack Finance measures the level of news which is related to coronavirus and panic. The values range from 0 to 100 depicting 10.0 value as 10 percent of total of news globally making buzz and panic related to coronavirus. It can be extracted for country specific Information as well (Here values are taken for India only). As the value increases it implies the increased level of panic in media regarding the Covid-19. So, it can be observed here that as WHO declared Coronavirus as "pandemic" on 11th March 2020, a sharp increase in panic created can be witnessed here reaching to value up to 9.8 by 16th March 2020. Then, as the government of India announced Lockdown as a precautionary measure for social distancing to curb the virus dissemination on 20th March 2020 to be started from 22nd March 2020, the panic index was at its peak high in this duration at 11.9.

Similarly, sentiment across all entities mentioned in the news alongside the coronavirus is measured through the Sentiment index and values ranges between 100 to -100, -100 depicting most negative. Here, overall sentiment witnessed is negative over the data period with most negative at the time of lockdown 2.0 announcement on 13th April 2020. Media Coverage Index provides percentages of corona news among all sample news sources with values between 0 to 100. After the declaration by WHO as pandemic, the coverage in media has seen an increasing trend.

Table : Regression results for Panic, Sentiment & Media Coverage dependence on Covid-19

	Panic Index (ln)		Sentiment Index (ln)		Media Coverage Index (ln)	
OLS Eq.	$\alpha_0 + \alpha_1 (ln\ Cases)_t + \varepsilon_t$	$\alpha_0 + \alpha_1 (ln\ Deaths)_t + \varepsilon_t$	$\alpha_0 + \alpha_1 (ln\ Cases)_t + \varepsilon_t$	$\alpha_0 + \alpha_1 (ln\ Deaths)_t + \varepsilon_t$	$\alpha_0 + \alpha_1 (ln\ Cases)_t + \varepsilon_t$	$\alpha_0 + \alpha_1 (ln\ Deaths)_t + \varepsilon_t$
Constant (α_0)	-0.025605 (-0.5564)	-0.137277 (0.0135)*	-0.06527 (-0.1774)	-0.050362 (-0.1297)	0.00043 (-0.9762)	-0.0086 (-0.3881)
Covid-19 Cases (α_1)	0.185809 (-0.2175)		0.408743 (0.0158)*		0.05084 (-0.3095)	
Covid-19 Deaths (α_1)		0.676149 (0.0009)*		0.174168 (-0.1378)		0.09192 (0.0120)*
R^2	0.26	0.24	0.08	0.05	0.01	0.14

*(Notes: the values in parentheses are p-values and identifies the significance level at 1%, 5% & 10% as *, **, *** respectively, and corresponding coefficients are reported)*

The above table represents the results of OLS Regression run to determine the relationship between the indexes taken under consideration (panic index, sentiment index and media coverage index) and the total reported number of cases and deaths due to Covid -19 in India. For every Index two equations are tested, one with the Covid cases and other with the number of deaths associated with Covid. So, in all six equations are reported vertically in Table 1. The regression results from the table reveal that panic index and media coverage index is significant to the number of deaths and not to the number of cases, whereas sentiment index is significant to number of cases reported. It can be iterated that even the numbers of cases and deaths are not very high in terms of Indian context as compared to other countries like US, but mortality is the reason for panic and media coverage. The negative sentiment is because of contagiousness of the disease and not the mortality.

Table 2: Regression Results EGARCH(1,1) MODEL Mean and Variance Equation

Dependent Variable →	**NIFTY 50**	**NIFTY AUTO**	**NIFTY BANK**	**NIFTY METAL**	**NIFTY REALTY**	**NIFTY EMCG**
Conditional Mean Equation	**Return**$_t = \alpha_0 + \alpha_1 LD + \alpha_2 MCI + \alpha_3 MPI + \alpha_4 SI + \varepsilon_t$					
Lockdown	1.980654	1.681503	-0.282976	-0.601692	-0.6593	0.21603
Dummy(LD)	(0.0038)*	(0.0969)**	(-0.3676)	(0.0004)*	(0.0000)*	(0.0016)*
Media Cov.	-1.919077	-2.397785	1.21516	0.421498	-1.0232	0.38527
Index(ln)	(-0.6266)	(-0.5202)	(-0.5124)	(-0.7653)	(-0.5315)	(0.0000)*
Panic	2.705331	1.705982	0.29753	0.428038	1.16804	0.47021
Index(ln)	(0.0219)*	(-0.2672)	(-0.637)	(-0.4537)	(0.0001)*	(0.0000)*
Sentiment	0.617385	0.644276	-0.293307	-1.129934	-0.739	-0.0189
Index(ln)	(-0.7594)	(-0.7198)	(-0.6893)	(0.0000)*	(0.0031)*	(-0.2551)
Conditional Variance Equation	$Log(\sigma^2_t) = \beta_0 + \beta_1 (\lvert \varepsilon_{t-1} \rvert / \sigma_{t-1}) + \beta_2 (\varepsilon_{t-1}/\sigma_{t-1}) + \beta_3 log^2_{t-1} + \beta_4 LD$					
L.arch (β_2)	0.429796	0.051258	0.005341	0.029657	0.31187	0.255
	(0.0211)*	(-0.7559)	(-0.9786)	(-0.746)	(0.0213)*	(0.0000)*
L.garch (β_3)	-0.498612	-0.702307	-0.21419	-0.783994	-0.552953	-0.687974
	(0.0127)*	-0.1243	-0.8616	(0.0000)*	(0.0053)*	(0.0000)*
Lockdown dummy	1.160687	2.12178	0.341524	-1.650583	-1.031353	0.030277
(VR) (β_3)	(0.0756)***	(0.0141)**	(-0.6479)	(0.0502)***	(-0.184)	(-0.9528)
Constant(β_0)	-0.887903	-1.180578	0.231286	0.673857	0.327568	-0.143032
	(0.0564)***	(0.0196)*	(-0.2671)	(0.0000)*	(0.0000)*	(0.0000)*

