SEYBOLD Report
ISSN: 1533 - 9211
DOI: 10.5281/zenodo.7223442

STOCK MARKET REACTION TO COVID: ANALYSES OF COUNTRIES WITH HIGH INCIDENCE OF CONFIRMED CASES

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Abstract:
The volatility of stock market is an estimate of how much the total value of the stock market goes up and down. When external events cause uncertainty, stock market volatility might rise. We can estimate the likelihood of getting a certain result using volatility estimate and the central tendency. The present study analyzed the impact of the Covid on the volatility of the stock market indices of the top five countries in number of the Covid confirmed cases applying the Autoregressive Conditional Heteroscedasticity (ARCH) family models (GARCH, GARCH-M, TGARCH & EGARCH) models. For this objective, daily return of market indices from 03 June, 2019 to 23 Feb, 2022 have been analyzed. Further the study period has been divided in five periods according to different waves of the Covid. The main finding revealed that volatility shocks are quite persistent and the impact of old news on volatility is significant for all indices. Whereas EGARCH output supports the existence of leverage effect in stock return at all stock exchanges during the period studied.

Keywords: Uncertainty, Conditional Heteroscedasticity, Volatility, Leverage Effect, Stock Exchange, Likelihood

Introduction:

The novel corona virus (Covid) is projected to become one of the most economically costly pandemics in recent history just because of the tremendous human and health crises. According to financial sources, the pandemic is causing havoc on the world-wide economy and monetary market. Ever since financial crises, many equity markets around the world have witnessed significant falls. To gain a better understanding of new corona virus pandemic's consequences, this study investigate at the influence of Covid on the daily stock markets returns of the top five countries in Covid confirmed cases from 03 June, 2019 to 23 Feb, 2022. The economic consequences of the Covid pandemic have been felt in every country as a result of the internal profile connected to corona virus spreading and the steps taken to curb it and enhanced by globalization and connectivity of economics. The spread of Covid diseases, the imposed

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ISSN: 1533 - 9211
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movement restriction measures and the global economic uncertainty would all have a detrimental impact on stock market in most countries. The increased number of cases could be due to a variety of factors. As an outcome, the duration of Covid waves varies across countries. The duration of lockdown (Wikipedia) has been considered as the first wave and data from Worldometer (daily Covid confirmed cases) has been used to determine the second and third waves' length. We examine how the stock markets of five nations responded to the several waves of the Covid outbreak as well as the pre-Covid era.

Table 1: Time Period of Covid Waves

	Wave1	Wave 2	Wave 3
USA	11/03/2020 to 29/06/2020	12/11/2021 to 01/02/2021	12/12/2021 to 23/02/2022
INDIA	11/03/2020 to 29/06/2020	01/04/2021 to 09/06/2021	12/12/2021 to 23/02/2022
BRAZIL	11/03/2020 to 29/06/2020	11/03/2021 to 01/07/2021	12/12/2021 to 23/02/2022
UK	11/03/2020 to 29/06/2020	12/12/2020 to 30/01/2021	12/12/2021 to 23/02/2022
FRANCE	11/03/2020 to 29/06/2020	17/10/2020 to 18/11/2020	12/12/2021 to 23/02/2022

(Sources: Author's calculation based on data from Worldometer and Wikipedia)

Theoretical Review:

The concept of measuring and estimating stock price volatility is crucial in finance. The following studies of Mandelbrot (1963), Fama (1965) and Black (1966) provided leptokurtosis and leverage effect of stock return in financial markets. This section will give a quick summary of the most important empirical findings from researchers.

Many researcher have found that time series model based on the main assumption of constant variance were ineffective in estimating stock return movements. As a result, Eagle (1982) recommended using ARCH models that allow the conditional variance to change over time as a function of previous errors while keeping the unconditional variance constant. Applying the ARCH model sheds light on some of the model's flaws, allowing them to be overcome.

