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Volatility Pattern and Risk Sensitivity in DSE: Pre and Post Market Shutdown due to COVID-19

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Abstract

This paper examines the volatility pattern and risk sensitivity of investors under pre and post COVID stock market shutdown period in DSE by using TGARCH-M (1,1) model. It is found that the investors are not risk sensitive under any circumstances because δ coefficient is insignificant which indicates that the investors are not compensated for risk by additional return. Volatility clustering is remarkably higher in the post shutdown period than that of the pre shutdown period. Influence of old news is more prominent during pre-COVID shutdown period than in the post-COVID shutdown period. Volatility is stationarity persistent and dries out at a very slower rate during pre-COVID shutdown but conditional variance process is explosive in the post COVID shutdown situation. The values of γ coefficients confirm the presence of significant leverage effect in DSE during both the periods but it is remarkably high in the post shutdown period.

Keywords: COVID-19, DSE, volatility, leverage effect, TGARCH (1,1)-M

1. Introduction

COVID-19 pandemic has created significant adverse impacts on almost all the sectors all over the world and the stock market is not an exception. Though the financial crisis 2008 is considered to be the greatest crisis after the great depression of 1929 to 1931, the shock of COVID-19 on the overall economy is not far behind in terms of severity. Stable and reliable capital market is inevitable for consistent economic growth. COVID-19 has made an impact on stock markets all over the world, like Dow Jones, S & P, Nikkei have fallen significantly in the first half of 2020 (Sansa, 2020). Economic turmoil associated with COVID-19 pandemic has had wide ranging and severe impacts on financial markets and the overall stock market declined over 30% by March 2020 (Wikipedia). Due to COVID-19 Colombo Stock

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Exchange closed its operation three times in March 2020 because of a colossal drop in all share prices (Colombo Stock Exchange). On the other hand, in comparison to other world markets, the financial market of China remains stable and strong despite being COVID-19 first detected in China (Xinhua, 2020).

The Institute of Epidemiology, Disease Control and Research (IEDCR) detected the first COVID-19 patient in Bangladesh on March 8, 2020, and the first death occurred on March 18, 2020 (Financial Express, 2020). Albeit COVID was detected on March 8, 2020, adverse impacts of COVID occurred in the Bangladesh stock market from the very beginning of 2020 due to huge turmoil in the world market. The Bangladesh Securities and Exchange Commission (BSEC) suspended market operations from March 26, 2020, to May 30, 2020, because of curbing Covid-19's unexpected impact on the stock market since it may be a cause of potential long-term catastrophe to the national economy. The Bangladesh Securities and Exchange Commission (BSEC) adopted a floor pricing strategy for all listed securities a few days before the market shutdown in order to reverse the regularly decreasing market patterns. The Dhaka Stock Exchange (DSE) reopened its trading on May 31, 2020, more than two months after the shutdown due to the COVID-19 outbreak.

Since the stock market has been considered as most sensitive and volatile in nature, the COVID-19 situation entices us to conduct a massive investigation for depicting the movement of stock market under these circumstances. Some empirical studies have examined the impact of the novel coronavirus on stock markets in developed and emerging economies. In this regard, the present literature yielded a variety of results. Applying a simple regression Albulescu (2020) has examined whether the number of instances and death rates due to COVID within and outside China were influenced by the financial market volatility. He used the VIX index and data span covers from January 20, 2020, to February 28, 2020. He observed that the VIX was influenced only by new instances outside China, and the death rate had a positive and large impact. Moreover, the spread of COVID-19 enhances financial market volatility. Using quadratic GARCH and EGARCH models with dummy variables, Adenomon et al. (2020) investigated the effects of COVID-19 on the Nigerian stock market and found that COVID-19 had a detrimental impact on Nigerian stock returns. According to Baek et al. (2020), the volatility of financial markets is directly linked with the financial risk of assets. To observe the stock market's reaction to the incidence of COVID-19, Baker et al. (2020) used a text-based method. They found that stock market volatility was higher during the COVID-19 pandemic than that another times.

