COVID-19 impact on stock market: Evidence from the Indian stock market

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This paper has been empirically investigated the existence of the day-of-the-week effect by using closing daily data for Nifty 50, Nifty 50 Midcap, Nifty 100, Nifty 100 Midcap, Nifty 100 Smallcap, and Nifty 200 for before and during the COVID-19 health crisis. This study used secondary data for all indices over the period 1 April 2005–14 May 2020. The present study used both dummy variable regression and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. The total study period is divided into two sub-periods, that is, during and before the COVID-19 health crisis. A negative return is found for Mondays when the during-COVID-19 health crisis period is examined; in contrast, it was positive for the before COVID-19 period. Tuesday's effect on index return is found statistically significant and positive for all indices during the COVID-19 crisis.

KEYWORDS
day-of-the-week effect, dummy variable, GARCH, stock market, volatility

1 | INTRODUCTION

The extant literature provides several empirical pieces of evidence on stock market responses to the major systemic events. The studies investigate the impact of major events such as pandemic disease severe acute respiratory syndrome (SARS) outbreak (Chen et al., 2007, 2018), natural disasters (Tavor & Teitler-Regev, 2019; Wang & Kutan, 2013), and political events (Bash & Alsaifi, 2019; Beaulieu et al., 2006; Ismail & Suhradjo, 2001; Nazir et al., 2014; Shanaev & Ghimire, 2019) on the stock markets. The negative impact of the recent COVID-19 outbreak on the world economy and capital markets is inevitable. In the initial phase of academic research on COVID-19, studies conducted by Al-Awadhi et al. (2020), Haiyue Liu et al. (2020), Ahmar and Val (2020), and Zhang et al. (2020) witnessed a negative impact of COVID-19 outbreak on stock markets. The stock prices change because of supply and demand. The stock price would fall when the number of people wanting to sell a stock is more than the number of people wanted to buy it (there would be greater supply than demand for that particular stock). The existence of anomalies has been recognized extensively for the previous two decades in financial markets. The most ubiquitous is the day-of-the-week effect. Stock market is efficient when all the information including private as well as public reflects in the stock price itself (Paital & Panda, 2018). The day-of-the-week effect patterns have been examined extensively in different financial markets. The stock markets will react adversely due this outbreak in the short run, but in the long run, markets eventually automatically correct themselves and again start increasing (Gormsen & Koijen, 2020). The day-of-the-week patterns have been investigated extensively in different markets. Studies (Aggarwal & Rivoli, 1989; Cross, 1973; French, 1980; Keim & Stambaugh, 1984; Rogalski, 1984) document that the distribution of stock returns varies according to the day-of-the-week. The “weekend effect” indicates that returns on stock are abnormally higher on some days of the week than on other days (Dubois & Louvet, 1996; Gibbons & Hess, 1981). The average return on Monday is significantly less than the average return over the other days of the week (Berument & Kiymaz, 2001). The day-of-the-week regularity is not limited to the U.S. equity market. It is also documented that the day-of-the-week regularity is present in other international equity markets (Barone, 1990; Jaffe & Westerfield, 1985; Solnik & Bousquet, 1990) and other financial markets including the futures market, treasury bill market, and bond market (Cornell, 1999).

According to the efficient market hypothesis (otherwise known as the efficient market theory), when there is a pattern in the returns of a share, the share market is supposed to follow a random walk due to market anomalies. There are a number of market anomalies in...
existence; some anomalies are appearing once and then disappearing, whereas other anomalies are frequently observed. Market anomalies also include the day-of-the-week effect, also known as Monday effect, the weekend effect, or intraday effect. An extensive body of research has examined the weekend effect (Alagidede, 2008; Berument & Dogan, 2012; Brusa & Liu, 2004; Chukwuogor, 2007). The “traditional” view of a weekend effect is that stocks tend to exhibit lower return on Mondays compared to Fridays, due to investor behavior (Du Toit et al., 2018). The reason for large returns on Fridays compared to Mondays is that portfolios are mostly sold on Mondays, as investors re-evaluate their portfolios on a Monday after bad news released over the weekend (Lakonishok & Maberly, 1990). However, there are some papers which reveal no significant day-of-the-week effects with regards to volatility, so this finding has not been confirmed. The existence of the “weekend effect” on the stock market has resulted in inconsistent evidence (Bhana, 1985; Chukwuogor, 2007; Coutts & Sheikh, 2002; Kalidas et al., 2013; Mbululu & Chipeta, 2012; Plimsoll et al., 2013). The purpose of the present study is to investigate the day-of-the-week effect on Nifty 50, Nifty 50 Midcap, Nifty 100, Nifty100 midcap, Nifty 200, Nifty 100 Smallcap. The purpose is to identify calendar anomalies using day-of-the-week-effect, whether there is a significant difference among weekdays’ returns. Including introduction, this paper consists of four sections. Next section provides a detailed review literature on the day-of-the-week and weekend effect on index returns. Section 3 discusses the data and methodology used for the study. This is followed by the discussion on empirical results of the study. The last section provides the conclusion.