Bollerslev (1986) suggested a modified variant called Generalized ARCH (GARCH), which allowed for a larger memory and more dynamic lag structure. Not only does GARCH share the ARCH model's primary condition that conditional variance is defined as a linear function of prior sample variance, but it also allows for the inclusion of lagged conditional variances. Many scholars have produced more modified version of ARCH model. Such as Engle et.al.(1987), who proposed the GARCH to break the rigidity of the ARCH parameters, which supported that positive and negative excess returns impacted variance of return significantly. According to empirical evidence, excess returns and stock market variation have a negative connection. Since then, new proposed members to the GARCH family models have been suggested to solve the limitation of each model. Many empirical studies, Bekaert and Harvey (1999), Aggarwal

DOI: 10.5281/zenodo.7223442

et.al.(1999), Brook and Burke(2003) and Olowe (2009), thought the same way that the GARCH is the best model to describe the data and evaluate the volatility. Yalami and Sevil (2008), Miron and Tudor(2010) and Su (2010) approaches were based on comparing several asymmetric model proposed before such as TGARCH, PGARCH, EGARCH and GARCH-M. Their findings confirmed that asymmetric models play a critical role in volatility prediction for daily stock returns in different nations. GARCH model exhibits higher fitness in estimation of volatility in comparison to other types of asymmetric GARCH family models.

The impact of covid is critical, especially since the virus' first breakout occurred in China, largest hub for international investment in Asia continent. As we discussed the impact of Covid , we can refer to a number of past studies on the economic implications of the infectious viral epidemics. When it comes to the impact on stock markets, DeLisle claims that the 2003 SARS pandemic cost as much as the Asian crisis, with losses estimated at $3 trillion in GDP and $ 2 trillion in equity in financial markets. Nippani and washer investigated the impact of SARS on Canada, China, Hongkong, Indonesia , Singapore etc., and concluded that SARS solely damaged China and Vietnam financial markets. Del and Paltrinieri looked at the monthly flows and results of 78 mutual funds based on African countries from 2006 to 2015 and concluded that Ebola and the Arab spring had a significant impact on fund flows, influencing fund performance, spending and market returns.

Macciocchi et.al. Investigated the short-term economic impact of Zika virus outbreak on Brazil, Argentina and Mexico and findings indicate that market indices of these three latin American and Caribbean countries did not show large negative returns except Brazil the day after each shock. The average return varied from 0.90 percent to 4.87 percent depending on the circumstances and country. Using an event study approach, Minghsiang Chen, Shawnandg and Gon investigated the impact of SARS outbreak on the efficiency of Taiwanese hotel stocks and discovered that seven publically traded hotel companies experienced steep declines in income and stock price during the SARS outbreak period. On and after the day of SARS outbreak, Taiwanese hotel stocks showed large negative impact on hotel stock performance.

The impact of the SARS pandemic on china's long term relationship with four markets was studied by Chenet et.al. Their findings indicate the presence of a time varying co integration link in aggregated stock price indices and they also revealed that long term connection of china with the four markets has been reduced by SARS pandemics.

The goal of our study is to update the data utilized in prior studies for measuring volatility and analyzing the leverage effect for five countries. Study time period includes important Covid pandemic period that have influenced the global financial market. Such crises are likely to expand the importance of measuring and projecting stock market volatility, making it easier for businesses and financial decisions.

Objectives of the Study:-

The objectives of the study are following:

i. To investigate the impact of Covid outbreak on stock market volatility.
ii. To study the hedging effectiveness of the stock indices.

DOI: 10.5281/zenodo.7223442

iii. To check the leverage effect.
iv. To suggest some measure to policy makers, government and investors to curb the excess volatility.

Sources of Data:

The current study only uses secondary data in its analysis

The five most effected countries (USA, INDIA, BRAZIL, FRANCE, UK) in Covid confirmed cases have been studied using daily data from stock market indices (NYSE, NSE, BVSP, EURONEXT 100, LSE). As of February 23, 2022, these countries accounted roughly 42% of all confirmed cases internationally (Worldometer). The closing stock prices of stock market indices for the period June 03, 2019 to February 23, 2021 have been collected from the Yahoo Finance websites.

