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# Volatility and asymmetric analysis of Indian indices during Covid-19 pandemic period

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**Abstract.** *Analyzing the volatility and asymmetry in the stock market plays a vital role in financial economics and it is essential to financial intermediaries and also to the various practitioners of stock markets. The uninvited Covid-19 pandemic distresses each and every sector in the world; stock markets are not free from it. In this study, an attempt has been made to study the volatility and asymmetric effects in Indian stock market indices during the Covid-19 pandemic period. Daily data from January 2018 to June 2021 were collected to analyze the volatility and asymmetries. The data is classified as two categories as before pandemic announcement and after pandemic announcement. GARCH, TGARCH and EGARCH models are used to find the volatility and asymmetries during the study period. The GARCH results proves that there exist the stability conditions and the asymmetric GARCH models assure that there exist leverage effects in the index returns for both before pandemic and after pandemic period, and the results also confirms the volatility persistence is very high during after pandemic period as compared to before pandemic period.*

**Keywords:** Asymmetric volatility, Stock Market, Covid-19 pandemic, GARCH, TGARCH and EGARCH.

**JEL Classification:** N15, E32.

## Introduction

“Volatility modeling provides a simple approach to calculating value at risk of a financial position in risk management” (Tsay, 2005). Analyzing the volatility in the stock market plays a vital role in financial economics and it is crucial to financial intermediaries and practitioners in stock market. The basic statistical risk measurement is identified as volatility measurement. Volatility can be measured using single instrument or can as well be measured using entire portfolio of instruments. Random variability of the stock return can be measured with the help of stock returns volatility. Conditional volatility models such as ARCH and GARCH type models consider the time-varying nature of volatility. ARCH and GARCH models are symmetric models, in which equal weights are given to negative and positive variability. EGARCH, TGARCH are asymmetric models, which gives different weights to negative and positive variability. The uninvited Covid-19 pandemic distresses each and every sector in the world; stock markets are not free from it. “Even in its pre-pandemic phase, Covid-19 has severely affected the real economy, with a negative impact on trade, transport, tourism industries” (Albulescu, 2021). “The significance of health news searches as a good predictor of stock returns since the emergence of the pandemic” (Salisu and Vo, 2020). In this research attempt both symmetric and asymmetric ARCH type models are used to study the impact of Covid-19 pandemic in the Indian stock market volatility.

## Literature review

The measure of volatility of stock index returns helps to reduce the uncertainty and risk to certain extent. Forecasting perfect market volatility is difficult work, but there are various models and techniques are available to study the volatility, but not all of them are results equally for all the stock markets. “ARCH/GARCH models can provide good approximation for capturing the characteristics of Ammam Stock Exchange” (Rousan and Al-Khouri, 2005). “GARCH models have a strong background and crossed 30 years of the fast progress of GARCH-type models for investing the volatility of market data. Many researchers proved that GARCH is the most suitable model to analyze the volatility of stock return with big volumes of data. GARCH (1, 1) model with a generalized distribution of residual has more advantages in volatility assessment than other models” (Bhowmik and Wang, 2020). “The shocks to the global economy from Covid-19 have been faster and severe. Market has become more volatile as a result of pandemic” (Sharma, 2020). “The stock markets recorded several shock waves starting from February 2020, whereas the financial volatility continued to increase in the context of Covid-19 uncertainty” (Albulescu, 2021).

## Data and methodology

The data collected from two largest India’s leading stock exchanges of Bombay Stock Exchange (BSE) and National stock Exchange (NSE). Three indexes of BSE namely BSE Sensex Index, BSE 100 Index and BSE 200 Index and three indexes of NSE namely NSE Nifty 50 Index, Nifty 100 Index and Nifty 200 Index were selected in this study. The daily data from the period of 01.01.2018 to 06.30.2021 were selected, it consist of 860 observations. The data is categorized as before Covid-19 pandemic and after Covid-19 pandemic. Data from 01.01.2018 to 12.31.2019 is considered as before Covid-19 pandemic period and data from 01.01.2020 to 06.30.2021 is considered as after Covid-19 pandemic period. Daily returns are calculate using the formula $R_t = (LnP_t - LnP_{t-1}) \times 100$. Summary statistics is calculated for whole sample period, before pandemic period and after pandemic period. The unit-root problem is detected with the help of Augmented Dickey-Fuller test. Before applying ARCH family models it is essential to check for ARCH effect in the data set, hence ARCH LM test is calculated. After finding ARCH effect in the residuals the ARCH family models of GARCH, TGARCH and EGARCH are applied to check the volatility and asymmetries in series.