2 | LITERATURE REVIEWS

The coronavirus pandemic 2019 (COVID-19) has created a significant turmoil in the global economic activity (Baldwin & Di Mauro, 2020) and in stock markets around the world (Fama, 1981; Huang & Krakaw, 1984; Vassalou, 2003). The stock prices change because of supply and demand. The stock price would fall when the number of people wanting to sell a stock is more than the number of people wanted to buy it (there would be greater supply than demand for that particular stock). The stock markets will react adversely due to outbreak in the short run, but, in the long run, markets eventually automatically correct themselves and again start increasing (Gormsen & Koijen, 2020). The continental crisis could mainly affect stockholders' wealth due to the bank-run effect (the public to lose confidence in solvent banks) and the informational effect (the information about asset quality could lead investors to revise their valuation of other banks; Aharony & Swary, 1983). Due to feverish stock price reactions to COVID-19, the aggregate stock market fell strongly. So, recent health crisis morphed into a financial and economic crisis (Ramelli & Wagner, 2020). The recent health crisis has impacted almost all financial markets worldwide, in particular, stock and share prices trend dropped continuously and significantly. The Dow Jones and S&P share prices in the United States have dropped by over 20%. It had a significant impact on the financial markets in China and USA, evidence from Shanghai stock exchange and New York Dow Jones share markets (Sansa, 2020). Behavior of stock market is an early and visible evidence of the recent COVID-19 pandemic. It has adversely impacted the stock market (Baker et al., 2020; Ichino et al., 2020).

Alexakis and Xanthakis (1995) investigate the day-of-the-week effect on the Greek stock market. They used the GARCH-M model within the time-period between January 1985 and February 1994, which investigates the volatility, which is considered nonconstant over time. This study carried out takes into account that the variance is dependent over time. Total time period is divided into two subperiods, one in which it operated under backward statutory conditions, and the recent one, that is since 1988, during which significant changes have been introduced affecting all market players. The results of the study reflect a positive return is found for Mondays for both total period and first subperiod. On the other hand, Tuesday shows negative returns. The results of French (1980) indicate that positive returns for Friday and negative returns for Monday, which runs counter to both of these hypotheses. The hypothesis used in the analysis of the stock markets in various countries is that because the Monday closing price entails the events of 3 days, the standard deviation should be higher compared to that of the other days, while only a significantly higher dispersion for this day would also indicate the effect of risk in determining daily returns (Jacobs & Levy, 1988). Cross (1973) exhibited nonrandomness in stock returns while observing return distribution of different days of the week. The study found negative returns on Monday and positive returns on Friday. Abraham and Ikenberry (1994) have explored the hypothesis for United States and individual investors and concluded that exert a selling pressure on Monday and to some extent on Tuesday. Jaffe et al. (1989) found that the negative effect occurred when the market return was negative the previous week, the effect being insignificant when the market return was positive.

Choudhry (2000) examined the day-of-the-week effect on seven emerging Asian stock markets returns and conditional variance (volatility). This study used the GARCH model and daily returns from India, Indonesia, Malaysia, Philippines, South Korea, Taiwan, and Thailand. The data for the period from January 1990 to June 1995 are used for this study. It found the presence of the day-of-the-week effect on both stock return and volatility. Although both the return and volatility are not identical in all seven cases, the effect may be due to a possible spill-over from Japanese stock. Keim and Stambaugh (1984) documented high Friday return and low Monday return have been dubbed the “day-of-the-week” effect and the “weekend (Monday) effect.” Berument and Kiyaz (2001) have done a study on stock market volatility and checked the presence of the day-of-the-week effect. For this study, they used the S & P 500 market index, within the time period of January 1973 and October 1997. They concluded that there was a day-of-the-week effect presence in both volatility and return equations.

Hui (2005) analyzed the day-of-the-week effects in Asia–Pacific and U.S. stock markets during the financial crisis 1997. Nonparametric
technique, Wilcoxon rank sum test, was being adopted in the paper. The empirical results of this study reveal that there are no significant day-of-the-week effects in all countries except Singapore. Hourvouliades (2009) investigate the day-of-the-week effect during the financial crisis. This study selected six regional equity markets including five emerging countries; these countries are Turkey, Bulgaria, Romania, Ukraine and Cyprus, and one mature, that is, Greece. The evidence from this study showed mixed evidence; in the more developed markets, the day-of-the-week effect gradually fades away during the second subperiod.

This study will focus on the period of April 2005 to that of May 2020 to examine the day-of-week effects for Indian stock market. In particular, we want to examine the impact of novel coronavirus (COVID-19) health crisis and the recent collapse of the Indian stock market and its significance to the day-of-the-week effects. Based on literature review, our hypotheses are as follows:

**Hypothesis 1.** No difference exists in the returns across the days of the week during recent COVID-19 crisis.

**Hypothesis 2.** No difference exists in the returns across the days of the week before COVID-19 crisis.

### 3 Data and Methodology

This paper has empirically investigated the existence of day-of-the-week effect by using closing daily data for Nifty 50, Nifty 50 Midcap, Nifty 100, Nifty100 midcap, Nifty 200, Nifty 100 Smallcap. This study used secondary data for all indices over the period 1 April 2005 to 14 May 2020. All the data are obtained electronically from https://www.investing.com. The daily closing price of the index has been considered for this study. The logarithmic percentage index return is calculated as follows:

\[ R_t = \ln \left( \frac{p_{t+1}}{p_t} \right) \]

### Table 1 Variable descriptions

| Dummy variables | Descriptions of the variables |
|-----------------|-------------------------------|
| \( D_{1t} \) | \( D_{1t} = 1 \) if it is Tuesday and 0 otherwise |
| \( D_{2t} \) | \( D_{2t} = 1 \) if it is Wednesday and 0 otherwise |
| \( D_{3t} \) | \( D_{3t} = 1 \) if it is Thursday and 0 otherwise |
| \( D_{4t} \) | \( D_{4t} = 1 \) if it is Friday and 0 otherwise |