Tools of Analysis:

The analysis of data is done through various statistical tools, including descriptive statistics, the unit root test, the ARCH effect test, and the generalized autoregressive conditional heteroscedasticity (GARCH) model and others.

As in real life, the assumption of symmetric effect of volatility is frequently violated. To overcome this issue asymmetric GARCH family model (EGARCH, GARCHM, TGARCH) have been employed on the same data set to have a clear view of volatility.

The use of descriptive statistics enables us to overlook the data at first. Finally, we conduct the AECH test which is the first assumption for running the ARCH family models to achieve the goals of the present study. If this assumption holds true, we could use ARCH family models to analyze our data. The ARCH model is expended into the GARCH model. The GARCH family model has been rapidly seen to produce more accurate results. Therefore GARCH model has become the standard technique for showing instability in monetary framework data. Many studies have looked into the co-integration of stock indices in monetary economics in the past. As a conclusion, the present study utilized ARCH family models to analyze the daily stock return of the five countries stock markets in order to capture the volatility causes by the Covid outbreaks shocks.

The present study used GARCH models to monitor the news element in this sample. The GARCH models also understand the different types of dynamic behaviors of stock markets due to the good or bad news. The EGARCH model aids in the investigation of shock, which may have a significant impact on the difference since a negative shock in the system creates more significant loss in returns than positive shock contributions. Ultimately, the TARCH model estimates the magnitude and relative contribution of negative shocks in a system that brings down variation.

Descriptive Statistics-in the present study include the mean as a measure of central tendency and standard deviation, skewness and kurtosis as a measure of variability, Jargue-Bera (JB) test was used to confirm normal distribution of returns.

The returns are calculated as follow:

$$r_{it} = \frac{p_{it} - p_{it-1}}{p_{it-1}}$$

DOI: 10.5281/zenodo.7223442

Where,

p_{it} are the closing prices of a given index I on day t.

p_{it-1} are the closing prices of a given index on day t-1.

To provide better understanding, time graph of daily returns of market indexes were shown.

Unit root test-the unit root test is used to test whether a data series is stationary or not. If a change in time does not create a change in the shape of a time series, it is said to be stationary. It means that the mean, variance and autocorrelation pattern do not vary over time. Augumented Dickey Fuller (ADF) test is used to test the null hypothesis being the existence of non-stationary.

H_0 : There is unit root (non-stationary).

ARCH Model- Autoregressive conditional heteroscedasticity (ARCH) indicates that the series in question has a time varying variance (heteroscedasticity) that depends on (condition on) lagged effects (autocorrelation). This test was developed by Engle in 1982.The ability to capture stylized features of the real world has made the ARCH model become a very important econometric model. Similarly, apart from the time varying conditional mean of financial series, most of them also exhibit changes in volatility structures. Hence, to model such series, homoscedastic model cannot be used but a simple autoregressive (AR) process can be.

Mean equation

$$X_t^2 = a_0 + a_1 X_{t-1}^2 \dots\dots + a_p X_{t-p}^2 + \mu_t$$

Where

X_t^2 as a measure of volatility

If a_1 is zero, then there is no volatility clustering

Variance equation

$var(\mu_t) = h_t = \mu_t^2 = b_0 + b_1\mu_{t-1}^2 + \dots\dots\dots. + b_p\mu_{t-p}^2$

If there is no autocorrelation in the error variance, we have

$H_0 : b_1 = b_2 \dots\dots.. = b_p = 0$

Then

$h_t = b_0$ Means there is no ARCH effect.

We do not directly observe h_t, Engle has shown that running the following regression can easily test the preceding null hypothesis:

$h_t = \hat{\mu}_t^2 = b_0 + b_1\hat{\mu}_{t-1}^2 + b_2\hat{\mu}_{t-2}^2 + \dots\dots. b_p\hat{\mu}_{t-p}^2 + e_t$

$= b_0 + \sum_1^p b_1\hat{\mu}_{t-p}^2$

In this case h_t denotes the OLS residuals obtained from the original regression model. ARCH model simultaneously examines the mean and variance of a variable.

