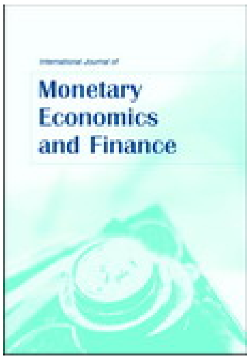


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# Impact of novel coronavirus outbreak-related announcements on pharmaceutical stocks: empirical evidence from an emerging market

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# Impact of novel coronavirus outbreak-related announcements on pharmaceutical stocks: empirical evidence from an emerging market


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**Abstract:** This study uses the event study method to examine the impact of COVID-19 outbreak-related announcements on the returns and volatility of 74 exchange-listed Indian pharmaceutical stocks. We find significant negative effects of pandemic-related announcements on stock returns and volatility in an emerging market, particularly during the declaration of a global pandemic. Further, small-cap stocks are hit harder than large-cap and mid-cap stocks. We also use abnormal volatility to assess the outbreak's impact on market volatility. We also find waning effects in the post-event window analysis. Our findings are consistent with current literature.

**Keywords:** event study; market model; abnormal return; abnormal volatility; emerging market; COVID-19; global pandemic.

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## 1 Introduction

The novel coronavirus disease 2019 (COVID-19) has claimed 317 million confirmed cases and 5.53 million deaths worldwide as of 12 January 2022.[1] The COVID-19 pandemic had a greater negative impact on financial markets than any previous pandemic (Baker et al., 2020), and neither emerging nor developed markets have been immune to the impacts (Pandey and Kumari, 2021a). However, the emerging markets, being less experienced, have been more sensitive than the developed markets (Harjoto et al., 2021; Pandey and Kumari, 2021a, 2021b). Both markets have experienced similar pandemic effects (Heyden and Heyden, 2021; Mirza et al., 2020; Pandey and Kumari, 2021a, 2021b). Exhaustive event study methodology and better insight of parametric and non-parametric test statistics could be found in Brown and Warner (1980, 1985), Dimson (1979), Dyckman et al. (1984). While Boehmer et al. (1991), Campbell and Wesley (1993), Corrado (1989), Corrado and Zivney (1992), and Cowan (1992) evidence the methodology, Ataullah et al. (2011), Kolari and Pynnönen (2010, 2011) and Park (2004) are an extension of event study methodologies (see Pandey and Kumari, 2021b for more literature). This event study is based on a review of the above literature. However, very few event studies have been conducted to examine the impact of COVID-19. Although event study literature lacks studies on the impact of COVID-19 on financial markets, sufficient literature evidencing the impacts of COVID-19 on financial markets and other financial assets are available. We focus on the studies that examine the impacts on stock returns and volatility.

### *1.1 Event studies on impacts of COVID-19 on stock returns*

Heyden and Heyden (2021) used the event study methodology with a sample of 867 firms to conclude that the US and European stock markets reacted differently to different pandemic news announcements. Pandey and Kumari (2021a) conducted an event study with 49 sample indices from developed and emerging markets to see how emerging and developed markets reacted to the COVID-19. Mazur et al. (2021) looked into the effects of the COVID-19 impacts on the S&P1500 firms using event study methodology to find that while natural gas, food, healthcare, and software stocks experienced positive returns, those in petroleum, real estate, entertainment, and hospitality sectors experienced negative returns. Pandey and Kumari (2020) used the event study method with 25 listed stocks to conclude the negative and significant impact of COVID-19 on the Indian tourism and hospitality industry. In their event study, Goodell and Huynh (2020) used a sample of 49 industries and evidenced no US market reaction on 30 January 2020 with an overall positive impact on medical and pharmaceutical products. Mittal and Sharma (2021) employed the event study method to examine the impacts of the first COVID-19 fatality on the Bombay Stock Exchange's healthcare and pharmaceutical index. They evidenced significant positive average and cumulative average abnormal returns during the event window. Using the event study method, Kumari et al. (2022) examine the impacts of the COVID-19 pandemic on the airline industry.

### *1.2 Event studies on impacts of COVID-19 on volatility*

In their event study, Kim et al. (2020) concluded that food-borne epidemics negatively impact the restaurant industry. Akhtaruzzaman et al. (2021) provide evidence of high return volatility during the COVID-19 period in China and G7 countries. Mirza et al. (2020) conducted an event study using 266 funds to demonstrate that the investment funds in Europe yielded negative cumulative abnormal returns (CARs) as the pandemic escalated Ali et al. (2020) examined how the returns and volatility in global markets are affected with the pandemic changing its center from China to Europe and the United Nations. David et al. (2020) showed a significant negative impact on eleven stock indices. These eleven stock indices included the Nifty. Maneenop and Kotcharin (2020), while examining the short-term impact on global airline stocks using an event study method, provide evidence for the overreaction of the market in event3 (event2 in our case), i.e., "the global pandemic declaration on 11 March 2020". Topcu and Gulal (2020) examined a sample of 26 emerging markets to see how COVID-19 affected these markets. They found that emerging markets in Asia were impacted more adversely than emerging markets in Europe. They also find that the impacts have fallen from mid-April onwards, and the stimulus packages led to market recovery. Zhang et al. (2020) show that COVID-19-related uncertainties have made the global markets highly volatile and unpredictable.

Studies on previous pandemic effects provide for significant negative impact on the hospitality and tourism industry in an emerging economy (Chen et al., 2009, 2007), although Chen et al. (2009) provide evidence for positive impacts on biotech stocks.