### Table 2 Descriptive statistics

|                           | NIFTY100 MIDCAP | NIFTY 100 | NIFTY 200 | NIFTY 50 | NIFTY 50 midcap | NIFTY 100 Smallcap |
|---------------------------|-----------------|-----------|-----------|----------|-----------------|-------------------|
| **Descriptive statistics (during Covid-19 crisis)** | | | | | | |
| Mean                      | -0.005407       | -0.004032 | -0.004180 | -0.004104 | -0.005290       | -0.007292         |
| Median                    | -0.003452       | -0.002562 | -0.002045 | -0.003349 | -0.002235       | -0.001756         |
| Maximum                   | 0.052735        | 0.080907  | 0.078009  | 0.084003  | 0.062262        | 0.038050          |
| Minimum                   | -0.141488       | -0.136951 | -0.137440 | -0.139038 | -0.161268       | -0.141489         |
| SD                        | 0.030246        | 0.033567  | 0.033119  | 0.034472  | 0.034472        | 0.030678          |
| Skewness                  | -1.638857       | -0.947942 | -1.02350  | -0.889531 | -1.581714       | -1.804986         |
| Kurtosis                  | 8.237154        | 6.271935  | 6.457481  | 6.117423  | 8.449982        | 8.057926          |
| Jarque-Bera               | 104.9708        | 39.32481  | 44.39774  | 35.42932  | 109.2013        | 106.1899          |
| Probability               | 0.0000*         | 0.0000*   | 0.0000*   | 0.0000*   | 0.0000*         | 0.0000*           |
| Sum                       | -0.356849       | -0.266094 | -0.275872 | -0.270855 | -0.349163       | -0.481286         |
| Sum Sq. Dev.              | 0.059464        | 0.073238  | 0.071298  | 0.077241  | 0.075774        | 0.061172          |
| **Descriptive statistics (before Covid-19 crisis)** | | | | | | |
| Mean                      | 0.000413        | 0.000416  | 0.000399  | 0.000412  | 0.000375        | 0.000268          |
| Median                    | 0.001348        | 0.000615  | 0.000882  | 0.000502  | 0.001646        | 0.001456          |
| Maximum                   | 0.056954        | 0.052357  | 2.282477  | 0.051825  | 0.065349        | 0.064135          |
| Minimum                   | -0.091802       | -0.065062 | -2.269176 | -0.060973 | -0.115354       | -0.112157         |
| SD                        | 0.010841        | 0.009389  | 0.073759  | 0.009405  | 0.013509        | 0.012636          |
| Skewness                  | -0.592513       | -0.191141 | 0.197282  | -0.109443 | -0.589136       | -0.834901         |
| Kurtosis                  | 6.507937        | 5.551381  | 871.9234  | 5.432347  | 6.747806        | 7.413725          |
| Jarque-Bera               | 1,196.761       | 580.9856  | 65.907650 | 520.6271  | 1,347.292       | 1943.916          |
| Probability               | 0.0000*         | 0.0000*   | 0.0000*   | 0.0000*   | 0.0000*         | 0.0000*           |
| Sum                       | 0.865360        | 0.870875  | 0.834886  | 0.862779  | 0.786326        | 0.562081          |
| Sum Sq. Dev.              | 0.246095        | 0.184604  | 11.39218  | 1.85234   | 0.382143        | 0.334363          |

*Indicates rejecting H0 at 5% level of significance.
where, $R_t$ stands for index return at time $t$, $ln$ is natural logarithm, $Price_t$ and $Price_{t-1}$ are two consecutive daily closing price.

A dummy variable regression model is fitted to examine the days of the week and weekend effect as follows:

$$R_t = \alpha_1 + \beta_1 D_{1t} (\text{Tue}) + \beta_2 D_{2t} (\text{Wed}) + \beta_3 D_{3t} (\text{Thu}) + \beta_4 D_{4t} (\text{Fri}) + \epsilon_t \quad (1)$$

where $R_t$ represents index return at time $t$. $D_{1t}$, $D_{2t}$, $D_{3t}$, and $D_{4t}$ are the dummies for Tuesday, Wednesday, Thursday, and Friday, respectively, which are defined in the following (Table 1).

To avoid the dummy variable trap in the model, we have excluded the Monday's dummy in the equation. Here, the coefficient $\alpha_1$ represents the average return on Monday. Where as, the coefficient $\beta_1$-$\beta_4$ values show the shifts in the average returns from the benchmark day (here, Monday). A statistically significant $\alpha_1$ confirms the presence of weekend effect in the market. Similarly, a statistically significant values of $\beta_i$ (where, $i = 1, 2, 3, \text{and} 4$) confirm the presence of weekdays effect in the market. A statistically significant negative/positive $\beta_1$ indicates that the average return on Tuesday is lower/higher than the average return on Monday. In a similar way, we can interpret the remaining days as well. In the financial time series data, there is a high chance to face autocorrelation as well as heteroskedasticity problems in the simple regression model. The autocorrelation and heteroskedasticity problems are detected through DW and ARCH-LM statistics, respectively. To overcome these problems, we analyzed the day-of-the-week and weekend effect through Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The conditional mean equation takes care of autocorrelation issues in the error term, and the conditional variance equation takes care of heteroskedasticity issues in the error variance. The conditional mean and variance equation are expressed as follows:

**Conditional Mean Equation**

$$R_t = \alpha_1 + \Psi_1 R_{t-1} + \beta_1 D_{1t} (\text{Tue}) + \beta_2 D_{2t} (\text{Wed}) + \beta_3 D_{3t} (\text{Thu}) + \beta_4 D_{4t} (\text{Fri}) + \epsilon_t \quad (2)$$

$$\epsilon_t \sim (0, h_t)$$

**Conditional Variance Equation**

$$h_t = \phi_1 + \sum_{i=1}^{p} \sigma_i ^2 \epsilon_{t-i} + \sum_{j=1}^{q} \delta_j \epsilon_{t-j}^2 + \epsilon_t \quad (3)$$