GARCH Model:

GARCH originator is Tim Bollerslev in 1986.this model capture long lags in the shock with few parameters. Conditional variance (h) at time depends on the past values of the shocks captured by the lagged square error term (μ_t^2)and past value of itself (h_t). Obviously, the ARCH (p) models discussed in above section are simply GARCH(p,0) models in which there is no memory in the process for past conditional variance prediction.

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GARCH(p,q): $h_t \; = \emptyset + \sum_{k=1}^{p} \theta_1 \; h_{t-k} + \sum_{i=1}^{q} b_i \mu_{i=1}^{q}$ ....eq(1)

If p=0, equation eq (1) reduces to ARCH (q)

Where

θ_k is the GARCH coefficient

For stationarity $\theta_1 + b_1 < 1$. If greater than 1, an integrated GARCH process has occurred.

ARCH-M Model:

ARCH- in-mean effects provide a second explanation, along with the leverage effect, for volatility asymmetries. If volatility risk is priced, an anticipated increase in volatility will rise the required rate of return and necessitate an immediate asset price decline to allow for higher future returns. This causality from volatility to prices has been labeled the volatility feedback effect. Although it suggests a causal effect opposite to the leverage effect, which involves the reverse causality from returns to volatility, the two may be observationally equivalent if the causality lag is smaller than the time between observations

Mean: $Y_t = \alpha + \beta X_t + \theta h_t + \mu_t$and

$$Y_t = \alpha + \beta X_t + \theta\sqrt{h}_t + \mu_t$$

The GARCH (h_t) term in the mean equation substantially improves the GARCH term in the variance equation.

Variance equation:

$$h_t = \gamma_0 + \sum_{i=1}^{p} \theta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j \hat{\mu}_{t-j}^2$$

Insignificant h_t in mean equation reveals risk premium not hedging against risky asset or the asset held may not be risky.

TGARCH Model:

TGARCH model captures asymmetric effects of events such as discoveries, terrorism, mergers and acquisition on h_t. i.e. $b_i u_{t-i}^2 > 0$ or $b_i u_{t-i}^2 < 0$. Dummy variable assume value 1 for bad news ($u_t < 0$) and 0 for good news (u_t>0)

TGARCH (p, g):

$h_t = \emptyset + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} (b_i + \gamma_i D_{t-i})\, u_{t-i}^2$

EGARCH Model:

GARCH (p, q) models are extended ARCH models that deliver the same advantages as ARCH but require a lower number of parameters to be estimated under inequality constraints. Therefore, similarity to ARCH, GARCH successfully captures thick tailed returns and volatility clustering. However, it is not well suited to capture what we have called the 'leverage effect' because the conditional variance is a function only of the magnitudes of the lagged squared residuals and not of their signs.

In exponential GARCH model of Nelson (1991), it depends on both the size and the sign of lagged residuals. Therefore, EGARCH is an ideal framework to capture the leverage effects and more generally, the existence of asymmetries in conditional variance.

Good news – volatility decreases

Bad news- volatility increases

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EGARCH (p, q):

$$\text{Log}\,(h_t) = \emptyset + \sum_{i=1}^{q} \eta_i \left|\frac{u_{t-i}}{\sqrt{h_{t-i}}}\right| + \sum_{i=1}^{q} \lambda_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} + \sum_{k=1}^{p} \theta \Delta_k \log\,(h_{t-k})$$

Where;

Log (h_t) = leverage effect exponential; estimates are non-negative

λ = asymmetric effect

H_0: $\lambda_1 = \lambda_2 = \lambda_3 = \ldots\ldots = 0$ (symmetric effect)

H_0 is rejected when λ < 0 Bad news generates larger volatility than good news.