The literature review suggests two gaps in the COVID-19 event study literature. Firstly, available literature focuses on the global market as a whole (Ali et al., 2020; Heyden and Heyden, 2021; Pandey and Kumari, 2021a, 2021b), and more studies are available on developed markets (Goodell and Huynh, 2020; Heyden and Heyden, 2021; Maneenop and Kotcharin, 2020; Mazur et al., 2021; Mirza et al., 2020), but very few studies focus on emerging economies (Mittal and Sharma, 2021; Pandey and Kumari, 2020). Secondly, while Goodell and Huynh (2020) conducted an event study to examine the impact of COVID-19 on 49 industries in the United States, including the pharmaceutical industry, Mittal and Sharma (2021) used an event study to witness the impact on the Healthcare and Pharmaceutical sector in India using the index prices. Although Mittal and Sharma (2021) provide evidence of COVID-19 impacts on the pharmaceutical sector, the firm-level analysis is yet to be done. We aim to add to the COVID-19 event study literature by conducting the first event study on the pharmaceutical stocks listed in an emerging market like India. Further, we also introduce abnormal volatility (AV) in this study.

The pharmaceutical sector has received significant investor's attention during the pandemic. Healthcare systems of developed nations, including Italy, France, and UK, failed to control the pandemic. No prescribed medicines were available. However, the supporting medications kept the sector busy with its supplies to the healthcare systems. The market waited for the good news, and at that time, only two news seemed to be good, viz., a vaccine for the virus and a proper medicine for the treatment of the infections. The two medicines, hydroxychloroquine, and chloroquine were widely used as a treatment for COVID-19. On 28 March 2020, the United States Food and Drug Administration (USFDA) issued an Emergency Use Authorization (EUA) allowing the use of these drugs to treat certain hospitalised patients. Being the biggest supplier of these drugs, India experienced huge orders from developed nations, significantly from the United States. Zydus Cadila and Ipca Laboratories limited are amongst the largest manufacturers of these drugs.

There were clinical trials on the peak. The demand for pharmaceutical products was not at pause. Patients, specially COVID-19 patients, were yet advised over-the-counter medicines during the preliminary stage of the infection. It is expected that the pandemic outbreak does not impact the demand in this sector, and this would indeed hold the value of the pharmaceutical firms. Owing to this, either a neutral or positive response on the pharmaceutical stocks is expected, as also found in Chen et al. (2009), Goodell and Huynh (2020), and Rao et al. (2021). However, the overall market sentiment may wave out the stock returns in this sector in the short run. Based on these facts, we develop the hypothesis that "the abnormal returns on and around the event days are not significant" for the Indian pharmaceutical stocks.

## 2 Objective, scope, and methodology

### *2.1 Objective and scope*

This study examines the impacts of the COVID-19-related announcements on the listed Indian pharmaceutical stocks. For this purpose, we selected two announcements made by the World Health Organisation (WHO) and analysed the daily abnormal returns (ARs) around the selected event dates. The null hypothesis constructed for testing abnormal returns' significance is that "the abnormal returns are not significant on and around the event days."

Significant abnormal returns will indicate that the announcements have impacted the listed Indian pharmaceutical stocks and indicate that the stock market incorporates the new information. We also examine the post-event window period abnormal returns. Further, we also aim to provide evidence for abnormal volatility during the study period.

## 2.2 Sample and selection criteria

The study examines the impacts of two major COVID-19-related announcements on the exchange-listed Indian pharmaceutical stocks. Hence, the sample consists of the Indian pharmaceutical stocks listed on the National Stock Exchange (NSE) and the Bombay Stock Exchange (BSE). We selected the top 100 pharma stocks based on their market capitalisation, and the following selection criterion was adopted to arrive at the final sample:

1. must be listed on both BSE & NSE
2. must have traded during the estimation and the event period
3. the trading data must be available on the NSE website.

A final sample of 74 pharmaceutical stocks was selected based on the sample selection criterion for which the daily high, low, and closing prices have been collected from https://www.nseindia.com/

## 2.3 Methodology

We have used the Brown and Warner (1980, 1985) standard event methodology in this study. Hence, in the very first instance, we determine the event dates. We consider two significant event dates, viz. 30 January 2020 and 11 March 2020. The former is when the outbreak was declared a 'Public Health Emergency of International Concern' (hereafter e1), while the latter is when the outbreak was declared a 'Global Pandemic' (hereafter e2). The estimation period is 90 days which ranges between t-120 to t-31, and the event window consists of 61 days ranging between t-30 to t+30, where t is the event day.

We use the AR and the AV to examine the COVID-19 outbreak's impacts on pharmaceutical stocks. The ordinary least squares (OLS) market model yields better results (Dyckman et al., 1984; Mackinlay, 1997). Hence, for calculating the ARs, we run a regression using the NSE-Nifty index's actual returns as the independent variable over the estimation period to estimate the expected return on each day in the event window (equation (1)). First, we calculate the actual returns as the natural log of the current day's closing figure divided by the previous day's closing figure (Elad and Bongbee, 2017). The difference between the actual return so calculated and the expected return estimated through the regression is the AR that will be tested for significance (equation (2)).

$$ER_{st} = \alpha + \beta . LR_{mt} \tag{1}$$

$$AR_{st} = LR_{st} - ER_{st} \tag{2}$$

where

$ER_{st}$ is the estimated return of stock $s$ on day $t$

$\alpha$ & $\beta$ is the intercept and slope coefficients of the OLS regression model

$LR_{mt}$ is the log return of the market index (NIFTY) on day $t$

$AR_{st}$ is the abnormal return of the stock $s$ on day $t$

$LR_{st}$ is the log return of the stock $s$ on day $t$.