Here, this conditional means equation is just an extension of Equation (1), the dummy variable regression equation, by including an autoregressive term of the return series. The minimum SC and AIC criteria are used for selection of the number of autoregressive terms. In Equation (2), $\alpha_1$ is the intercept coefficient, which measures direction and the degree of weekend effect that is Monday effect on index return, the coefficients $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ measures direction, and the degree of week days effect (Tuesday, Wednesday, Thursday, and
**TABLE 4**  Dummy variable regression results

\[ R_t = \alpha + \beta_1 D_{1t} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \epsilon_t \]

### Nifty 50 (during COVID-19 crisis)

| Variable   | Coefficients | SE    | t-statistics | Probability |
|------------|--------------|-------|--------------|-------------|
| Intercept  | −0.030847**  | 0.008631 | −3.574147   | 0.0007      |
| Tuesday    | 0.041566*    | 0.012704 | 3.271879    | 0.0018      |
| Wednesday  | 0.031932**   | 0.012206 | 2.616157    | 0.0112      |
| Thursday   | 0.030900**   | 0.012206 | 2.531629    | 0.0139      |
| Friday     | 0.032219**   | 0.012704 | 2.536132    | 0.0138      |

### Nifty 50 (before COVID-19 crisis)

| Variable   | Coefficients | SE    | t-statistics | Probability |
|------------|--------------|-------|--------------|-------------|
| Intercept  | 0.000363     | 0.000520 | 0.698047    | 0.4852      |
| Tuesday    | −0.000256    | 0.000738 | −0.347360   | 0.7283      |
| Wednesday  | 0.000382     | 0.000738 | 0.518324    | 0.6043      |
| Thursday   | −0.000165    | 0.000740 | −0.222697   | 0.8238      |
| Friday     | 0.000370     | 0.000741 | 0.499063    | 0.6178      |

### Nifty 100 (during COVID-19 crisis)

| Variable   | Coefficients | SE    | t-statistics | Probability |
|------------|--------------|-------|--------------|-------------|
| Intercept  | −0.029816*   | 0.008420 | −3.541173   | 0.0008      |
| Tuesday    | 0.040188*    | 0.012393 | 3.242678    | 0.0019      |
| Wednesday  | 0.031061**   | 0.011907 | 2.608563    | 0.0114      |
| Thursday   | 0.029646**   | 0.011907 | 2.489750    | 0.0155      |
| Friday     | 0.030798**   | 0.012393 | 2.485067    | 0.0157      |

### Nifty 100 (before COVID-19 crisis)

| Variable   | Coefficients | SE    | t-statistics | Probability |
|------------|--------------|-------|--------------|-------------|
| Intercept  | 0.001038**   | 0.000520 | 1.997747    | 0.0458      |
| Tuesday    | −0.000745    | 0.000738 | 1.009915    | 0.3126      |
| Wednesday  | −0.000756    | 0.000737 | 1.025826    | 0.3050      |
| Thursday   | −0.000281    | 0.000739 | 0.380208    | 0.7038      |
| Friday     | −0.001235    | 0.000740 | 1.668827    | 0.0952      |

### Nifty 200 (during COVID-19 crisis)

| Variable   | Coefficients | SE    | t-statistics | Probability |
|------------|--------------|-------|--------------|-------------|
| Intercept  | −0.029531*   | 0.008317 | −3.550819   | 0.0007      |
| Tuesday    | 0.039313*    | 0.012242 | 3.211373    | 0.0021      |
| Wednesday  | 0.030633**   | 0.011762 | 2.604484    | 0.0115      |
| Thursday   | 0.029223**   | 0.011762 | 2.484858    | 0.0157      |
| Friday     | 0.030287**   | 0.012242 | 2.474056    | 0.0162      |

### Nifty 200 (before COVID-19 crisis)

| Variable   | Coefficients | SE    | t-statistics | Probability |
|------------|--------------|-------|--------------|-------------|
| Intercept  | −0.000615    | 0.003578 | −0.171755   | 0.8636      |
| Tuesday    | 0.006322     | 0.005072 | 1.246367    | 0.2128      |
| Wednesday  | 0.000825     | 0.005075 | 0.162522    | 0.8709      |
| Thursday   | 0.001084     | 0.005094 | 0.212818    | 0.8315      |
| Friday     | −0.003215    | 0.005091 | −0.631610   | 0.5277      |

### NIFTY 50 midcap (during COVID-19 crisis)

| Variable   | Coefficients | SE    | t-statistics | Probability |
|------------|--------------|-------|--------------|-------------|
| Intercept  | −0.030435*   | 0.008656 | −3.515986   | 0.0008      |

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(Continued)

$$R_t = a_1 + \beta_1 D_{1t}(\text{Tue}) + \beta_2 D_{2t}(\text{Wed}) + \beta_3 D_{3t}(\text{Thu}) + \beta_4 D_{4t}(\text{Fri}) + \epsilon_t$$

| Day   | $\hat{a}_t$ | $\hat{\beta}_t$ | $R^2$   | D-W Stat | F Stat | ARCH LM (5)* |
|-------|-------------|-----------------|---------|----------|--------|--------------|
| Tuesday | 0.037273* | 0.012741 | 2.925319 | 0.0048   |        |              |
| Wednesday | 0.032451** | 0.012242 | 2.650924 | 0.0102   |        |              |
| Thursday  | 0.029551** | 0.012242 | 2.414005 | 0.0188   |        |              |
| Friday    | 0.028685** | 0.012741 | 2.251293 | 0.0280   |        |              |

R-squared: 0.155544; D-W Stat: 2.228741; F Stat: 2.808963 (0.033099); ARCH LM (5)*: 2.582570 (0.7640)