Results:

Descriptive Statistics:

Table 2: Stock returns distributions for full sample

	Indices				
	US	INDIA	BRAZIL	FRANCE	UK
Mean	0 .000487	0.004011	0.000405	0.000395	0.000515
Minimum	-0.118341	-0.014798	-0.147797	-0.119722	-0.143761
Maximum	0.100365	0.006839	0.139082	0.08176	0.153385
SD.	0.014625	0.001167	0.019496	0.013411	0.020586
Skewnss	-0.988858	-6.825142	-1.138260	-1.330933	0.194700
Kurtosis	19.75349	107.6391	19.56651	17.25975	13.05842
JB Statistic	8158.266*	313190.6*	7887.944*	6157.961*	2921.492
ADF	-8.814122*	-9.068212*	-33.22870*	-26.61259*	-27.39918*
ARCH (t stat.)	9.626326*	18.51564*	12.67667*	2.965525*	3.665617*
Observations	688	675	677	702	692
(A) Before covid period(3 June,2019 to 10 March,2020)					
Mean	0.000434	0.000236	0.000527	0.003320	0.001468
Minimum	-0.085298	-0.062532	-0.121738	-0.080873	-0.096646
Maximum	0.043797	0.050339	0.071421	0.776352	0.153385

SD.	0.012124	0.017236	0.017188	0.056342	0.021569
Skewnss	-2.172125	-0.150556	-2.424987	13.11417	1.0343764
Kurtosis	17.71112	4.291306	18.95620	180.8381	17.02699
JB Statistic	1911.728*	13.84536*	2224..981*	266593.1*	1699.828*
ADF	3.147074**	-10.67983*	-0.10314***	-13.97455*	-14.45827*
ARCH(t stat.)	3.884827*	1.653573***	5.80862*	-0.073788	0.693516*
Observations	195	189	192	198	200
(B) Sample for first wave period of covid					
Mean	-0.001501	- 0.000493	- 0.002269	-0.000661	-0.000326
Minimum	-0.118341	-0.080571	-0.147797	-0.057034	-0.096646
Maximum	0.078620	0.149167	0.139082	0.044379	0.068911
SD.	0.030931	0.032324	0.038278	0.021398	0.028103
Skewnss	-1.009196	1.435830	-0.910144	-0.624974	-0.443683
Kurtosis	6.584420	8.695395	9.195188	3.196962	4.699339
JB Statistic	50.06084*	122.0519*	119.8697*	4.670058***	10.56611*
ADF	-13.90722*	-10.07331*	-17.28589*	-8.928152*	-13.94022*
ARCH(t stat.)	-0.526645	0.561054	1.524671	-0.015037	1.493668
Observations	71	72	69	70	69

(C)After first wave period

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Mean	-0.001577	- 0.001791	0.000514	0.001053	0.000772
Minimum	-0.031398	-0.045276	-0.121738	-0.033863	-0.028552
Maximum	0.031349	0.039108	0.028168	0.058679	0.038381
SD.	0.010336	0.010969	0.013934	0.011977	0.014190
Skewnss	-0.234746	0.482600	0.070565	0.693096	0.061450
Kurtosis	3.760862	5.062705	2.060237	6.811659	2.659298
JB Statistic	3.19335	38.89774*	2.671587	81.565931*	0.426343
ADF	-5.494409*	-12.24612*	-11.67167*	-10.77767*	-11.14776*
ARCH(t stat.)	-0.250135	1.276609	-1.447665	-0.619194	-0.458524
Observations	96	180	71	119	78

(D) Second wave period

Mean	-0.001373	- 0.001406	0.001382	0.000625	-0.003468
Minimum	-0.025535	-0.017743	-0.026463	-0.022497	-0.039690
Maximum	0.017949	0.039108	0.022189	0.016839	0.045116
SD.	0.008986	0.010035	0.009424	0.009334	0.021024
Skewness	-0.387479	1.359819	-0.215899	-0.639763	0.236980
Kurtosis	3.403664	6.206583	2.886477	3.020936	2.634741
JB Statistic	1.686071	32.41077*	0.647844	2.251736	0.343133
ADF	-8.432674*	-6.411076*	-10.87632*	-6.691636*	-4.067367*
ARCH(t stat.)	-0.206390	-0.534292	-0.452351	-1.065355	-0.080200