**Table 1.** *Formulas of GARCH and its extension models*

| Model | Expansion | Formula |
|---|---|---|
| GARCH | Generalized Autoregressive Conditional Heteroscedasticity | $\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \beta\sigma^2_{t-1}$ |
| TGARCH | Threshold Generalized Autoregressive Conditional Heteroscedasticity | $\sigma^2_t = \alpha_0 + \alpha_1 u^2_{t-1} + \beta\sigma^2_{t-1} + \gamma u^2_{t-1} I_{t-1}$ |
| EGARCH | Exponential Generalized Autoregressive Conditional Heteroscedasticity | $ln(\sigma_t^2) = \omega + \beta\, ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[ \frac{\lvert u_{t-1} \rvert}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$ |

## Empirical results

The empirical results consist of summary statistics, ADF stationarity test, ARCH LM test and GARCH, TGARCH and EGARCH results. Table 2 presents the summary statistics for whole sample period, for before pandemic period and for after pandemic period. The mean values are around 0 and standard deviation values are greater during after pandemic period. At before pandemic period the skewness values are positive, it shows the mode is greater than the mean value. But after pandemic period the skewness values are negative; it illustrates that the mean values are greater than the mode. Positive skewness indicates the frequent small losses and few extreme gains achieved during the before pandemic period. The values of skewness lie between ±1, it signifies moderately skewed distribution. The kurtosis values are greater than 3, signifies that the distribution is leptokurtic in nature; whereas after pandemic the kurtosis values are peaked greater than before pandemic period. The Jarque-Bera probability values are less than 0.05%, it shows that the distribution is not normally distributed.

**Table 2.** *Results of summary statistics and normality test*

| Des. Statistics | BSE SENSEX Index | | | BSE 100 Index | | | BSE 200 Index | | |
|---|---|---|---|---|---|---|---|---|---|
| | OVERALL | BEFORE | AFTER | OVERALL | BEFORE | AFTER | OVERALL | BEFORE | AFTER |
| Mean | 0.000511 | 0.000406 | 0.000649 | 0.000441 | 0.000225 | 0.000725 | 0.000445 | 0.000179 | 0.000795 |
| Std. Dev | 0.013379 | 0.008275 | 0.01801 | 0.013041 | 0.008447 | 0.01732 | 0.012859 | 0.00844 | 0.017007 |
| Skewness | -1.657 | 0.499739 | -1.6548 | -1.760 | 0.4888 | -1.8535 | -1.853 | 0.4628 | -1.97933 |
| Kurtosis | 24.88144 | 6.503777 | 17.2178 | 24.78867 | 6.6748 | 18.09729 | 25.22856 | 6.5664 | 18.77672 |
| Jarque-Bera | 17611.88 | 271.0395 | 3311.938 | 17516.97 | 295.2351 | 3755.959 | 18261.60 | 277.18 | 4111.925 |
| Probability | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| | NIFTY 50 Index | | | NIFTY 100 Index | | | NIFTY 200 Index | | |
| Mean | 0.000511 | 0.000406 | 0.000649 | 0.000441 | 0.000225 | 0.000725 | 0.000445 | 0.000179 | 0.000795 |
| Std. Dev | 0.013379 | 0.008275 | 0.01801 | 0.013041 | 0.008447 | 0.1732 | 0.012859 | 0.00844 | 0.017007 |
| Skewness | -1.657 | 0.499739 | -1.6548 | -1.760 | 0.4888 | -1.8535 | -1.853 | 0.4628 | -1.97933 |
| Kurtosis | 24.88144 | 6.503777 | 17.2178 | 24.78867 | 6.6748 | 18.09729 | 25.22856 | 6.5664 | 18.77672 |
| Jarque-Bera | 17611.88 | 271.0395 | 3311.938 | 17516.97 | 295.2351 | 3755.959 | 18261.60 | 277.18 | 4111.925 |
| Probability | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Before going for any analysis in time series data, it is crucial to check for volatility clustering, stationarity of the data, heteroscedasticity and autocorrelation in the residuals. The result of Augmented Dickey-Fuller test of stationarity is presented in the Table 3.