Dependent Variable →	NIFTY 50	NIFTY AUTO	NIFTY BANK	NIFTY METAL	NIFTY REALTY	NIFTY EMCG
Conditional Mean Equation	$\textbf{Return}_t = \alpha_0 + \alpha_1 LD + \alpha_2 MCI + \alpha_3 PI + \alpha_4 SI + \varepsilon_t$					
Lockdown	-0.401601	-0.181736	-0.022221	0.444255	-0.20883	-0.570652
Dummy(LD)	(-0.1403)	(0.0238)*	(-0.8618)	(0.0290)*	(-0.4855)	(-0.305)
Media Cov.	1.897853	-0.113655	0.459246	-4.59246	1.106421	1.79029
Index (ln)	(-0.2164)	(-0.8256)	(-0.4627)	(0.0000)*	(-0.5182)	(-0.5014)
Panic	0.244231	0.742886	-1.510269	0.12828	0.39072	-1.021401
Index (ln)	(-0.6351)	(0.0000)*	(0.0000)*	(-0.8069)	(-0.5252)	(-0.3816)
Sentiment	0.088792	-0.134788	-0.617241	-0.394099	-0.370801	-1.309217
Index (ln)	(-0.8123)	(-0.1192)	(0.0000)*	(-0.2033)	(-0.6682)	(-0.1576)
Conditional Variance Equation	$\textbf{\textit{Log}}\,(\sigma^2_t) = \beta_0 + \beta_1 (\lvert \varepsilon_{t-1} \rvert / \sigma_{t-1}) + \beta_2 (\varepsilon_{t-1}/\sigma_{t-1}) + \beta_3\, log^2_{t-1} + \beta_4 LD$					
L.arch (β_2)	-0.005451	0.014507	-0.137419	-0.196971	0.000546	-0.601525
	(-0.9797)	(-0.9047)	(-0.6185)	(-0.1574)	(-0.9977)	(0.0150)*
L.garch (β_3)	-0.573577	0.475824	-0.149212	-0.776287	-0.145577	-0.32886
	(0.0975)***	(0.0000)*	(-0.48)	(0.0000)*	(-0.9121)	(-0.4283)
Lockdown	0.661208	0.081368	1.416949	0.337033	0.40202	-0.570652
dummy(VR) (β_4)	(-0.4894)	(0.0981)***	(0.0153)*	(-0.6803)	(-0.6165)	(-0.305)
Constant (β_0)	0.102135	-0.040588	0.194377	-0.130457	0.207079	0.204002
	(-0.6384)	(0.0998)***	(0.0041)*	(-0.2161)	(-0.2935)	(-0.4696)

*(Notes: the values in parentheses are p-values reported and identifies the significance level at 1%, 5% & 10% as *, **, *** respectively, and corresponding coefficients are reported. Variables Lockdown Dummy(LD), Panic Index, Sentiment index & Media Cov. Index, all are mean equation variables and Variables L.arch and L.garch defines the conditional variance equation and represents values of β_2 & β_3 defining leverage effect and persistence in volatility and lockdown dummy(VR) represents β_4 which is the coefficient for lockdown dummy as variance regressor)*

The above table (Table 2) describes the influence generated by panic, sentiments and media coverage in the market returns and volatility of different sectoral indices considered for the purpose of analysis under study. Panic Index is measuring the significance of panic created due to media coverage in returns. And has been proved significant for the sectors like Realty, FMCG, IT, Pharma, and the benchmark index Nifty 50. Media Coverage Index coefficient is significant for only two sectors. So, the more proportion of news related to Covid-19 in media does not impact the market returns to great extent with the exceptions for the sectoral indices returns for FMCG as well as Media. Overall, the sentiment index during the study period is defining the negative sentiment pertaining in the market as depicted in graph (Figure 2). The coefficients of conditional mean equation found significant for the Indices of Metals, Realty and Pharma.