Similarly, we use the NSE-Nifty's actual volatility as the independent variable for calculating the AVs (equation (5)). Following Floros (2009), we calculate the actual volatility as "the first logarithmic difference between the intraday high and low values" (equations (3) and (4)). The difference between the actual and estimated volatility is the AV that will be tested for significance (equation (6)).

$$V_{st} = Ln(H_{st}) - Ln(L_{st}) \tag{3}$$

$$V_{mt} = Ln(H_{mt}) - Ln(L_{mt}) \tag{4}$$

$$EV_{st} = \alpha + \beta.V_{mt} \tag{5}$$

$$AV_{st} = V_{st} - EV_{st} \tag{6}$$

where

$V_{st}$ is the simple measure of the volatility of the stock *s* on day *t*

$V_{mt}$ is the simple measure of the volatility of the market index (NIFTY) on day *t*

$H_{st}$ and $L_{st}$ are the high and low figures of the stock *s* on day *t*

$H_{mt}$ and $L_{mt}$ are the high and low figures of the market index (NIFTY) on day *t*

$EV_{st}$ is the estimated volatility of stock *s* on day *t*

$\alpha$ & $\beta$ is the intercept and slope coefficients of the OLS regression model

$\mathrm{AV}_{\mathrm{st}}$ is the abnormal volatility of the stock *s* on day *t*.

For each sample stock, we have 151 observations each for AR and AV. Accordingly, 11174 observations are available for e1 and e2, each for AR and AV. We calculate the cumulative abnormal return (CAR) and cumulative abnormal volatility (CAV) of [–1,1], [–1,5], and [–1,13] periods for each of the stocks in both the events (equations (7) and (8)).

$$CAR_T = \sum_{s=1}^{n} AR_{st} \tag{7}$$

$$CAV_T = \sum_{s=1}^{n} AV_{st} \tag{8}$$

where

$CAR_T$ is the sum of the abnormal returns of stock s for the period *T*

$CAV_T$ is the sum of the abnormal volatility of stock *s* for the period *T*.

After that, we aggregate the abnormal returns and volatility across different stocks. We add the individual stock's ARs on each day in the event window and then divide the total AR on each day by the sample size, i.e., the number of stocks. The resultant is the average abnormal return (AAR) (equation (9)). Similarly, using the individual stock's AVs, we calculate the average abnormal volatility (AAV) (equation (10)). The AARs become the basis of calculating the cumulative average abnormal return (CAAR).

$$AAR_t = \frac{1}{N}\sum_{s=1}^{N} AR_{st} \tag{9}$$

$$AAV_t = \frac{1}{N}\sum_{s=1}^{N} AV_{st} \tag{10}$$

where

$AAR_t$ denotes the average abnormal return on day $t$

$AAV_t$ denotes the average abnormal volatility on day $t$

$N$ is the number of stocks.

We aggregate the estimation period standard deviation across different stocks. First, we add the estimation period variance of each of the stocks and divide the aggregate variance's square root, with the sample size (equation (11)). The resultant is the aggregated estimation period standard deviation. Next, we divide the AARs with the respective aggregated estimation period standard deviation to arrive at the test statistics (Brown and Warner, 1980, 1985) (equation (12)). Similarly, we calculate the test statistics for the CAARs (equation (13)).

$$\sigma_{N,e,r} = \sqrt{\frac{\sum_{s=1}^{N} \sigma_{s,e,r}^2}{N^2}} \tag{11}$$

$$t_{AARt} = \frac{AAR_t}{\sigma_{N,e,r}} \tag{12}$$

$$t_{CAARt} = \frac{CAAR_t}{\sigma_{N,e,r}\sqrt{N_{t+1}}} \tag{13}$$

where

$\sigma_{N,e,r}$ is the aggregate estimation period standard deviation for returns of N stocks

$\sigma_{s,e,r}$ is the estimation window standard deviation for returns of stock $s$

$t_{AARt}$ and $t_{CAARt}$ are the test statistics for AARs and CAARs on day $t$

$N_{t+1}$ denotes the absolute value (ignores the –ve sign) of event day $t$ plus 1.

### *2.4 Interpretation of results*

Based on the critical t-value in Table 1, the test statistic values obtained are used to interpret the empirical results. Further, the shorter window AARs and CAARs will also be tested for significance (as in Kolari and Pynnönen (2010), Mackinlay (1997), Pandey and Kumari (2021c), Park (2004), and many similar studies). If the calculated values are within the given range, the null hypothesis will be accepted, indicating that the AARs are insignificant. Significant negative values imply a negative impact, whereas significant positive values imply a positive impact.

**Table 1** Critical t-values

| *Sector* | *N* | *df* | *Critical t-value* | |
|---|---|---|---|---|
| | | | *1 % level* | *5% level* |
| All Data | 74 | 73 | –2.65 to + 2.65 | –1.99 to + 1.99 |
| Large-cap & Mid-cap | 15 | 14 | –2.98 to + 2.98 | –2.15 to + 2.15 |
| Small-cap | 44 | 43 | –2.70 to + 2.70 | –2.02 to + 2.02 |

*N* is the sample size, and df indicates the degree of freedom.

## 3 Empirical results and discussion

We move to quantitative analysis with 11174 daily ARs and AVs observations for each event. Since we use non-parametric tests for testing the significance, we do not conduct the normality test. The descriptive statistics of the CARs and CAVs of 3-day, 7-day, and 15-day window in e1 and e2 have been depicted in Table 2.