DOI: 10.5281/zenodo.7223442

Observations	53	44	78	33	23
(E)After Second wave period					
Mean	0.000600	- 0.000702	- 0.001454	0.000747	-0.000517
Minimum	-0.024179	-0.016775	-0.037805	-0.042805	-0.143761
Maximum	0.021158	0.029941	0.036626	0.031780	0.095620
SD.	0.007820	0.007643	0.014199	0.008521	0.019441
Skewnss	-0.278266	0.592687	-0.202840	-0.655414	-1.302351
Kurtosis	3.706659	4.560921	2.827995	6.454825	15.74205
JB Statistic	7.349278**	20.00826*	0.898003	126.8692*	1895.825*
ADF	-15.38877*	-9.963408*	-12.80311*	-17.10343*	-16.16292*
ARCH(t stat.)	2.649429*	0.814278	0.095455	-0.271330	1.855297***
Observations	218	125	111	223	269
(F) Third wave					
Mean	-0.000830	- 0.000224	0.000889	-0.000485	-0.000331
Minimum	-0.016595	-0.029370	-0.024229	-0.039121	-0.036822
Maximum	0.018365	0.031583	0.019424	0.020688	0.034680
SD.	0.009299	0.011710	0.009650	0.011258	0.015584
Skewnss	0.111781	0.445763	-0.234649	-0.809297	-0.210208
Kurtosis	2.110484	3.480355	2.928015	4.239206	2.642342
JB Statistic	1.717487	2.051118	0.469629	8.830388*	

					0.622033
ADF	-5.099996*	-6.143078*	-6.534420*	- 6.597177*	-6.760688*
ARCH(t stat.)	-0.769167	2.227701**	-0.107246	-0.424839	0.278185
Observations	49	48	50	51	49

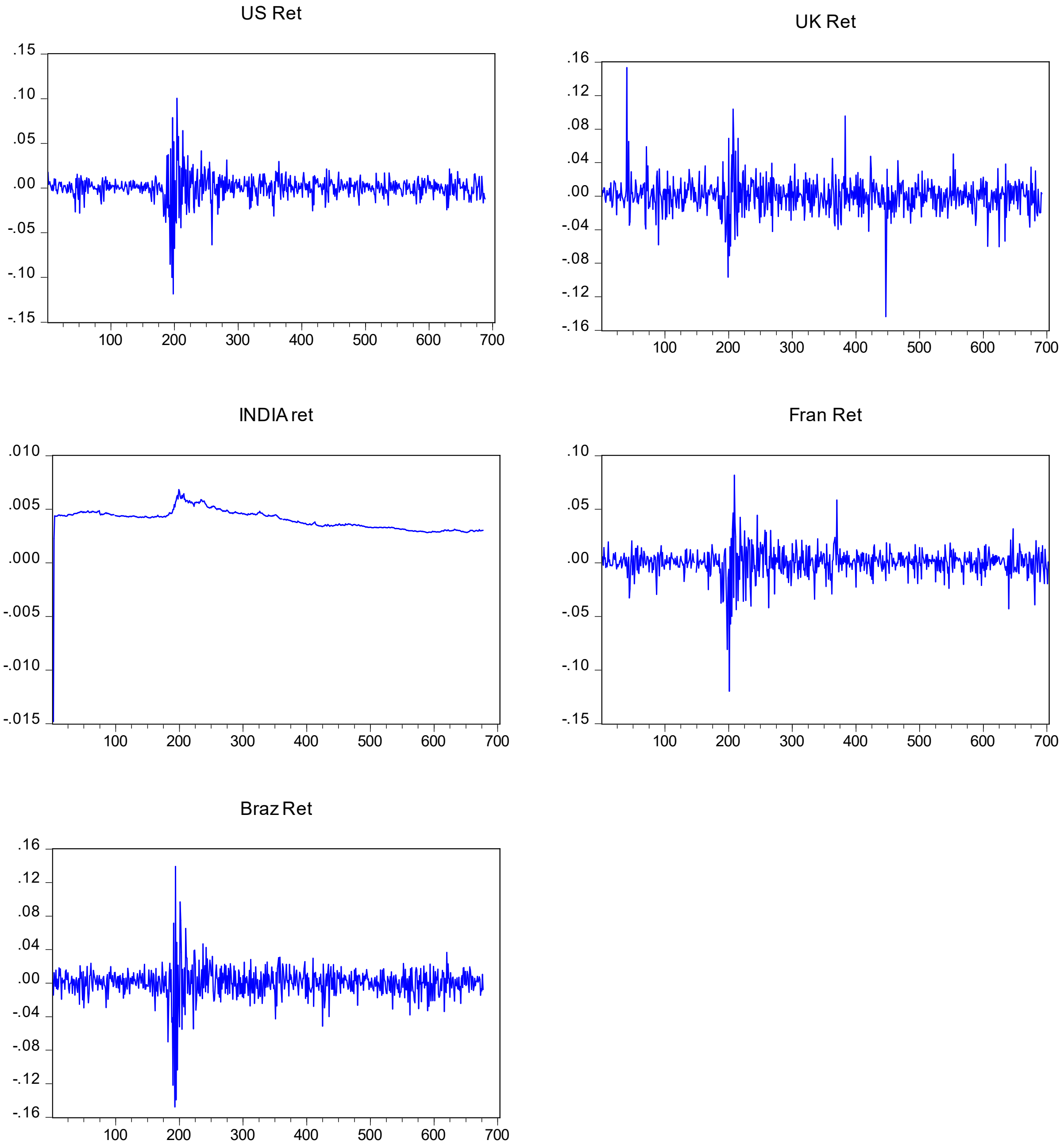
Note-* denotes the significance at 1% level, ** denotes signicance at 5% level and ***denotes significance at 10% level.