Nifty 50 midcap (before COVID-19 crisis)

| Day   | $\hat{a}_t$ | $\hat{\beta}_t$ | $R^2$   | D-W Stat | F Stat | ARCH LM (5)* |
|-------|-------------|-----------------|---------|----------|--------|--------------|
| Tuesday | −0.000259 | 0.000951 | −0.272065 | 0.7856   |        |              |
| Wednesday | −0.000931 | 0.000950 | −0.979504 | 0.3274   |        |              |
| Thursday  | 0.000134  | 0.000955 | 0.140178  | 0.8885   |        |              |
| Friday    | −0.002709* | 0.000955 | −2.836269 | 0.0046   |        |              |

R-squared: 0.003874; D-W Stat: 1.761823; F Stat: 2.961729 (0.018679); ARCH LM (5)*: 472.0176 (0.0000)

NIFTY 100 Smallcap (during COVID-19 crisis)

| Day   | $\hat{a}_t$ | $\hat{\beta}_t$ | $R^2$   | D-W Stat | F Stat | ARCH LM (5)* |
|-------|-------------|-----------------|---------|----------|--------|--------------|
| Tuesday | 0.029133** | 0.011625 | 2.506130  | 0.0149   |        |              |
| Wednesday | 0.027537** | 0.011169 | 2.465562  | 0.0165   |        |              |
| Thursday  | 0.024528** | 0.011169 | 2.196206  | 0.0319   |        |              |
| Friday    | 0.024777** | 0.011625 | 2.131454  | 0.0371   |        |              |

R-squared: 0.129304; D-W Stat: 1.758059; F Stat: 2.264732 (0.072441); ARCH LM (5)*: 0.005981 (0.4152)

NIFTY 100 Smallcap (before COVID-19 crisis)

| Day   | $\hat{a}_t$ | $\hat{\beta}_t$ | $R^2$   | D-W Stat | F Stat | ARCH LM (5)* |
|-------|-------------|-----------------|---------|----------|--------|--------------|
| Tuesday | −0.000296 | 0.000555 | −0.533614 | 0.0007   |        |              |
| Wednesday | −0.000988 | 0.000736 | −1.342508 | 0.1795   |        |              |
| Thursday  | −0.000130 | 0.000738 | −0.176227 | 0.8601   |        |              |
| Friday    | −0.001711** | 0.000739 | −2.315743 | 0.0206   |        |              |

R-squared: 0.002002; D-W Stat: 1.673539; F Stat: 1.756107 (0.134867); ARCH LM (5)*: 494.1309 (0.0000)

Note: Authors calculation based on the data obtained from https://www.investing.com. * and ** indicate significant at 1% and 5% levels, respectively.

Friday) on index return. In Equation (3), $h_t$ is the conditional variance of $\epsilon_t$. $\Phi_1$ is the constant term, $\omega_1$ is the Auto Regressive Conditional Heteroscedasticity (ARCH) coefficient which measures the influence of past squared residuals, that is, $\epsilon_{t-1}^2$ on recent volatility, $\omega_2$ is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) coefficient which measures the influence of recent past period’s volatility on current volatility at time $t$. Here, $\omega_1 + \omega_2 \leq 1$. In the conditional variance equation, $\Phi_1$ is the intercept coefficient, which measures direction and the degree of weekend effect that is Monday effect on index return.
### Table 5: GARCH (1, 1) test results

#### Conditional mean equation: \( R_t = \alpha_1 + \psi_1 R_{t-1} + \beta_2 D_{2t} + \beta_3 D_{3t} + \beta_4 D_{4t} + \epsilon_t \)

#### Conditional variance equation: \( h_t = \omega + \Sigma p_i \epsilon_{t-i}^2 + \Sigma q_j \sigma_{t-j}^2 + \epsilon_t \)

| Variable                | Coefficients | SE     | t-statistics | Probability |
|-------------------------|--------------|--------|--------------|-------------|
| Nifty 50 (during COVID-19 crisis) |              |        |              |             |
| Intercept (\( \alpha_1 \)) | -0.010565*   | 0.002403 | -4.395795   | 0.0000      |
| Tuesday (\( \beta_1 \))    | 0.015560**   | 0.004886 | 3.184537    | 0.0014      |
| Wednesday (\( \beta_2 \)) | 0.018676*    | 0.004971 | 3.757304    | 0.0002      |
| Thursday (\( \beta_3 \))   | 0.010971**   | 0.004758 | 2.305678    | 0.0211      |
| Friday (\( \beta_4 \))     | 0.005370     | 0.004811 | 1.116236    | 0.2643      |
| **Variance equation**      |              |        |              |             |
| C                         | 0.328554     |        | 2.286535    | 0.0223      |
| RESID(-1) 2               |              |        |              |             |
| GARCH(-1)                 |              |        | 3.146296*   | 0.0017      |
| R-squared: 0.081112; D-W Stat: 2.379322; ARCH LM (5)*: 4.819309 (0.4383) | | | | |
| **Nifty 50 (before COVID-19 crisis)** |              |        |              |             |
| Intercept (\( \alpha_1 \)) | 0.000803**   | 0.000326 | 2.462782    | 0.0138      |
| Tuesday (\( \beta_1 \))    | -0.000249    | 0.000495 | -0.502321   | 0.6154      |
| Wednesday (\( \beta_2 \)) | 3.26E-05     | 0.000513 | 0.063535    | 0.9493      |
| Thursday (\( \beta_3 \))   | -0.000162    | 0.000477 | -0.339417   | 0.7343      |
| Friday (\( \beta_4 \))     | 2.70E-05     | 0.000463 | 0.058247    | 0.9536      |
| **Variance equation**      |              |        |              |             |
| C                         | 5.808981     |        | 14.19601    | 0.0000      |
| RESID(-1) 2               |              |        |              |             |
| GARCH(-1)                 |              |        | 142.3818*   | 0.0000      |
| R-squared: 0.000268; D-W Stat: 1.883340; ARCH LM (5)*: 3.084463 (0.6870) | | | | |
| **Nifty 100 (during COVID-19 crisis)** |              |        |              |             |
| Intercept (\( \alpha_1 \)) | -0.010654*   | 0.002561 | -4.160750   | 0.0000      |
| Tuesday (\( \beta_1 \))    | 0.014523*    | 0.004854 | 2.992144    | 0.0028      |
| Wednesday (\( \beta_2 \)) | 0.018416*    | 0.004894 | 3.762715    | 0.0002      |
| Thursday (\( \beta_3 \))   | 0.011207**   | 0.004802 | 2.334052    | 0.0196      |
| Friday (\( \beta_4 \))     | 0.005940     | 0.004773 | 1.244541    | 0.2133      |
| **Variance equation**      |              |        |              |             |
| C                         | 0.264042     |        | 2.288735    | 0.0221      |
| RESID(-1) 2               |              |        |              |             |
| GARCH(-1)                 |              |        | 3.056383*   | 0.0022      |
| R-squared: 0.082719; D-W Stat: 2.363569; ARCH LM (5)*: 4.736292 (0.4489) | | | | |