**Table 3.** *Results of Augmented Dickey-Fuller test of stationarity*

| ADF Test | SENSEX | BSE 100 | BSE 200 | Nifty 50 | Nifty 100 | Nifty 200 |
|---|---|---|---|---|---|---|
| T-Statistics | -9.98637 | -9.78185 | -9.6835 | -9.8470 | -9.755579 | -9.66427 |
| Prob. | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Critical values at 5% | -1.9411 | -1.9411 | -1.9411 | -1.94115 | -1.941195 | -1.941195 |
| Durbin Watson | 2.0056 | 2.00524 | 2.00576 | 2.004573 | 2.004901 | 2.00537 |

**Table 4.** *Results of ARCH LM test*

| | SENSEX | | | BSE 100 | | | BSE 200 | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Coefficient | t-value | p-value | Coefficient | t-value | p-value | Coefficient | t-value | p-value |
| Constant | 5.50E-05 (0.000273) | 7.07009 (4.1614) | 0.0000 (0.0000) | 5.83E-05 (0.000257) | 7.06715 (4.1152) | 0.0000 (0.0000) | 5.88E-06 (0.000273) | 7.1729 (4.161) | 0.0000 (0.0000) |
| $e^2_{t-1}$ | 0.197162 (0.1520) | 4.43435 (2.9555) | 0.0000 (0.0033) | 0.18166 (0.1374) | 4.07341 (2.66614) | 0.0001 (0.0080) | 0.1726 (0.1520) | 3.8637 (2.955) | 0.0001 (0.0033) |
| | | | | | | | | | |
| F-statistics | 19.66350 (8.7314) | p-value (F) | 0.0000 (0.0033) | 16.5926* (7.1083) | p-value (F) | 0.0001 (0.0080) | 14.9282* (8.7351) | p-value (F) | 0.0001 (0.0033) |
| Obs.R-squared | 18.97663 (8.5793) | p-value (Chi-Square) | 0.0000 (0.0034) | 16.11093# (7.01175) | p-value (Chi-Square) | 0.0001 (0.0081) | 14.54296# (8.5793) | p-value (Chi-Square) | 0.0001 (0.0034) |
| | Nifty 50 | | | Nifty 100 | | | Nifty 200 | | |
| Variable | Coefficient | t-value | p-value | Coefficient | t-value | p-value | Coefficient | t-value | p-value |
| Constant | 0.000144 (0.000266) | 5.1587 (4.1670) | 0.0000 (0.0000) | 0.000141 (0.000255) | 5.17816 (4.1269) | 0.0000 (0.0000) | 0.000141 (0.000252) | 5.1821 (4.08317) | 0.0000 (0.0001) |
| $e^2_{t-1}$ | 0.171041 (0.14700) | 5.07909 (2.8432) | 0.0000 (0.0047) | 0.15994 (0.135934 | 4.74076 (2.6249) | 0.0000 (0.0090) | 0.15516 (0.1308) | 4.5954 (2.5244) | 0.0000 (0.0120) |
| | | | | | | | | | |
| F-statistics | 25.79722 (8.0841) | p-value (F) | 0.0000 (0.0047) | 22.4748* (6.8902) | p-value (F) | 0.0000 (0.0090) | 21.11817* (6.3729) | p-value (F) | 0.0000 (0.0120) |
| Obs.R-squared | 25.10102 (7.9526) | p-value (Chi-Square) | 0.0000 (0.0048) | 21.9509# (6.7999) | p-value (Chi-Square) | 0.0000 (0.0091) | 20.6578# (6.2981) | p-value (Chi-Square) | 0.0000 (0.0121) |

**Note:** *indicates F-Statistics values and # indicates observed R-squared values.
Values in parenthesis indicates the after pandemic period.

The t-statistics values are lesser than the critical values and the p-value is less than 5% level; hence it is concluded that the index returns are stationary during the period. ARCH LM test is presented in the Table 4. The p-value of F-Statistics and p-value of chi-square is less than 0.05% for both before pandemic period and after pandemic period. It signifies that there exists ARCH effect in the residuals. Table 5 indicates the results of GARCH, TGARCH and EGARCH models. With respect to GARCH models, C refers to constant, the coefficient of constant terms are positive and statistically significant at 5 percent level. The ARCH and GARCH terms are positive and statistically significant at 5 percent level; and ARCH and GARCH values together are close to one, it satisfies the stability conditions it refers the shocks to the conditional variance will be highly persistence, signifies that the high changes in the returns tend to be followed by high changes and small changes tends to be followed by the small changes for a certain period.