**Table 2** Descriptive statistics of the CARs and CAVs

| *Descriptive statistics* | | *e1* | | | *e2* | | |
|---|---|---|---|---|---|---|---|
| | | *[–1,1]* | *[–1,5]* | *[–1,13]* | *[–1,1]* | *[–1,5]* | *[–1,13]* |
| CARs | N | 74 | 74 | 74 | 74 | 74 | 74 |
| | Mean | –1.831 | –1.515 | –2.082 | –10.141 | –15.744 | –14.995 |
| | Standard error | 0.549 | 1.111 | 1.974 | 0.971 | 1.504 | 2.104 |
| | Median | –1.814 | –2.377 | –3.755 | –9.881 | –17.494 | –12.100 |
| | Standard deviation | 4.723 | 9.553 | 16.985 | 8.354 | 12.935 | 18.102 |
| CAVs | N | 74 | 74 | 74 | 74 | 74 | 74 |
| | Mean | 0.088 | 0.253 | 0.542 | 0.339 | 0.688 | 1.336 |
| | Standard error | 0.007 | 0.017 | 0.034 | 0.020 | 0.039 | 0.071 |
| | Median | 0.080 | 0.237 | 0.515 | 0.343 | 0.729 | 1.399 |
| | Standard deviation | 0.061 | 0.143 | 0.295 | 0.172 | 0.333 | 0.608 |

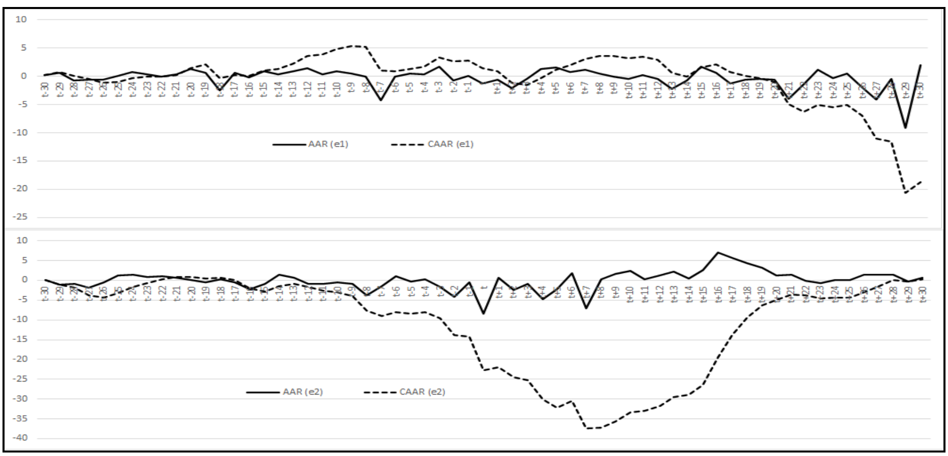
*Source*: Author's calculation

With high mean abnormal returns and volatility, Table 2 exhibits that the e1 abnormal returns and volatility have been less impacted, but the COVID-19 related global announcements have significantly impacted e2 abnormal returns and volatility. The e2 occurred in mid-March 2020, and the major crash could be noticed (Mazur et al., 2020). To provide empirical evidence, we further analyse the data in four parts: the entire sample, the capitalisation-wise sample, the post-event window period, and the abnormal volatility.

### *3.1 Impact of the outbreak on pharmaceutical stocks*

We present the AARs and CAARs for both events in Figure 1. Out of the 61-day event window, 30 negative AARs have been noticed in e1, with only 10 negative values during the pre-event day period. In comparison, 27 negative AARs have been noticed in e2, with 18 negative figures in the pre-event day period. Since e1 occurred before e2 and the market players already expected e2, the information is reflected by the market returns beforehand. The post-event day period evidence 19 and 8 negative AAR values in e1 and e2, respectively. It may be because e1 was not an anticipated event until it was declared a ‘public health emergency of international concern’, and the nations were advised to implement lockdowns and restrictions. There are only 22 negative CAARs in e1, including six negative values for the pre-event day period. In comparison, 51 negative CAARs have been noticed in e2, including 23 negative values in the pre-event day period. The post-event day CAARs evidence 15 and 28 negative values in e1 and e2, respectively. The gap between the AAR(e2) and CAAR(e2) curves is seen widening from *t*-11 onwards, with the gap being recovered from *t*+7 onwards, i.e., mid-April 2020 onwards, the market is seen recovering (Topcu and Gulal, 2020). Therefore, a negative impact has been noticed during e2 more than that in e1.

**Figure 1** AAR and CAAR-line during the event window in e1 and e2




*Source*: Based on the author’s calculation in MS-excel

The test statistics for the AARs and CAARs for both events are presented in Table 3. We find 11 significant pre-event day AARs for both the events, including 4 and 8, negatively significant in e1 and e2. While 16 and 19 post-event day AARs with 9 and 4 are negatively significant in e1 and e2, respectively. The AAR is negative and significant for both e1 and e2.

We find nine significant CAARs in the pre-event day period and 19 significant CAARs in the post-event day period in e1, with 12 negative and significant CAARs in the post-event day period only. The CAARs have been negatively significant in e2 through days t-9 to t+20. The event day CAAR is positively significant in e1 and negatively significant in e2. Negative and significant CAARs until t+20 in e2 indicate that the pharmaceutical stocks have been negatively impacted. Our results are in line with previous literature on epidemics (Chen et al., 2009, 2007; Pandey and Kumari, 2020).

The shorter window analysis has been presented in Table 4. The {–7,+7}, {–3,+3} and {–1,+1} AARs in e1 are not significant. The {–7,+7} CAAR is not significant, indicating that the impact of e1 on stock returns is not significant. The {–3,+3} and {–1,+1} CAARs are significant and indicate that the news had a short-term impact on the returns. However, the AARs and CAARs for all the short windows are significant in e2, indicating a significantly negative impact on the pharmaceutical industry's returns.