(Continues)
Conditional mean equation: $R_t = \alpha_1 + \Psi_1 R_{t-1} + \beta_1 D_{1t}(\text{Tue}) + \beta_2 D_{2t}(\text{Wed}) + \beta_3 D_{3t}(\text{Thu}) + \beta_4 D_{4t}(\text{Fri}) + \epsilon_t$

| Variance equation | \( \phi_1 + \sum_{i=1}^{\infty} \phi_i \sigma_i^2 + \sum_{i=1}^{\infty} \delta_i \sigma_i^2 + \epsilon_t \) |

### Nifty 100 (before COVID-19 crisis)

| Intercept \((\alpha_1)\) & 0.000977* & 0.000329 & 2.972401 & 0.0030 |
| Tuesday \((\beta_1)\) & -0.000124 & 0.000461 & -0.268171 & 0.7886 |
| Wednesday \((\beta_2)\) & -0.000329 & 0.000501 & -0.655620 & 0.5121 |
| Thursday \((\beta_3)\) & -0.000193 & 0.000505 & -0.381623 & 0.7027 |
| Friday \((\beta_4)\) & -0.000513 & 0.000498 & -1.029667 & 0.3032 |

### Variance equation

| \( C \) & 6.442531 & 0.0000 |
| \( \text{RESID}(-1)^2 \) & 14.63304 & 0.0000 |
| \( \text{GARCH}(-1) \) & 139.9923* & 0.0000 |

R-squared: 0.000026; D-W Stat: 1.860377; ARCH LM (5)*: 3.233048 (0.6641)

### Nifty 200 (during COVID-19 crisis)

| Intercept \((\alpha_1)\) & -0.001084* & 0.002582 & -4.198520 & 0.0000 |
| Tuesday \((\beta_1)\) & 0.014455* & 0.004830 & 2.992881 & 0.0028 |
| Wednesday \((\beta_2)\) & 0.018136* & 0.004852 & 3.737700 & 0.0002 |
| Thursday \((\beta_3)\) & 0.011489* & 0.004857 & 2.365248 & 0.0180 |
| Friday \((\beta_4)\) & 0.006385 & 0.004700 & 1.358421 & 0.1743 |

### Variance equation

| \( C \) & 0.251803 & 0.8012 |
| \( \text{RESID}(-1)^2 \) & 2.298744 & 0.0215 |
| \( \text{GARCH}(-1) \) & 1.358421 & 0.1743 |

R-squared: 0.084245; D-W Stat: 2.346547; ARCH LM (5)*: 4.679429 (0.4562)

### Nifty 200 (before COVID-19 crisis)

| Intercept \((\alpha_1)\) & -0.000615 & 0.036956 & -0.016630 & 0.9867 |
| Tuesday \((\beta_1)\) & 0.006322 & 0.055972 & 0.112948 & 0.9101 |
| Wednesday \((\beta_2)\) & 0.000825 & 0.058132 & 0.014189 & 0.9887 |
| Thursday \((\beta_3)\) & 0.001084 & 0.065358 & 0.016586 & 0.9868 |
| Friday \((\beta_4)\) & -0.003215 & 0.043298 & -0.074260 & 0.9408 |

### Variance equation

| \( C \) & 4.851642 & 0.0000 |
| \( \text{RESID}(-1)^2 \) & 9.505933 & 0.0000 |
| \( \text{GARCH}(-1) \) & 7.490403* & 0.0000 |

R-squared: 0.001733; D-W Stat: 3.249133; ARCH LM (5)*: 724.0037 (0.0000)

### NIFTY 50 midcap (during COVID-19 crisis)
TABLE 5 (Continued)

| Conditional mean equation: $R_t = \alpha_1 + \Psi_1 R_{t-1} + \beta_1 D_1(Tue) + \beta_2 D_2(Wed) + \beta_3 D_3(Thu) + \beta_4 D_4(Fri) + \epsilon_t$ | Conditional variance equation: $h_t = \Phi_1 + \sum_{i=1}^{p} \phi_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \delta_j h_{t-j} + \omega_i \epsilon_t^2$ |
|---|---|
| Intercept ($\alpha_1$) | -0.012468* |
| Tuesday ($\beta_1$) | 0.014496** |
| Wednesday ($\beta_2$) | 0.017792* |
| Thursday ($\beta_3$) | 0.013200** |
| Friday ($\beta_4$) | 0.007166 |
| Variance equation | |
| C | 0.266396 |
| RESID(-1) 2 | 2112075 |
| GARCH(-1) | 2218642** |
| R-squared: 0.087740; D-W Stat: 2.298615; ARCH LM (5)*: 5.253362 (0.0357) |