Asymmetric models distinct between positive and negative news. Both the TGARCH and EGARCH are used for studying the asymmetries; EGARCH is used for maximizing gains and TGARCH is used for minimizing the losses. Form the results of TGARCH model it is found that, before pandemic period the alpha ($\boldsymbol{\alpha}$) values are negative and not statistically significant, although after pandemic period the alpha ($\boldsymbol{\alpha}$) values are negative but statistically significant at 1% level. Alpha ($\boldsymbol{\alpha}$) and gamma ($\boldsymbol{\gamma}$) together are lesser than the alpha ($\boldsymbol{\alpha}$). Gamma makes a huge impact in the behavior of the series. The E-GARCH model helps to find the leverage effect in the index returns. The negative and statistically significant E-GARCH value assures that there exist leverage effects in the index returns for both before pandemic and after pandemic period. It indicates that a positive shock has less effect on the conditional variance compared to a negative shock or negative news. The alpha ($\boldsymbol{\alpha}$) value in E-GARCH model indicates the size effect of the news and the lambda ($\boldsymbol{\lambda}$) value indicates the sign effects of the news. The lambda ($\boldsymbol{\lambda}$) value are negative and statistically significant at 1% level, it signifies that there exist an inverse relationship between the news and volatility. With respect to beta ($\beta$) value, the volatility persistence is very high during after pandemic period as compared to before pandemic sample period.

## Conclusion

The volatility and asymmetric effects in Indian stock market indices during the Covid-19 pandemic period are studied in this research attempt. The mean values are around 0 and standard deviation values are greater during after pandemic period. At before pandemic period the skewness values are positive, but after pandemic period the skewness values are negative; it illustrates that the mean values are greater than the mode after pandemic period. The results of ADF test assures the returns are stationary during the period and the results of ARCH LM test confirms the ARCH effect exist in the residuals. The GARCH results proves that there exist the stability conditions it refers the shocks to the conditional variance will be highly persistence, signifies that the high changes in the returns tend to be followed by high changes and small changes tends to be followed by the small changes for a certain period. The asymmetric GARCH models assure that there exist leverage effects in the index returns for both before pandemic and after pandemic period. The volatility persistence is very high during after pandemic period as compared to before pandemic period.