Table 2 presents a summary of descriptive statistics of return series of all indices to the top 5 countries by Covid confirmed cases. The entire period of study from June, 2019 to may, 2022 was divided into six periods, the pre Covid(03 June,201 to 10 March,2020(table 2 part (A)), the first wave of Covid(11March,2020 -29June, 2020 (Table 2 Part(B)), after the first wave period (Table 2 part (C)), the second wave (Table 2 Part (D)), after the second wave (Table 2 Part (E)) and the third wave (Table Part(F)). Most important values which are presented in the table are Skewness, Kurtosis, Jargue-Bera(JB) statistic and ARCH effect. All the indices have negative daily returns during the first wave of Covid, whereas the pre Covid era has positive daily mean returns. Besides that the first wave of Covid period shows negative daily mean returns for all the indices, while the period following the first wave shows positive mean returns for Brazil, France and the United kingdom but the negative mean returns for the United States of America and India, denoting that the negative market reaction was strong in the early days of crisis.
During the first wave period, the lowest value of all indices was observed in the month of March 2020.when comparing to the other waves and the pre-Covid period, the primary indicators of risk, the standard deviation, is quite significant for all indices during the first wave.
Despite the fact that the mean daily returns after the first wave of Covid crisis period are positive and shows a significant recovery compared to the first wave. All indices have large standard deviation values compared to the pre Covid period.
In general, two important statistics when examining time series are the skewness and kurtosis. During the first wave of Covid crisis, all indices have a stronger negative skewness than other waves of Covid. When the initial wave of Covid is compared to later waves of covid, all indices have a higher kurtosis value, indicating a leptokurtic return distribution. In comparison to the first wave of the covid, the third wave of covid has lower negetive skewness and lower kurtosis value of return distribution.
The Jarque-Bera(JB)test determines that the returns in the first wave of Covid are abnormal. In after first wave period , returns are abnormally distributed only for India and France but normally distributed for four indices during second and third wave of crisis Furthermore, four indicators in the third wave of Covid crisis show a period of stability but all indices in the same phase have a higher standard deviation than normal times.
The Augumented Dickey Fuller (ADF) test and the heteroscedasticity test results show that four indices in level form have a higher test statistic than the critical value. Thus reject the null

ISSN: 1533 - 9211
DOI: 10.5281/zenodo.7223442

hypothesis of the presence of a unit root and indicating that the indices are stationary in their level form at 1percent level. However the Indian index has maintained stationary at the first difference level. All the indices' heteroscedasticity test probability values for full sample are significant invalidating the null hypothesis that there is no ARCH effect.