**Table 3** Test statistics for the AARs and CAARs of e1 and e2

| *Days* | $t_{AAR(e1)}$ | $t_{CAAR(e1)}$ | $t_{AAR(e2)}$ | $t_{CAAR(e2)}$ | *Days* | $t_{AAR(e1)}$ | $t_{CAAR(e1)}$ | $t_{AAR(e2)}$ | $t_{CAAR(e2)}$ |
|---|---|---|---|---|---|---|---|---|---|
| t–30 | 0.66 | 0.12 | 0.06 | 0.01 | t | –4.01[a] | 4.48[a] | –16.13[a] | –43.81[a] |
| t–29 | 1.67 | 0.43 | –2.15[b] | –0.38 | t+1 | –1.87 | 1.85 | 1.40 | –29.99[a] |
| t–28 | –2.03[b] | 0.06 | –1.63 | –0.69 | t+2 | –6.19[a] | –2.06[b] | –4.88[a] | –27.31[a] |
| t–27 | –1.89 | –0.30 | –3.74[a] | –1.41 | t+3 | –1.29 | –2.43[b] | –1.74 | –24.52[a] |
| t–26 | –1.73 | –0.64 | –1.00 | –1.63 | t+4 | 3.79[a] | –0.48 | –9.06[a] | –25.98[a] |
| t–25 | 0.17 | –0.62 | 2.39[b] | –1.19 | t+5 | 4.64[a] | 1.46 | –4.17[a] | –25.42[a] |
| t–24 | 2.20[b] | –0.19 | 2.83[a] | –0.65 | t+6 | 2.18[b] | 2.17[b] | 3.39[a] | –22.25[a] |
| t–23 | 0.98 | 0.00 | 1.81 | –0.29 | t+7 | 3.52[a] | 3.28[a] | –13.65[a] | –25.64[a] |
| t–22 | –0.36 | –0.07 | 1.94 | 0.11 | t+8 | 1.48 | 3.58[a] | 0.50 | –24.01[a] |
| t–21 | 0.89 | 0.12 | 1.15 | 0.36 | t+9 | –0.02 | 3.39[a] | 2.97[a] | –21.84[a] |
| t–20 | 3.82[a] | 0.95 | 0.00 | 0.37 | t+10 | –1.28 | 2.85[a] | 4.66[a] | –19.42[a] |
| t–19 | 1.89 | 1.40 | –0.81 | 0.19 | t+11 | 0.84 | 2.97[a] | 0.59 | –18.42[a] |
| t–18 | –7.36[a] | –0.25 | 0.58 | 0.33 | t+12 | –1.60 | 2.41[b] | 2.39[b] | –17.03[a] |
| t–17 | 1.72 | 0.14 | –1.16 | 0.07 | t+13 | –6.84[a] | 0.50 | 4.39[a] | –15.24[a] |
| t–16 | –0.48 | 0.03 | –4.20[a] | –0.95 | t+14 | –2.18[b] | –0.08 | 0.99 | –14.47[a] |
| t–15 | 2.81[a] | 0.74 | –1.57 | –1.37 | t+15 | 4.93[a] | 1.15 | 4.88[a] | –12.79[a] |
| t–14 | 0.95 | 1.01 | 2.59[b] | –0.75 | t+16 | 1.69 | 1.53 | 13.59[a] | –9.11[a] |
| t–13 | 2.68[a] | 1.76 | 1.33 | –0.42 | t+17 | –3.99[a] | 0.54 | 10.89[a] | –6.29[a] |
| t–12 | 4.28[a] | 3.01[a] | –1.78 | –0.93 | t+18 | –1.98 | 0.08 | 8.42[a] | –4.19[a] |
| t–11 | 0.99 | 3.42[a] | –1.70 | –1.46 | t+19 | –1.38 | –0.23 | 6.08[a] | –2.72[a] |
| t–10 | 2.62[b] | 4.36[a] | –0.80 | –1.76 | t+20 | –1.83 | –0.63 | 2.44[b] | –2.12[b] |
| t–9 | 1.58 | 5.07[a] | –1.81 | –2.42[b] | t+21 | –12.04[a] | –3.18[a] | 2.73[a] | –1.49 |
| t–8 | –0.16 | 5.29[a] | –7.16[a] | –4.94[a] | t+22 | –4.13[a] | –3.97[a] | –0.29 | –1.52 |
| t–7 | –12.96[a] | 1.03 | –2.68[a] | –6.18[a] | t+23 | 3.57[a] | –3.16[a] | –1.44 | –1.78 |
| t–6 | –0.17 | 1.04 | 1.88 | –5.90[a] | t+24 | –0.96 | –3.29[a] | 0.10 | –1.72 |
| t–5 | 1.32 | 1.66 | –0.53 | –6.59[a] | t+25 | 1.32 | –2.96[a] | 0.16 | –1.66 |
| t–4 | 0.87 | 2.21[b] | 0.65 | –6.93[a] | t+26 | –5.77[a] | –4.02[a] | 2.81[a] | –1.09 |
| t–3 | 5.27[a] | 5.10[a] | –3.18[a] | –9.33[a] | t+27 | –12.50[a] | –6.31[a] | 2.94[a] | –0.51 |
| t–2 | –2.06[b] | 4.70[a] | –7.99[a] | –15.39[a] | t+28 | –1.44 | –6.47[a] | 2.73[a] | 0.00 |
| t–1 | 0.36 | 6.01[a] | –1.03 | –19.58[a] | t+29 | –27.39[a] | –11.36[a] | –0.55 | –0.10 |
| t | –4.01[a] | 4.48[a] | –16.13[a] | –43.81[a] | t+30 | 5.80[a] | –10.13[a] | 1.22 | 0.12 |

*t* indicate the test statistic. [a]Significant at p-value of 0.01 (1% level); [b] Significant at p-value of 0.05 (5% level).

*Source*: Author's calculation

**Table 4** Shorter window test statistics

| *Window* | $t_{AAR(e1)}$ | $t_{CAAR(e1)}$ | $t_{AAR(e2)}$ | $t_{CAAR(e2)}$ |
|---|---|---|---|---|
| –7 to + 7 | –0.44 | –1.71 | –3.85[a] | –14.90[a] |
| –3 to + 3 | –1.40 | –3.70[a] | –4.79[a] | –12.68[a] |
| –1 to + 1 | –1.84 | –3.19[a] | –5.25[a] | –9.10[a] |

*t* indicate the test statistic. [a]Significant at a p-value of 0.01 (1% level). t indicates the test statistic. e1 and e2 are the event1 and event 2, respectively.