**Table 5.** *Results of GARCH, TGARCH and EGARCH models*

| | | BSE SENSEX | | | | BSE 100 INDEX | | | | BSE 200 INDEX | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Coefficient | Std.error | Z-Stat | Prob. | Coefficient | Std.error | Z-Stat | Prob. | Coefficient | Std.error | Z-Stat | Prob. |
| GARCH | C | 4.45E-06 | 2.26E-06 | 1.9681 | 0.049 | 6.40E-06 | 3.15E-06 | 2.029 | 0.0424 | 8.21E-06 | 3.85E-06 | 2.1338 | 0.0329 |
| | | (9.24E-06) | (3.15E-06) | (2.933) | (0.0034) | (1.07E-05) | (3.33E-06) | (3.211) | (0.0013) | (1.13E-05) | (3.32E-06) | (3.390) | (0.0007) |
| | ARCH($\alpha$) | 0.142921 | 0.039247 | 3.6415 | 0.0003 | 0.169815 | 0.041791 | 4.0634 | 0.0000 | 0.181700 | 0.04268 | 4.2569 | 0.0000 |
| | | (0.1596) | (0.03243) | (4.920) | (0.0000) | (0.1552) | (0.03289) | (4.720) | (0.000) | (0.153369) | (0.0320) | (4.7926) | (0.0000) |
| | GARCH(β) | 0.801255 | 0.06266 | 12.786 | 0.0000 | 0.751177 | 0.07692 | 9.7653 | 0.0000 | 0.713908 | 0.08805 | 8.1079 | 0.0000 |
| | | (0.8033) | (0.0405) | (19.82) | (0.0000) | (0.7948) | (0.0438) | (18.13) | (0.000) | (0.7910) | (0.0436) | (18.14) | (0.0000) |
| TGARCH | C | 4.40E-06 | 1.34E-06 | 3.2711 | 0.0011 | 4.45E-06 | 1.48E-06 | 3.00785 | 0.0026 | 4.60E-06 | 1.51E-06 | 3.0498 | 0.0023 |
| | | (6.89E-06) | (1.14E-06) | (6.052) | (0.0000) | (6.93E-06) | (9.79E-07) | (7.0774) | (0.000) | (7.03E-06) | (9.74E-07) | (7.2221) | (0.0000) |
| | ARCH($\alpha$) | 4.35E-05 | 0.02255 | 0.00192 | 0.9985 | -0.00171 | 0.02105 | -0.0815 | 0.9350 | -0.00342 | 0.01990 | -0.171 | 0.8635 |
| | | (-0.0475) | (0.01851) | (-2.567) | (0.0103) | (-0.0529) | (0.0190) | (-2.781) | (0.0054) | (-0.0559) | (0.0202) | (-2.768) | (0.0056) |
| | TGARCH($\gamma$) | 0.271084 | 0.06046 | 4.4830 | 0.0000 | 0.29649 | 0.05914 | 5.0133 | 0.0000 | 0.30615 | 0.0599 | 5.1068 | 0.0000 |
| | | (0.234) | (0.037) | (6.226) | (0.0000) | (0.2251) | (0.0350) | (6.421) | (0.000) | (0.2226) | (0.03436) | (6.4785) | (0.0000) |
| | GARCH(β) | 0.80805 | 0.040896 | 19.7588 | 0.0000 | 0.80169 | 0.0420 | 19.0522 | 0.0000 | 0.79756 | 0.04279 | 18.637 | 0.0000 |
| | | (0.882) | (0.0146) | (60.247) | (0.0000) | (0.8855) | (0.0142) | (62.341) | (0.0000) | (0.88587) | (0.0146) | (60.642) | (0.0000) |
| EGARCH | C | -1.2366 | 0.2396 | -5.1590 | 0.0000 | -1.09083 | 0.2320 | -4.7013 | 0.0000 | -1.0425 | 0.22226 | -4.690 | 0.0000 |
| | | (-0.3821) | (0.0795) | (-4.806) | (0.0000) | (-0.4010) | (0.0809) | (-4.954) | (0.0000) | (-0.4048) | (0.0805) | (-5.0237) | (0.0000) |
| | ARCH($\alpha$) | 0.2135 | 0.06535 | 3.2668 | 0.0011 | 0.19041 | 0.06234 | 3.0543 | 0.0023 | 0.17026 | 0.05829 | 2.9205 | 0.0035 |
| | | (0.1317) | (0.0507) | (2.597) | (0.0094) | (0.1089) | (0.04541) | (2.398) | (0.0164) | (0.0963) | (0.0428) | (2.2481) | (0.0246) |
| | EGARCH($\lambda$) | -0.1993 | 0.03678 | -5.4177 | 0.0000 | -0.22556 | 0.0355 | -6.3410 | 0.0000 | -0.2303 | 0.03427 | -6.721 | 0.0000 |
| | | (-0.155) | (0.0212) | (-7.299) | (0.0000) | (-0.1495) | (0.0202) | (-7.374) | (0.0000) | (-0.1500) | (0.0197) | (-7.5965) | (0.0000) |
| | GARCH(β) | 0.8906 | 0.02329 | 38.231 | 0.0000 | 0.90339 | 0.02225 | 40.596 | 0.0000 | 0.906699 | 0.02120 | 42.750 | 0.0000 |
| | | (0.9673) | (0.0066) | (146.35) | (0.0000) | (0.9631) | (0.00668) | (144.04) | (0.0000) | (0.9616) | (0.00675) | (142.40) | (0.0000) |
| | | Nifty 50 INDEX | | | | Nifty 100 INDEX | | | | Nifty 200 INDEX | | | |
| GARCH | C | 5.20E-06 | 2.60E-06 | 2.00323 | 0.0452 | 6.15E-06 | 3.10E-06 | 1.981589 | 0.0475 | 8.16E-06 | 3.86E-06 | 2.117281 | 0.0342 |
| | | (1.07E-05) | (3.54E-06) | (3.0281) | (0.0025) | (1.13E-05) | (3.52E-06) | (3.19800) | (0.0014) | (1.21E-05) | (3.58E-06) | (3.3758) | (0.0007) |
| | ARCH($\alpha$) | 0.151375 | 0.040938 | 3.697623 | 0.0002 | 0.156479 | 0.043203 | 3.621972 | 0.0003 | 0.175984 | 0.043004 | 4.092318 | 0.0000 |
| | | (0.1618) | (0.0348) | (4.6463) | (0.0000) | (0.158922) | (0.03425) | (4.6390) | (0.0000) | (0.15663) | (0.03361) | (4.6601) | (0.0000) |
| | GARCH(β) | 0.783359 | 0.068862 | 11.37583 | 0.0000 | 0.765397 | 0.078211 | 9.786257 | 0.0000 | 0.721964 | 0.08647 | 8.349315 | 0.0000 |
| | | (0.7913) | (0.0453) | (17.450) | (0.0000) | (0.7876) | (0.04615) | (17.067) | (0.0000) | (0.784415) | (0.046) | (17.0525) | (0.0000) |