NIFTY 50 midcap (before COVID-19 crisis)

| Intercept ($\alpha_1$) | 0.001061** |
| Tuesday ($\beta_1$) | 1.039758 |
| Wednesday ($\beta_2$) | -0.000904 |
| Thursday ($\beta_3$) | -5.84977 |
| Friday ($\beta_4$) | -0.001623** |
| Variance equation | |
| C | 7.554555 |
| RESID(-1) 2 | 1586887 |
| GARCH(-1) | 1188088* |
| R-squared: 0.002704; D-W Stat: 1.761039; ARCH LM (5)*: 2.986370 (0.7021) |

NIFTY 100 Smallcap (during COVID-19 crisis)

| Intercept ($\alpha_1$) | -0.014581* |
| Tuesday ($\beta_1$) | 0.016391* |
| Wednesday ($\beta_2$) | 0.018776* |
| Thursday ($\beta_3$) | 0.016455* |
| Friday ($\beta_4$) | 0.011254 |
| Variance equation | |
| C | 0.271684 |
| RESID(-1) 2 | 2030279 |
| GARCH(-1) | 2833986* |
| R-squared: 0.074961; D-W Stat: 1.779833; ARCH LM (5)*: 0.851568 (0.9736) |

NIFTY 100 Smallcap (before COVID-19 crisis)

| Intercept ($\alpha_1$) | 0.000709 |
| Variance equation | |
| C | 0.271684 |
| RESID(-1) 2 | 2030279 |
| GARCH(-1) | 2833986* |
| R-squared: 0.074961; D-W Stat: 1.779833; ARCH LM (5)*: 0.851568 (0.9736) |

(Continues)
TABLE 5 (Continued)

| Conditional mean equation: $R_t = \alpha_1 + \Psi_1 R_{t-1} + \beta_1 D_{2T}(\text{Tue}) + \beta_2 D_{2T}(\text{Wed}) + \beta_3 D_{2T}(\text{Thu}) + \beta_4 D_{2T}(\text{Fri}) + \epsilon_t$ |
|---------------------------------------------------------------|
| Tuesday ($\beta_1$) | 0.001018 | 0.000581 | 1.754018 | 0.0794 |
| Wednesday ($\beta_2$) | 0.000178 | 0.000565 | 0.315473 | 0.7524 |
| Thursday ($\beta_3$) | 0.000125 | 0.000618 | 0.202592 | 0.8395 |
| Friday ($\beta_4$) | 0.000313 | 0.000597 | 0.524262 | 0.6001 |

| Variance equation |
|-------------------|
| $\sigma^2_t = \phi_1 + \sum_{i=1}^{p} \phi_i \sigma^2_{t-i} + \sum_{j=1}^{q} \delta_j \epsilon^2_{t-j} + \epsilon_t$ |
| Tuesday ($\phi_1$) | 10.75607 | 0.0000 |
| Wednesday ($\phi_2$) | 18.96775 | 0.0000 |
| Thursday ($\phi_3$) | 79.29535 | 0.0000 |

R-squared: 0.001778; D-W Stat: 1.975475; ARCH LM (5): 3.171062 (0.6736)

| NIFTY100 MIDCAP (during COVID-19 crisis) |
|-----------------------------------------|
| Intercept ($\alpha_1$) | $-0.011817^*$ | 0.003315 | $-3.564722$ | 0.0004 |
| Tuesday ($\beta_1$) | 0.014043** | 0.005920 | 2.372274 | 0.0177 |
| Wednesday ($\beta_2$) | 0.017036* | 0.004802 | 3.547471 | 0.0004 |
| Thursday ($\beta_3$) | 0.013872* | 0.005013 | 2.767129 | 0.0057 |
| Friday ($\beta_4$) | 0.008709 | 0.004921 | 1.769734 | 0.0768 |

| Variance equation |
|-------------------|
| $\sigma^2_t = \sigma^2_{t-1} + \epsilon^2_t$ |
| Tuesday ($\phi_1$) | 0.257164 | 0.7971 |
| Wednesday ($\phi_2$) | 2.030392 | 0.0423 |
| Thursday ($\phi_3$) | 2.457389** | 0.0140 |

R-squared: 0.079694; D-W Stat: 2.165905; ARCH LM (5): 3.091828 (0.0658)

| NIFTY100 MIDCAP (before COVID-19 crisis) |
|-----------------------------------------|
| Intercept ($\alpha_1$) | $0.001272^*$ | 0.000380 | 3.343975 | 0.0008 |
| Tuesday ($\beta_1$) | $-0.000389$ | 0.000502 | $-0.775281$ | 0.4382 |
| Wednesday ($\beta_2$) | $-0.000809$ | 0.000546 | $-1.482344$ | 0.1382 |
| Thursday ($\beta_3$) | $-0.000110$ | 0.000548 | $-0.200818$ | 0.8408 |
| Friday ($\beta_4$) | $-0.000762$ | 0.000529 | $-1.441101$ | 0.1496 |

| Variance equation |
|-------------------|
| $\sigma^2_t = \sigma^2_{t-1} + \epsilon^2_t$ |
| Tuesday ($\phi_1$) | 9.518787 | 0.0000 |
| Wednesday ($\phi_2$) | 15.71263 | 0.0000 |
| Thursday ($\phi_3$) | 98.81277 | 0.0000 |

R-squared: 0.000457; D-W Stat: 1.672431; ARCH LM (5): 3.761102 (0.5843)

Note: Authors calculation based on the data obtained from https://www.investing.com. * and ** indicate significance at 1% and 5% levels, respectively.
RESULT ANALYSIS

Descriptive statistics

This part analyzes the stochastic properties of the stock return of Nifty 50, Nifty Midcap 50, Nifty 100, Nifty Midcap 100, Nifty Smallcap 100, Nifty 200 for the before COVID-19 and during COVID-19 period. The descriptive statistics for all indices are reported in Table 2. To check the normality of the frequency distribution in each indices series, the skewness and kurtosis are considered. The result of descriptive statistics reveals that distributions of all indices are skewed. The null hypothesis of Jarque-Bera test statistics is a joint hypothesis of the skewness being zero and the excess kurtosis being zero. The Jarque-Bera normality test results reveal that null hypothesis is rejected at 1% levels of significance, which is concluding that none of the indices is normally distributed.