Bora and Basistha (2021) have used the GJR GARCH model to explore the influence of COVID-19 on the volatility of BSE Sensex and NSE Nifty in India. The BSE Sensex became more volatile during COVID-19 than the NSE Nifty. Applying GARCH, EGARCH and TGARCH, Bhunia and Ganguly (2020) also found the presence of volatility and leverage effect before and during the Covid-19 pandemic in some selected international stock markets. Based on GDP, Chaudhary et al. (2020), found the influence of the COVID-19 pandemic on the stock market indices of the top 10 countries, where COVID-19 pandemic enhanced the volatility of these indices. Duttilo et al. (2020) have used the TGARCH (1, 1)-M model with exogenous dummy variables to investigate the influence of the two waves of COVID-19 infections on the return and volatility of euro area stock markets. The first wave of COVID-19 infections had a major influence on stock market volatility in euro zone nations, while the second wave had a significant impact only on the stock market volatility in Belgium.

Engelhardt et al. (2021) have observed the influence of trust on stock market volatility during the COVID-19 outbreak by examining indices of 47 stock markets. They found that the stock market volatility is lesser in high-trust countries. Liu et al. (2020) have studied a short-term impact of COVID-19 on stock markets in 21 major affected countries from February 21, 2019, to March 18, 2020. According to their findings, COVID-19 has a significant negative influence on returns. By using quadratic GARCH and EGARCH models with dummy variables, Osagie et al. (2022) have discovered the serious impact of COVID-19 on the stock returns in Nigeria. Hizarci and Zeren (2020) have investigated the effect of COVID-19 on stock markets in China, South Korea, Italy, Germany, and Spain. Using a cointegration test they have found a long-term relationship between the number of deaths caused by COVID-19 and the stock market returns.

Yousef (2020) used GARCH and GJR-GARCH models with dummy and control variables to assess the influence of the COVID-19 on stock market volatility in G7 countries. The COVID-19 epidemic exacerbated stock market volatility in G7 countries. Shehzad et al. (2020) have used the Asymmetric Power GARCH model with dummy variables to examine the impact of the global financial crisis and COVID-19 on the S & P 500, Nasdaq Composite Index, DAX 30, FTSE MIB, Nikkei 225, and SSEC stock market indices. They found, COVID-19 to have a greater impact on European and American markets than on Asian markets. Szczygielski et al. (2021) have also investigated the influence of COVID-19 on regional stock markets using the ARCH and GARCH approaches. Their findings demonstrated that the COVID-19 outbreak has a distinct influence on regional market returns and volatility, where Asian markets are more stable than the European, North, and Latin American markets.

We have gone through the findings of various research works related to the impact of COVID-19 on stock market returns in developed and emerging countries. Till now, very few studies have been conducted to examine the impact of COVID-19 on stock market volatility. In this paper, our intention is to make a comparison of the volatility patterns and risk sensitivity of investors between pre and post market shutdown due to COVID-19 in DSE.

2. Methods

The Dhaka Stock Exchange (DSE) Limited introduced DSE broad index (DSEX) and DSE 30 index (DS30) based on free float and S&P methodology with effect from January 28, 2013. DSEX is the broad index of the exchange (benchmark index) which will reflect around 97% of the total equity market capitalization. DS30 is constructed with 30 leading companies which can be said as an investable index of the exchange. DS30 index is taken under consideration as a proxy of the movement of blue-chip shares as compared to DSEX index. The daily closing value of the DSEX and DS30 indices of the Dhaka Stock Exchange are employed for the purpose of analysis in this study. Here, the study period for DSEX and DS30 indices cover for pre shutdown from January 20, 2014 to March 25, 2020 and post shutdown from May 31, 2020 to April 01, 2021 from the databank of the DSE, as available from the website of Dhaka Stock Exchange. Here, daily market returns at time t are calculated as:

$$R = log \frac{p_t}{p_{t-1}} \tag{1}$$

where, R refers to the market return, p_t refers to the price index on day t and p_{t-1} refers price index on day t-1. The justification for using logarithm is that the log normal returns are more likely to be normally distributed, which is the prerequisite condition for applying statistical techniques (Strong, 1992).