| | | BSE SENSEX | | | | BSE 100 INDEX | | | | BSE 200 INDEX | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Coefficient | Std.error | Z-Stat | Prob. | Coefficient | Std.error | Z-Stat | Prob. | Coefficient | Std.error | Z-Stat | Prob. |
| TGARCH | C | 4.68E-06 | 1.44E-06 | 3.26181 | 0.0011 | 4.43E-06 | 1.45E-06 | 3.056234 | 0.0022 | 4.77E-06 | 1.57E-06 | 3.026372 | 0.0025 |
| | | (6.89E-06) | (1.08E-06) | (6.39766 | (0.0000) | (6.78E-06) | (9.74E-07) | (6.95567 | (0.0000) | (7.18E-06) | (9.98E-07) | (7.2007) | (0.0000) |
| | ARCH($\alpha$) | -0.00042 | 0.020937 | -0.01991 | 0.9841 | -0.00344 | 0.019558 | -0.17565 | 0.8606 | -0.00429 | 0.019742 | -0.21709 | 0.8281 |
| | | (-0.0492) | (0.0189) | (-2.601) | (0.0093) | (-0.056) | (0.0191) | (-2.969) | (0.003) | (-0.0578) | (0.01987) | (-2.9123) | (0.0036) |
| | TGARCH($\gamma$) | 0.290443 | 0.062205 | 4.669108 | 0.0000 | 0.286111 | 0.060295 | 4.745195 | 0.0000 | 0.304203 | 0.061136 | 4.975818 | 0.0000 |
| | | (0.2271) | (0.0369) | (6.1424) | (0.0000) | (0.2275) | (0.035) | (6.4585) | (0.0000) | (0.2237) | (0.03442) | (6.4978) | (0.0000) |
| | GARCH($\beta$) | 0.797701 | 0.042726 | 18.67019 | 0.0000 | 0.807697 | 0.042971 | 18.79614 | 0.0000 | 0.798502 | 0.043743 | 18.25437 | 0.0000 |
| | | (0.8851) | (0.01448) | (61.109) | (0.0000) | (0.8882) | (0.0138) | (64.020) | (0.0000) | (0.886661) | (0.01439) | (61.6103) | (0.0000) |
| EGARCH | C | -1.28462 | 0.240564 | -5.34004 | 0.0000 | -1.12243 | 0.2255 | -4.97754 | 0.0000 | -1.03891 | 0.223973 | -4.63853 | 0.0000 |
| | | (-0.3865) | (0.0790) | (-4.887) | (0.0000) | (-0.3888) | (0.07923) | (-4.9079) | (0.0000) | (-0.4031) | (0.079287) | (-5.0852) | (0.0000) |
| | ARCH($\alpha$) | 0.210369 | 0.063359 | 3.320301 | 0.0009 | 0.177208 | 0.060306 | 2.938476 | 0.0033 | 0.167035 | 0.05826 | 2.86706 | 0.0041 |
| | | (0.1173) | (0.0476) | (2.462) | (0.0138) | (0.0988) | (0.0431) | (2.2915) | (0.0219) | (0.09174) | (0.04092) | (2.2420) | (0.025) |
| | EGARCH($\lambda$) | -0.22078 | 0.036016 | -6.13001 | 0.0000 | -0.22698 | 0.035661 | -6.36488 | 0.0000 | -0.23103 | 0.034728 | -6.65238 | 0.0000 |
| | | (-0.1535) | (0.0211) | (-7.254) | (0.0000) | (-0.1515) | (0.0199) | (-7.612) | (0.0000) | (-0.15064) | (0.0195) | (-7.6265) | (0.0000) |
| | GARCH($\beta$) | 0.885334 | 0.02285 | 38.7450 | 0.0000 | 0.89918 | 0.021426 | 41.96655 | 0.0000 | 0.906577 | 0.021482 | 42.20188 | 0.0000 |
| | | (0.96545) | (0.0065) | (148.28) | (0.0000) | (0.9639) | (0.00669) | (144.005) | (0.0000) | (0.9614) | (0.006777) | (141.878) | (0.0000) |

**Note:** Numbers in parenthesis indicates the values after COVID 19 pandemic period.

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