Introduction of lockdown dummy (LD) for the lockdown period beginning from 22nd March 2020 till the study period ending on 15th May 2020 has also proved significant for returns of various sectoral indices. Sectors including Auto, Metals, Realty, FMCG, IT and Media are the ones with strong influence of mobility control (lockdown dummy) on their returns. The returns of Nifty 50 have also shown significant results for the dummy variable. The lockdown dummy (LD) has also been introduced as a variance regressor as well while modelling the EGARCH(1,1) effect and its coefficient is identified as significant for returns of sectoral indices like Auto, Metals, IT and Pharma. Again Nifty 50, the benchmark index is found significant as well. For FMCG, Realty and Media it was significant in conditional mean equation but not as variance regressor whereas its vice versa for Pharma sector where it is significant as a variance regressor and not in the conditional mean equation.

Interestingly, returns of sectoral indices related to financial services, banking sector including both private banks as well as public sector banks have witnessed insignificant impact of all mean equation variables but persistence of conditional volatility and absorption of negative news from the market can be found significant in coefficients of conditional variance equation. The coefficients represented as L.arch and L.garch in the table under conditional variance equation defines the presence of leverage effect as well as perseverance in conditional volatility irrespective of market movements. The negative and significant coefficient for PSU Bank for arch effect pertains to absorption of negative news from the market and generation of risk associated during the study period.

Returns of few sectors may or may not be directly impacted but underlying conditional heteroscedasticity and presence of conditional volatility can be witnessed in almost all sectors. And Indian stock market return Index Nifty 50 has been identified significant for nearly all variables of mean equation as well as the variance equation except for sentiment and media coverage index.

DISCUSSION

As there is fallout in global markets, the sentiment in financial markets is unwelcoming across the globe. And in line with the global market trends, the gloomy financial markets in India are witnessing sharp volatility. Across various historical economic events it has been observed that Indian Stock Markets has a history of crash and retrieval. For instance, during "Asian Crisis" in the year 1996, Sensex witnessed a fall of 40% in 4 years but within a span of 1 year improved by 115%. Similarly, during "Tech Bubble" in 2000, there was a crash of 56% in approximately 2 years and depicted recovery of 138% in 3 years. The 2008 financial crisis also crashed Sensex by 61% within a year but soon recovered by 157% in 1.5 years. In current scenario, the crash is of almost 30% within a very short span of 3 months. COVID 19 is in its inception phase, so endgame of this crisis is not known and many are relating this event to Black Swan Event.

This study is a contribution to the emerging literature related to financial market returns and volatility during this pandemic. Use of artificial intelligence mechanisms to estimate the sentiments also explores a new field of research and further the same can be exploited as an intriguing field of research. The different industries are affected by the pandemic to varying degrees and their responsiveness also varies. The study comprehensively evaluates the effect on market returns of different sectoral indices and volatility witnessed in the current crisis situation. Investors could be resourced with the information provided in the paper regarding the market sentiments and its association with several sectoral indices returns. Statistically, the weight given to such news should be low in number to gauge return results but behaviourally individuals have great significance of such information and news in their lives and hence overreaction is demonstrated in their actions. Only thing is investors have to safeguard themselves from catching the falling knife.

CONCLUSION

The uncertainty associated with the outbreak is of course one of the major reason for high unpredictability and volatility in the financial markets during this course of time. Majority of sectoral indices have influence of mobility control and announcement of lockdown (LD) has been significant both as dummy variable and variance regressor. Returns may or may not be affected for some particular sectors but underlying conditional heteroskedasticity with negative coefficients predicts the effect of negative news more on the markets. The indices of sectors including Metals, FMCG, IT, Realty, Pharma and Nifty 50 have most coefficients significant, lesser coefficients significant for Media and least for financial services and banking sector. So, the news burdened with panic and negative sentiment has definitely contributed to an unusual level of volatility in the sectors stated to be most affected by the corona virus outbreak in the country India. On the other hand, announcement of various economic relief programs by government to calm the market at different points in the period of pandemic has reassured investors to a little extent. What form economies or financial markets all around the world will actually take place is very early to predict now as still the virus is in dissemination phase and to what extent it will damage the lives is unpredictable. It is true that people are absorbing information and panic association would be less as compared to initial outbreak but definitely the shock created by the outspread is large in magnitude and massive uncertainty in the financial markets can be visualized for the near time.

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Source: Johns Hopkins University; WHO; Worldometers; Ministry of Health and Family Welfare (India)

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