In our study, two unit root tests, Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP) tests have been used. The ADF test (Dicky and Fuller 1979, 1981) are based on the OLS regression equations:

$$\Delta y_t = \delta y_{t-1} + \sum_{i=1}^{m} \emptyset \Delta y_{t-i} + \varepsilon_t \tag{2}$$

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{m} \emptyset \Delta y_{t-i} + \varepsilon_t \tag{3}$$

$$\Delta y_t = \alpha + \gamma t + \delta y_{t-1} + \sum_{i=1}^{m} \emptyset \Delta y_{t-i} + \varepsilon_t \tag{4}$$

The null hypothesis (H_0) is that, the time series variable contains a unit root, that is, δ = 0.

From the view point of dealing serial correlation and heteroscedasticity in the errors, the PP test differs from the ADF test (Brooks, 2008). The PP tests is run by using equation:

$$\Delta y_t = \beta' D_t + \pi y_{t-1} + u_t \tag{5}$$

where, u_t is $I(0)$ and may be heteroscedastic and D_t is the deterministic component. Under null hypothesis (H_0), $\pi = 0$, the PP Z_t and Z_π statistics have the same asymptotic distribution as the ADF t-statistic.

The tendency of an asset's price to swing up or down is known as volatility. Increased volatility is interpreted as a sign of increased financial risk, which can have a negative impact on investment. Since the financial time series has special features like volatility clustering, leptokurtosis, and leverage effect, so normal time series models like OLS is substantially failed to capture the features. Engel (1982) first developed ARCH process that allows past error terms to vary over time and modeling non constant variance. Bollerslev (1986) developed a generalized ARCH which is GARCH model. But ARCH and GARCH have failed to capture the asymmetric response lie in the time series data. To overcome this problem, Nelson

(1991) developed EGARCH, Glosten, Jagannathan and Runkle (1993) developed GJR-GARCH, Zakoian (1994) developed TGARCH. Besides, Engel et al. (1987) provided an extension to the GARCH model where the conditional mean is an explicit function of conditional variance, which is known as the GARCH in mean (GARCH-M) model. This model directly made a tradeoff between time varying risk and expected return. To make a comparison between volatility pattern and risk sensitivity of investors between pre and post market shutdown due to COVID-19, we apply the TGARCH-M model because of its efficacy and ability to cover the wide range of asymmetric features in a parsimonious way.

Examination of the presence of heteroscedasticity in the financial time series data is inevitable before applying GARCH family models, and ARCH-LM test (Engle, 1982) is applied for testing the ARCH effect in the residuals. The specification of conditional standard deviation under TGARCH-M (1, 1) model can be written as follows:

Mean Equation:

$$r_t = \mu + \delta\sigma_t + \varepsilon_t; \quad \varepsilon_t \sim N(0, \sigma^2) \tag{6}$$

Variance Equation:

$$\sigma_t^2 = \omega + \alpha_1\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 \tag{7}$$

where, r_t is the stock return at time t, μ is the mean of r_t conditional on past information, the inequality restrictions $\omega > 0$, $\alpha_1 >= 0$, and $\beta_1 >= 0$ are imposed to ensure that the conditional variance (σ_t^2) is positive. The parameter δ in mean equation is called the risk premium parameter. The presence of σ_t in the mean equation provides a way to directly study the explicit tradeoff between risk and expected return. The significant influence of volatility on stock returns is captured by the coefficient of $\sigma_{t,}$ that is, δ. The coefficient δ represents the index of relative risk aversion (i.e., time-varying risk premium). A positive and statistically significant coefficient, δ, represents that the trader's trading stock is compensated by higher returns for carrying a higher degree of risk for the same period. If the coefficient, δ, is negative and statistically significant, it indicates that the investors are penalized for bearing risk as pointed out by Basher et al. (2007).

In variance equation, The constant term ω, which represents long-run variance or average variance, The ε_{t-1}^2, is the lag of the squared residuals from the mean (the ARCH term),: σ_{t-1}^2, prior period forecast variance (the GARCH term), the term $d_{t-1}\varepsilon_{t-1}^2$ captures asymmetry (the leverage effect) where, d_{t-1} is a dummy variable and indicates $d_{t-1} = 1$, if $\varepsilon_{t-1}<0$ and implies bad news and $d_{t-1} = 0$, if $\varepsilon_{t-1} \geq 0$ and implies good news. In this model, good news ($\varepsilon_{t-1} \geq 0$) and bad news ($\varepsilon_{t-1} < 0$) have different effects on conditional variance. The coefficient, γ is known as the asymmetry or leverage term. When $\gamma = 0$, the model is automatically converted to the standard GARCH form. Therefore, when the shock is positive (good news), its impact on conditional variance (volatility) can be determined by α. But, a negative shock (bad news) has an impact on volatility of $\alpha + \gamma$. If $\gamma > 0$, then the leverage effect exists and bad news ($\varepsilon_{t-1} < 0$) increase the volatility than the good news ($\alpha + \gamma > \alpha$). Hence, if the γ is positive and statistically significant, negative shocks have a larger effect on conditional variance (σ_t^2) than positive shocks.