*Source*: Author's calculation

The empirical evidence suggests rejecting the null hypothesis, indicating that the abnormal returns are significant and negative on and around event days. Furthermore, the longer and shorter window abnormal returns have been statistically significant and negative, suggesting substantial adverse effects of COVID-19 on the exchange-listed Indian pharmaceutical stocks.

## *3.2 Impact of the outbreak on large, medium, and small-cap pharmaceutical stocks*

The sample has been further divided into three parts, viz., large-cap (15), mid-cap (15), and small-cap (44). Table 5 presents the number of significant AARs and CAARs for large-cap, mid-cap, and small-cap stocks during both events. The AARs and CAARs in e1 are primarily positive or negligible for large and mid-cap stocks, while they are mostly negative for the small-cap stocks. It is also evident that the post-event day period experienced more significant abnormal returns than the pre-event day period indicating that the market reacted to the information.

**Table 5** Number of significant AARs and CAARs for different samples during both the event window

| *Event* | *Stock-Cap* | *AARt* | | *CAARt* | |
|---|---|---|---|---|---|
| | | *Pre* | *Event & Post* | *Pre* | *Event & Post* |
| e1 | Large | 2 (1) | 12 (7*) | 0 (0) | 2 (2) |
| | Medium | 2 (1) | 13 (7) | 10 (0) | 27* (1) |
| | Small | 8 (2) | 13 (9*) | 6 (6) | 13 (10) |
| e2 | Large | 11 (5) | 18 (6*) | 2 (1) | 29 (15*) |
| | Medium | 11 (6) | 14 (5*) | 3 (3) | 22 (22*) |
| | Small | 8 (6) | 16 (5*) | 9 (9) | 26 (26*) |

*indicate the significant value on the event day. The figures in parenthesis indicate negative and significant.

*Source*: Author's calculation

More negative significant AARs and CAARs in e2 have been noticed with significant negative event day CAARs for all sized stocks. While the large and medium-cap stocks have been moderately impacted in e2, the pre and post-event day negative CAARs indicate that the small-cap stocks have been hit hard. Thus, the global pandemic declaration has impacted differently to different sized stocks.

Test statistics for the shorter window analysis of the large, medium, and small-cap stocks in both the events are depicted in Table 6. It is evident from the table that in e1 only the CAARs for small-cap stocks are significant and negative for {–7,+7}, {–3,+3} and {–1,+1} windows. In e2, significant and negative AARs and CAARs are noticed for both medium and small-cap stocks, while only {–1,+1} AAR and all CAARs are negative and significant for the large-cap stocks. The e2 impacts supersede that of e1.

**Table 6** Test statistics for large, medium, and small-cap stocks during e1 and e2

| *Event* | *Window* | $t_{AAR(Large)}$ | $t_{CAAR(Large)}$ | $t_{AAR(Mid)}$ | $t_{CAAR(Mid)}$ | $t_{AAR(Small)}$ | $t_{CAAR(Small)}$ |
|---|---|---|---|---|---|---|---|
| e1 | –7 to + 7 | 0.06 | 0.22 | 0.54 | 2.07 | –0.71 | –2.74[a] |
| | –3 to + 3 | –0.40 | –1.07 | –0.42 | –1.11 | –1.27 | –3.37[a] |
| | –1 to + 1 | –1.17 | –2.02 | –0.66 | –1.14 | –1.43 | –2.49[b] |
| e2 | –7 to + 7 | –1.12 | –4.32[a] | –3.58[a] | –13.88[a] | –3.02[a] | –11.68[a] |
| | –3 to + 3 | –1.98 | –5.23 [a] | –4.46[a] | –11.79[a] | –3.65[a] | –9.67[a] |
| | –1 to + 1 | –4.88[a] | –8.46[a] | –4.80[a] | –8.32[a] | –3.55[a] | –6.14[a] |

*t* indicate the test statistic. [a]Significant at p-value of 0.01 (1% level) [b] Significant at p-value of 0.05 (5% level).

*Source*: Author's calculation

In the above analysis of longer and shorter event windows, we find that the reaction to the COVID-19 events has been different on different-sized firms. Many factors impact the stock returns based on the firm's size. The pandemic period has resisted the profitability of the firms. Firms have difficulty generating profits during periods of crisis, such as COVID-19, which has a negative impact on their stock prices (Ding et al., 2021). During a crisis, large and medium-cap firms generate higher profits than small-cap firms due to their financial stability. Although smaller firms tend to be riskier, they outperform large-cap firms in the long run (Fama and French, 1995). However, in the short run, during the event window, we find that small-cap firms have been more negatively impacted.

## 3.3 *Post-event window period analysis*

Initially, the market responded proactively to the pandemic (Ali et al., 2020; Ashraf, 2020), but the impact faded gradually (Topcu and Gulal, 2020). The results of the post-event window analysis are reflected in Table 7. The pattern of significant AARs and CAARs in this period has been used to conclude.

Table 7 depicts the test statistics for the AARs and CAARs for the post-event window period from the t+31 day (30 April 2020). In the 30 days post-event window, 10 AARs, and five CAARs are significant. While all the significant CAARs are negative, only six significant AARs are negative. The significant AARs and CAARs do not follow any pattern, and the negative abnormal returns are not continuous; the COVID-19 impacts seem to be falling gradually. We find four positive AARs in the last 10 days of the post-event window period. Our results support Topcu and Gulal (2020).