The ARCH effect is thus confirmed in the residuals of the time series model of returns. As a result, all of the criteria for employing the ARCH family model have been met. But ARCH effect is insignificant in all three waves of Covid crisis.



The graphs in figure 1 show the high volatility observed during the initial wave of Covid, taking into account all five market indices. Furthermore, the entire graph tends to indicate fluctuation, implying that current volatility will influence future volatility and return series appear to be mean restoring, indicating variables are stationary.

Table 3: Coefficients of ARCH family model for full sample

	Indices				
	US	India	Brazil	France	UK
ARCH	0 .150000***	-0.049962*	0.120968*	0.149909*	0.149830*
GARCH	0 .600000*	0.438635*	0 .838036*	0.599909*	0.599830*
GARCH -M	0.188117	-0.203608*	-0.144913	0.125986	-0.056290
T-GARCH	0.364327*	1.770311*	0.123407*	0.321789*	0.149592*
E-GARCH	-0.202550*	0.148941*	-0.117128*	-0.181020*	-0.149608*

Source: Authors' calculation by using Eviews 10 software

Table summarizes the result of ARCH family model for all stock indices. The conditional mean equation coefficient is positive and significant for all indices. The coefficient of constant variance term and the ARCH and GARCH parameters in the variance equation are positive and statistically significant for all indices. Both the ARCH effect (b) and the GARCH effect (θ) components in the conditional variance equation are related to news. Specifically b indicates recent news, and its value is statistically significant in this respect, implying that recent news has influenced stock market volatility. θ Reflects old news and the fact that its value is statistically significant suggest that it has caused market volatility. Large GARCH coefficients also indicate that shocks to conditional variance take a long time to fade away, implying that volatility is persistent. If the sum of the ARCH and GARCH coefficient (b+θ) is close to unity, there will be a 'shock' at time t that will last for a long period. In other words, a high value for b+θ denotes a long memory and shock could result in a permanent shift in future h_t value, showing that conditional variance is lasting. Simultaneously, the data suggest a mean reverting process, as the sum of ARCH and GARCH coefficient is smaller than one. In addition, the absolute value of b+θ determines the rate of mean reversion. The data show that the NSE (India) and BVSP (Brazil) have the fastest mean reversion, whereas the N100 (France) and LSE.G(UK) have the slowest mean reversion, respectively. The null hypothesis of no change in volatility can be rejected based on the results of the GARCH model. Instead the change in volatility has been proved significant.

To test the hedging effectiveness of stock indices, GARCH-M model is used and standard

DOI: 10.5281/zenodo.7223442
deviation is considered as the best measure of risk. The standard deviation terms are statistically significant only for NSE(INDIA). That mean investment in Indian stock exchange as an alternatives to other investment avenues is a good option. Investment in USA, Brazil, and France and UK stock exchanges is not completely hedged against risk during the sample period. A standard ARCH and GARCH model treats good news and bad news symmetrically. That is, their impact on asset volatility h_t is the same. By this we mean that since the residual term is squared, the only aspect of the invention that matter is its absolute value rather than its sign. However the impact of good and bad news on the stock markets may be asymmetric. The main target of the Threshold GARCH (TGARCH) model is to capture asymmetries in terms of negative and positive shocks. The coefficients of the GARCH model (asymmetric term or leverage term) is significant at 1 percent level for all stock indices indicates that there are asymmetries in the news. The difference in good and bad news on the stock indices is highest for India (1.77) and lowest for Brazil (0.12) Then EGARCH model used to check whether good news dominated or bad news. The results of EGARCH model are significant for all indices. Negatively significant coefficients showed that bad news has larger effect on the volatility of stock market returns than good news in stock indices of USA, Brazil, France and UK. But a coefficient is positive and significant in Indian stock market indicates good news dominates the Indian stock market.

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