3. Results and Discussion

Figure 1 depicts a variation of returns of the DSEX and DS30 return series under pre and post suspension of market operation due to the COVID shutdown using charting strategies. Both the return series are found to be fluctuating within the range of $\pm 1\%$ up to January, 2020 except a few outliers. But just after the detection of coronavirus in Bangladesh, the market became turmoil and the volatility of return went up which is depicted in the last part of figures a and b. To curb the fluctuation, the operation of the stock market was stopped from March 26, 2020 to May 30, 2020. After reopening of operation along with some policy measures, like floor price, variation of returns come under control which is depicted in figures c and d. We observe that post shutdown period returns have been hovering within the range of $\pm 1\%$ except for a very few cases.

Figure 1: Pre and post shutdown return series of DSEX and DS30

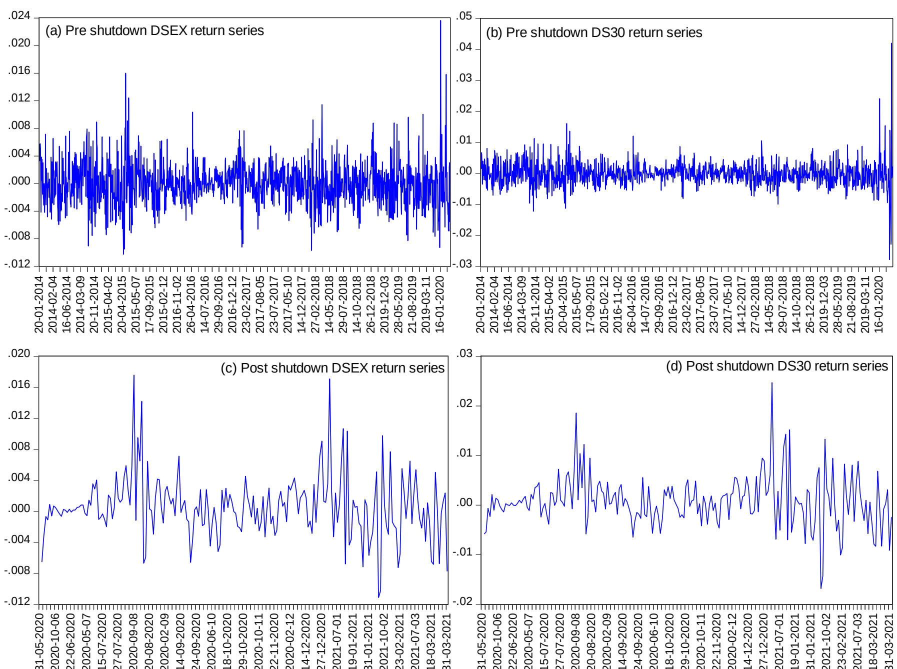

Table 1 shows the results of unit root (ADF, PP) tests for DSEX and DS30 indices under pre and post shutdown periods. It is observed that the ADF and PP tests reject the null hypothesis at 1% level of significance under all circumstances. So, the given time series data are stationary and fit for standard econometric analysis without differencing.