**Table 7** Post-event period test statistics for AARs and CAARs

| *Days* | $t_{AAR(pe)}$ | $t_{CAAR(pe)}$ | *Days* | $t_{AAR(pe)}$ | $t_{CAAR(pe)}$ |
|---|---|---|---|---|---|
| t+31 | 1.22 | –0.26 | t+46 | –0.15 | –1.72 |
| t+32 | –2.18[b] | –0.57 | t+47 | 0.19 | –1.67 |
| t+33 | –1.79 | –1.03 | t+48 | –2.71[a] | –2.04[b] |
| t+34 | –2.71[a] | –1.26 | t+49 | –0.88 | –2.15[b] |
| t+35 | –1.43 | –1.45 | t+50 | 1.18 | –1.96 |
| t+36 | –1.27 | –1.61 | t+51 | 1.67 | –1.71 |
| t+37 | –1.11 | –1.70 | t+52 | 2.62[b] | –1.33 |
| t+38 | –0.66 | –1.81 | t+53 | 1.21 | –1.16 |
| t+39 | –0.84 | –1.79 | t+54 | 3.05[a] | –0.74 |
| t+40 | 0.01 | –1.50 | t+55 | 3.97[a] | –0.20 |
| t+41 | 1.69 | –1.55 | t+56 | 0.92 | –0.08 |
| t+42 | –0.46 | –2.09[b] | t+57 | 0.82 | 0.03 |
| t+43 | –3.61[a] | –2.37[a] | t+58 | 6.25[a] | 0.85 |
| t+44 | –2.04[b] | –2.15[b] | t+59 | –2.12[b] | 0.57 |
| t+45 | 1.27 | –1.72 | t+60 | 0.65 | 0.64 |

*t* indicate the test statistic, and pe indicate post–event. [a]Significant at p-value of 0.01 (1% level); [b]Significant at p-value of 0.05 (5% level).

*Source*: Author's calculation

Table 8 exhibits the results of the post-event window period analysis of the CAARs of the large, mid, and small-cap stocks. The large-cap CAARs are positively significant, while the mid-cap CAARs are insignificant for all days through t+31 to t+60. The post-event window period CAARs for small-cap stocks have been negatively significant on 20 days in the given window. While positive and significant ARs for large-cap stocks and insignificant ARs for the mid-cap stocks are noticed, the small-cap stocks still suffer from the negative and significant ARs, indicating that the market is seen to be recovering the small-cap stocks are still embedded with the COVID-19 throwbacks.

**Table 8** Post-event window period test statistics for CAARs of the large, mid, and small-cap stocks

| *Days* | *Large-cap* | *Mid-cap* | *Small-cap* | *Days* | *Large-cap* | *Mid-cap* | *Small-cap* |
|---|---|---|---|---|---|---|---|
| | $t_{CAAR(pe)}$ | $t_{CAAR(pe)}$ | $t_{CAAR(pe)}$ | | $t_{CAAR(pe)}$ | $t_{CAAR(pe)}$ | $t_{CAAR(pe)}$ |
| t+31 | 5.14[a] | 0.42 | –1.27 | t+46 | 4.17[a] | 0.97 | –2.73[a] |
| t+32 | 5.63[a] | 0.52 | –1.70 | t+47 | 4.24[a] | 0.91 | –2.68[b] |
| t+33 | 5.19[a] | 0.06 | –1.99 | t+48 | 3.52[a] | 0.49 | –2.85[a] |
| t+34 | 4.86[a] | 0.39 | –2.24[b] | t+49 | 3.00[a] | 0.45 | –2.86[a] |
| t+35 | 4.53[a] | 0.58 | –2.43[b] | t+50 | 3.13[a] | 0.94 | –2.79[a] |
| t+36 | 4.58[a] | 0.28 | –2.54[b] | t+51 | 3.22[a] | 1.04 | –2.57[b] |
| t+37 | 4.52[a] | 0.25 | –2.61[b] | t+52 | 3.12[a] | 1.31 | –2.22[b] |
| t+38 | 4.25[a] | 0.28 | –2.69[b] | t+53 | 3.05[a] | 1.39 | –2.04[b] |

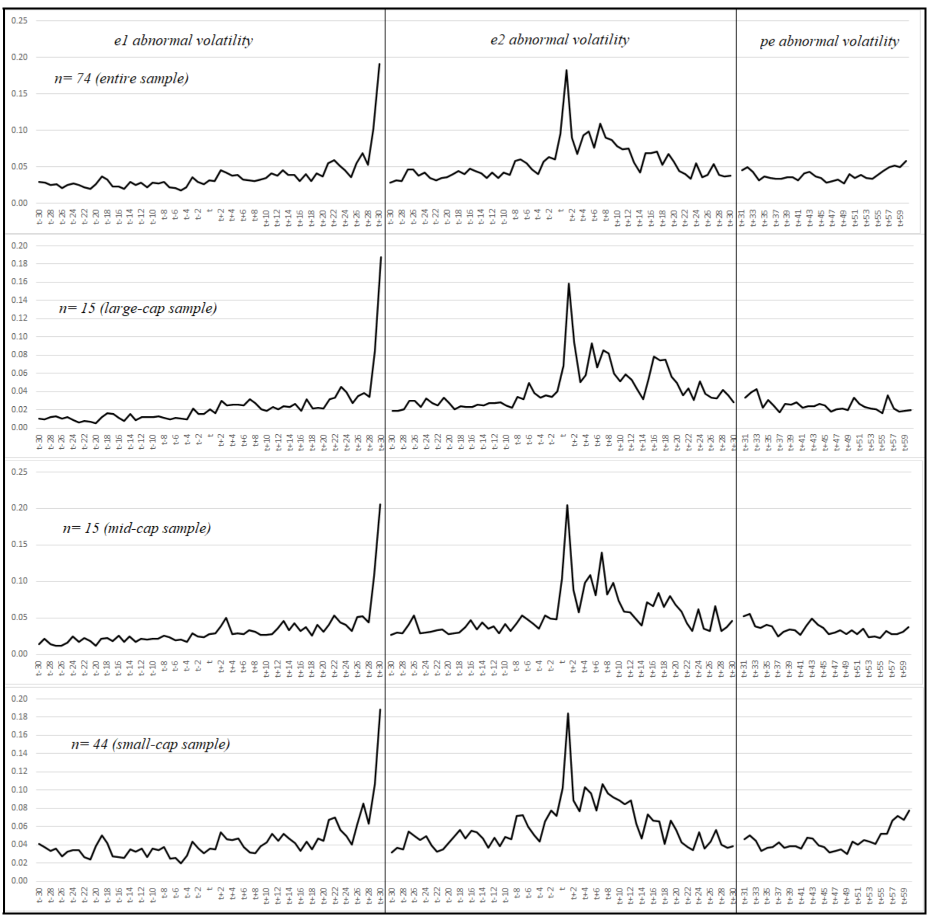
**Table 8** Post-event window period test statistics for CAARs of the large, mid, and small-cap stocks (continued)