Unit root test results

To avoid spurious estimation, we need to conduct some preestimation test such as unit root test. Generally, time series data exhibit non-stationary behavior, like trend effects and random walk which lead to a nonsense results while analyzing relationship between a given set variables. Therefore, to capture a stationary condition we employ Augmented Dickey-fuller (ADF, 1984) and Phillips-Perron (PP, 1988) unit root tests. The Augmented Dickey-fuller (ADF, 1984) and Phillips-Perron (PP, 1988) unit root test results are reported in Table 3. Both ADF and PP statistics are significant for before and during COVID-19 at 5% level suggesting that all the index return series, that is, Nifty 50, Nifty Midcap 50, Nifty 100, Nifty Midcap 100, Nifty Smallcap 100, Nifty 200 are stationary and can be useful for further time series analysis.

Dummy variable regression results

The dummy variable regression model for before and during COVID-19 results are reported in Table 3 for Nifty 50, Nifty Midcap 50, Nifty 100, Nifty Midcap 100, Nifty Smallcap 100. The dummy variable regression results show that there exists day-of-the-week (DOW) effect on all index return for during COVID-19 but no day-of-the-week (DOW) effect on all index return for before COVID-19 period (except Nifty 100, Nifty Midcap 100, Nifty Midcap50). The return (all indices) for during COVID-19 period is positive for all the days of the week except on Monday, the return is the highest on Thursday. The reported ARCH-LM and Durbin-Watson (DW) test statistics confirm no heteroscedasticity and autocorrelation problems in the during COVID-19 model. But, the reported ARCH-LM and Durbin-Watson (DW) test statistics of the COVID-19 model reflect there is presence of heteroscedasticity as well as serious autocorrelation problems in the model. To overcome these heteroscedasticity and serious autocorrelation problems, this study switched to GARCH (1, 1) model and the results are reported in Table 4 for Nifty 50, Nifty Midcap 50, Nifty 100, Nifty Midcap 100, Nifty Smallcap 100, Nifty 200.

4.4 GARCH model result

To overcome autocorrelation and heteroscedasticity issues, this study switched to Generalized Autoregressive Conditional Heteroskedasticity model, and the results of GARCH are reported in Table 5. The lower and upper panel of the Table 5 represent variance and mean equation, respectively. Based on the minimum Akaike information criterion (AIC) and Schwartz (SC) information criteria, one autoregressive term is included in the mean equation for all indices. The ARCH-LM test statistics is used after obtaining the autoregressive model residuals to analyze volatility characteristics. The reported ARCH-LM and Durbin-Watson (DW) test statistics confirm no heteroscedasticity and autocorrelation problems in both the model (before and during COVID-19 model). The coefficient $\alpha_1$ (the intercept coefficient) measures direction and the degree of weekend effect, that is, Monday effect on index return, it is negative and statistically significant at 1% level for all indices during COVID-19 crisis indicating a negative weekend effect on return. This finding is in contrast with some of the research studies which were found positive weekend effect on return (Du Toit et al., 2018; Mitra, 2016; Patil & Panda, 2018). The coefficient $\beta_1$ measures direction and the degree of days of the effect, that is, the Tuesday effect on index return; it is found to be statistically significant and positive level for all indices during COVID-19 crisis indicating a positive Tuesday effect on return. This finding is in contrast with Patil & Panda, 2018. In addition to this, we also found a positive Wednesday effect for all indices during COVID-19 crisis, and the returns on Tuesday are higher than the returns on Tuesday and Thursday. The empirical results suggest that the coefficient for Friday effect is statistically insignificant for all indices. The Monday effect coefficient ($\alpha_1$) for before-COVID-19 crisis is found to be statistically significant and positive return for all indices except Nifty200 (no Day-of-the-Week effect) and Nifty 100 smallcap (positive Tuesday effect).

5 CONCLUSION

The main objective of this study is to investigate the existence and possible changes of day-of-the-week effect before and during the COVID-19 health crisis. This paper has empirically investigated the existence of day-of-the-week effect by using closing daily data for Nifty 50, Nifty 50 Midcap, Nifty 100, Nifty100 midcap, Nifty 200, Nifty 100 Smallcap. The study period starts from 1 April 2005 to 14 May 2020. The ARCH-LM and Durbin-Watson (DW) test statistics of the COVID-19 model reflect there is presence of heteroscedasticity as well as serious autocorrelation problems in the model. To overcome these heteroscedasticity and serious autocorrelation problems, this study switched to Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. This study found a strong evidence of a negative return
for Mondays when the during-COVID-19 health crisis period is examined, but it is positive for the before-COVID-19 period. This finding is in contrast with some of the research studies which were found positive weekend effect on return (Du Toit et al., 2018; Mitra, 2016; Païtal & Panda, 2018). Tuesday effect on index return is found statistically significant and positive for all indices during COVID-19 crisis. In addition to this, the present study also revealed coefficients for Tuesday, Wednesday, Thursday, and Friday effect are insignificant for all index except Nifty 50 smallcap (Friday negative return) and Nifty 100 Midcap Tuesday positive return.

DATA AVAILABILITY STATEMENT
I used secondary data for this work. This study used secondary data for all indices over the period from 1st April 2005 to 14th May 2020. All the data are obtained electronically from https://www.investing.com.

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