Table 1: Estimated results of ADF and PP tests for DSEX and DS30 return series

	ADF test		PP test	
	Test Statistic	**p-value**		**Test Statistic**
		Pre-shutdown period		
DSEX	-32.22048	0.0000	DSEX	-32.22048
DS30	-32.51656	0.0000	DS30	-32.51656
		Post-shutdown period		
DSEX	-4.861593	0.0000	DSEX	-4.861593
DS30	-12.40862	0.0000	DS30	-12.40862

Table 2 contains the values of Obs*R^2 (TR^2) and corresponding p-value for the residuals of both DSEX and DS30 return series under pre and post shutdown period. It is observed that the probabilities of TR^2 are zero for pre-shutdown period and less than 1% for post lock down period. Therefore, the TR^2 parameters are significant at 1% level of significance. Sincethe null hypothesis is rejected (H_0: no conditional heteroscedasticity in residuals of return series) it indicates a strong evidence of the ARCH effects in the residuals series under all cases. The existence of ARCH effect in residuals series permit us to proceed for applying GARCH family model to capture volatility in return series.

Table 2: Estimated results of ARCH-LM test on residuals of mean models

ARCH-LM Test	**Pre-shutdown period**		**Post-shutdown period**	
	DSEX	**DS30**	**DSEX**	**DS30**
Obs* R^2 (TR^2)	110.5539	127.5309	6.902819	7.886655
p-value	0.0000	0.0000	0.0086	0.0050

Table 3 presents the results of the TGARCH-M (1,1) model to compare market scenario between pre- and post- COVID shutdown in DSE on the basis of volatility-return nexus, volatility persistence, and leverage effect. The value of δ is negative and insignificant for DSEX return series under pre shutdown period, which is not aligned with the proposition of portfolio theory. But it is possible theoretically in emerging markets as investors are not well aware of risk at times of particular volatility (Glosten et al., 1993). Since the nexus between risk-return (δ) for DSEX and DS30 is insignificant in all cases (pre and post COVID shutdown) it indicates that the investors' whether they invest in market portfolio (DSEX) or blue chips shares (DS30) are not risk sensitive. This is because risk is not logically compensated by additional return. Finding is thus an indication that the behavior of investors is not compatible with the theory of risk-return relationship. Therefore, it is a vital character of inefficient market, where investors take decision on the basis of gossip and rumor without making rationale judgment.

Besides this, the ARCH (α) and GARCH (β) coefficients for both return series under pre and post shutdown are significant at 1% level of significance, indicating that lagged error and lagged conditional variance have a significant impact on current volatility. The ARCH (α) parameters indicate the presence of volatility clustering (i.e., large positive change tends to be followed by large negative change and small positive change tendsto be followed by small negative change and vice versa) in both periods (Yakob and Delpachitra; 2006). Clustering effect in pre shutdown period (0.109008 and 0.082656) is remarkably lower than that of post shutdown period (0.750636 and 0.502035).

Table 3: Estimated results of the TGARCH-M (1,1) model

Co-efficients	Pre-Shutdown Period		Post-Shutdown Period	
	DSEX	**DS30**	**DSEX**	**DS30**
δ (coefficient of SD in mean equation)	-0.061241 (0.4392)	0.023691 (0.7677)	0.031202 (0.7561)	0.056152 (0.7073)
ω (constant)	2.41E-07 (0.0000)	2.21E-07 (0.0000)	5.31E-09 (0.9162)	1.40E-07 (0.5938)
α (ARCH Effect)	0.109008 (0.0000)	0.082656 (0.0000)	0.750636 (0.0000)	0.502035 (0.0000)
γ (Leverage effect)	0.136776 (0.0001)	0.090719 (0.0000)	-0.392495 (0.0181)	-0.244695 (0.0500)
β (GARCH Effect)	0.815571 (0.0000)	0.862515 (0.0000)	0.643195 (0.0000)	0.709117 (0.0000)
α + β	**0.924579**	**0.945171**	**1.393831**	**1.211152**

The β coefficient measures the impact of old news on current volatility. It is observed that, β coefficients are higher for pre shutdown period (0.815571 and 0.862515) than the post shutdown period (0.643195 and 0.709117) for both return series, which means the influence of old news on volatility was very important and prominent in prior to COVID shutdown period. But in post COVID shutdown period investors are giving more emphasis on current news rather than the old news, because COVID situation radically changed the behavior of various economic variables as well as attitude of human beings, which are not compatible with the long run historical pattern. Volatility persistence is measured by the sum of α and β. We also observed that the sum of α and β are 0.924579 and 0.945171 for DSEX and DS30 respectively under pre-COVID shutdown period. The value is 1.393831 for DSEX and 1.211152 for DS30 under post COVID shutdown period. The sum of α and β for both return series under pre shutdown is less than unity but is very close to one. It indicates that shocks to the conditional variance (volatility) are highly persistent. Since the values of the sum are less than one, there is a tendency to go back mean of the volatility series. The sum of α and β also is a rate of estimation at which the response function of shocks will decay on daily basis. Since the sum are close to unity, the shock will dry out very slowly and it is an indication of long memory (i.e., if there is any new shock, it will have an implication on return over a long period of time).