| *Days* | *Large-cap* $t_{CAAR(pe)}$ | *Mid-cap* $t_{CAAR(pe)}$ | *Small-cap* $t_{CAAR(pe)}$ | *Days* | *Large-cap* $t_{CAAR(pe)}$ | *Mid-cap* $t_{CAAR(pe)}$ | *Small-cap* $t_{CAAR(pe)}$ |
|---|---|---|---|---|---|---|---|
| t+39 | 3.96[a] | 0.08 | –2.57[b] | t+54 | 3.50[a] | 1.48 | –1.70 |
| t+40 | 4.16[a] | 0.63 | –2.43[b] | t+55 | 3.44[a] | 1.73 | –1.19 |
| t+41 | 3.77[a] | 0.61 | –2.41[b] | t+56 | 3.07[a] | 1.79 | –1.01 |
| t+42 | 3.77[a] | 0.06 | –2.84[a] | t+57 | 3.24[a] | 1.64 | –0.89 |
| t+43 | 3.50[a] | –0.11 | –3.05[a] | t+58 | 3.49[a] | 1.89 | –0.15 |
| t+44 | 3.91[a] | 0.42 | –3.01[a] | t+59 | 3.41[a] | 1.66 | –0.38 |
| t+45 | 4.08[a] | 0.83 | –2.68[b] | t+60 | 3.36[a] | 1.62 | –0.27 |

*t* indicate the test statistic, and pe indicate post-event. [a]Significant at p-value of 0.01 (1% level); [b]Significant at p-value of 0.05 (5% level).

*Source*: Author's calculation

**Figure 2** Abnormal volatility during e1, e2, and post-event period




*Source*: Based on the author's calculation in MS-excel

### 3.4 Analysis of abnormal volatility

The simple measure of volatility (Floros, 2009) has been used to calculate the abnormal volatility using the OLS market model. The AAVs for the entire sample and the capitalisation-wise sample have been plotted on the graph to visualise the volatility during different periods (see Figure 2).

The e1 abnormal volatility is seen following a similar trend for the entire sample, large-cap and mid-cap sample, while that for the small-cap sample, the abnormal volatility has been high and fluctuating with a large number of M-shaped movements. Towards the end of the e1, the abnormal volatility experienced a huge jump. The e2 abnormal volatility for all the samples is similar. The e2 abnormal volatility curve has experienced strong movement on and after the event day for all the samples indicating that the e2 impact has been more significant and negative.

The trend of post-event window period abnormal volatility for the entire sample and the large and mid-cap stocks is almost similar, but the small-cap stocks appear to be more volatile. Thus, the abnormal volatility analysis indicates that the e2 impacts have been more powerful, and the pandemic has worst hit the small-cap stocks. These results align with Akhtaruzzaman et al. (2021), Ali et al. (2020), and Baig et al. (2021). However, our results do not support the positive impacts on the health and pharma sector, as in Goodell and Huynh (2020).

## 4 Conclusions

The abnormal returns and volatility analysis reveal that the e2, which occurred in mid-March 2020, has impacted the stock returns and volatility the most (Mazur et al., 2021). However, the adverse effect is fading post-April 2020 onwards as the market is recovering, as in Topcu and Gulal (2020). The e2 impacts have been stronger than that in e1. The statistically significant returns indicate that pandemics negatively impact stock returns, as also found in previous literature (Chen et al., 2009, 2007; Pandey and Kumari, 2020). The shorter window analysis showed that the post-event day period impacts in e2 have been moderate for large-cap stocks and more adverse for the mid and small-cap stocks. With positive and significant ARs in large-cap stocks and insignificant ARs in the mid-cap stocks, the market for pharmaceutical stocks is recovering, but the small-cap stocks are still embedded with the COVID-19 throwbacks. Our results are contrary to Goodell and Huynh (2020), who found positive impacts on the health and pharma sector in a developed market. The small-cap stocks appear to be more volatile during the post-event window period. The abnormal volatility analysis provides empirical evidence of more powerful e2 impacts of the pandemic on the small-cap stocks. Similar volatility deterioration is found in previous studies (Akhtaruzzaman et al., 2021; Ali et al., 2020; Baig et al., 2021). This evidence shows that the simple measure of volatility regressed with the OLS market model yields results similar to other volatility studies.

## 5 Implications of the study

This study anticipates filling the event study literature gap to the extent that no study has particularly focused on pharmaceutical stocks and that, too, of an emerging market. We add to the literature the use of abnormal volatility as regressed with the market model of the simple volatility measure. This study's statistical evidence will guide the audience in understanding the market's return and volatility phenomenon during future pandemics or crisis periods. However, this study could be further continued with the sample, including the pharmaceutical stocks from a few more emerging markets.

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## Note

[1]https://www.worldometers.info/coronavirus