On the contrary, the sum of α and β is more than one for both return series under post shutdown period, which indicates that the shock to the conditional variance is highly persistent and conditional variance process is explosive. This is due to the presence of COVID-19 and variance process is not mean reverting.

It is also observed that the γ coefficients for both return series are significant at 1% level under pre shutdown period and at 5% level under post shutdown period.

The significant γ value confirms the presence of leverage effect (negative shocks have more impact on volatility than the similar magnitude of positive shocks) in DSE under both the pre and post lock down period. But it is remarkable that the absolute value of γ coefficients under post shutdown (-0.392495 and -0.244695) are much higher than the pre shutdown period (0.136776 and 0.080719), which is an indication of the higher leverage effect in the pre COVID shutdown than the post COVID situation. Due to the higher leverage effect as well as higher volatility persistence and clustering, investment in DSE becomes riskier in the post COVID shutdown period than earlier. To examine the validity of the TGARCH-M (1,1) model we have conducted the ARCH-LM test.

Table 4: Estimated results of ARCH-LM test on residuals of TGARCH-M (1,1) model

ARCH-LM Test	**Pre shutdown period**		**Post shutdown period**	
	DSEX	**DS30**	**DSEX**	**DS30**
Obs* R^2 (TR^2)	0.012569	0.014117	0.158902	2.30E-06
p-value	0.9107	0.9054	0.6902	0.9988

From Table 4, it is observed that the null hypothesis ($H_{0:}$ There is no ARCH effect) cannot be rejected at any level of significance. Therefore, ARCH-LM test indicates that there are no additional ARCH effects and the model TGARCH-M (1,1) is well -fitted and well -specified.

4. Conclusion

An attempt has been made in this study to examine the volatility pattern, leverage effect and risk-return behavior of DSE during the pre and the post COVID shutdown period. Based on TGARCH-M (1,1) model, we first observe that the δ coefficients for DSEX and DS30 are insignificant under pre and post COVID shutdown, indicating that the investors are not risk sensitive because the risk is not logically compensated by the additional return. It signifies that the behavior of investors is not compatible with the theory of risk-return relationship. It is a prominent sign of an inefficient market where investors take decisions on the basis of gossip and rumor.

Secondly, the significant ARCH (α) parameters divulge the presence of volatility clustering in both periods but the clustering effect in pre shutdown period (0.109008 and 0.082656) is remarkably lower than the post shutdown period (0.750636 and 0.502035).

Thirdly, β coefficients are higher for pre shutdown period (0.815571 and 0.862515) than the post shutdown period (0.643195 and 0.709117) for both return series, which indicates that the influence of old news on volatility was very important and prominent during prior COVID shutdown period than the post COVID shutdown period. It is because the COVID situation drastically changes the behavior of various economic variables as well as attitude of human being which are not compatible with long historical pattern.

Fourthly, volatility persistence, measured by the sum of α and β, is quite high, which are less than unity but very close to one for both return series under pre shutdown period. It indicates that the shocks to the conditional variance (volatility) are stationary, persistent and the shock will dry out very slowly. But, the sum of α and β are more than one for both return series under post shutdown period, indicating the shock to the conditional variance are highly persistent and conditional variance process is explosive. This is due to the presence of COVID and the variance process is not mean reverting.

Last, leverage effects (negative shocks have more impact on volatility than the similar magnitude of positive shocks) are prominent in DSE under both the pre and post lock down period. But it is remarkable that the absolute value of γ coefficients under post shutdown period (-0.392495 and -0.244695) are much higher than the pre shutdown period (0.136776 and 0.080719), which indicates that the leverage effect is higher in pre COVID shutdown than the post COVID situation. Due to the higher leverage effect as well as higher volatility persistence and clustering, investment in DSE becomes riskier in post COVID shutdown period than earlier.

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