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RESEARCH ARTICLE

Analyzing the impact of COVID-19 on global stock markets: An international comparative analysis

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Abstract

In 2020, during the first wave of COVID-19, a massive collapse was observed in the stock markets of all the economically wealthy and prominent countries all over the world. Consequently, the second and third waves of COVID-19 strike stock markets in 2021. The objective of the present study is to search for the effect of the pandemic on eight major stock exchanges across different continents, namely, SENSEX, Dow-Jones, NYSE Composite, FTSE 100, SSE Composite, Nikkei 225, MOEX and MASI, in 2020-2021. Various techniques assess nonlinear analysis, volatility, and the chaotic nature of these markets. The present study concludes that though all the indices are volatile and non-chaotic, some structural changes in pattern are identified in this time frame. The FTSE 100 stands out as a stable investment option, while the NYSE Composite is recommended primarily for long-term investments.

Keywords: Chaos, COVID-19, GARCH, Non-linearity, Stock, TGARCH, Volatility.

JEL Classification Codes: C01, C2, C5, C52, C87

Introduction

The COVID-19 pandemic that began in December 2019 in Wuhan, China, has resulted in a global health emergency and forced to implement a lockdown from January 23, 2020, which caused a major economic downturn. It has impacted both the global outlook and the economy, with many countries implementing strict quarantine policies that shut down economic activities. Consumers and firms have altered their usual consumption patterns, creating market abnormalities and panic. The pandemic has caused significant economic impacts on both advanced and emerging economies worldwide, such as the United States, India, UK, China, Japan, Russia and Morocco, leading to uncertainty and risk.

On March 22, 2020, the government of India announced the janta curfew and implemented a lockdown policy from March 24, 2020, to enforce social distancing practices and slow down the spread of COVID-19. This sudden lockdown caused a stoppage of various economic activities, leading to sharp volatility in India's financial market (Ram, 2020). The Bombay stock exchange (BSE) SENSEX dropped by 13.2% on March 23, 2020 (Mondal, 2020), which was the highest single-day decline since the Harshad Mehta Scam in 1991. Similarly, the Nifty also fell by almost 29% during this period. Some economists have described the effect of COVID-19 on the Indian stock market as a "black swan event" - an extremely unanticipated event with a highly negative impact. In the USA, the government imposed a lockdown one week earlier on March 15, 2020, causing the Dow Jones, S&P 500, and NASDAQ composite indices to slump to 12.9, 12, and 12.3%, respectively. This was the worst decline since the 1987 "Black Monday" market crash. UK president announced a lockdown on March 23, 2020, and FTSE All Share price dropped by almost 35% in that quarter (Griffith, Levell and Stroud, 2020). By the end of March, most of Russia was under lockdown. Amidst the pandemic, the conflict over oil prices between Saudi Arabia and Russia triggered a collapse in the oil market, subsequently causing a worldwide downturn in stock markets. The COVID-19 pandemic has caused disruptions in the supply chain and reduced production levels in factories while also leading to a decrease in consumption patterns. Over the next two years, nations globally witnessed multiple phases of lockdown with different timing and duration. According to the 2020 World Economic Forum report,

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financial markets experienced a significant surge in volatility by the end of February 2020 (WEF, 2020). This heightened volatility was attributed to widespread sell-offs by investors and traders aiming to safeguard their capital. Consequently, equity markets witnessed a substantial downturn, resulting in a 30% loss in market capitalization, surpassing the impact seen during the global financial crisis of 2009.

Many pieces of research have been carried out independently to analyze the effect of COVID-19 on the various attributes of the stock markets. But, very few of them have estimated the impact by considering randomness, non-linearity, volatility, and chaos together. Moreover, there is a scarcity of research that includes in-depth analysis of various volatility parameters. In this study, we have tried to perform a comparative study on the effect of COVID-19 on some global stock markets on the basis of non-linearity, volatility and chaos.

Review of Literature

The COVID-19 pandemic caused a significant decline in oil prices and a sharp increase in gold prices. Some experts have referred to this pandemic as "the greater financial crisis" (Weltman, 2020) and it has led to an increase in the risk of the global financial market (Zhang *et al*., 2020). The uncertainty and fear among investors have caused a significant reduction in their wealth. In just one week, from February 24, 2020, to February 28, 2020 (Ozili & Arun, 2020) the global stock market lost about US$6 trillion. The BSE index lost almost 10,000 points within a fortnight of COVID-19 initiation. In August 2020, S&P 500 lost 34% of its valuation (Statista Research Department, 2022). Similarly, the stock markets of Spain, Hong Kong, and China saw a decline of 25.1, 14.75, and 12.1%, respectively, between March 8, 2020, and March 18, 2020 (Shehzad *et al*., 2020). Additionally, KOSPI witnessed its lowest point in history after a decade, dropping below 1,600 (Loon, 2022).

The COVID-19 pandemic has significantly affected the global financial market, causing declines in oil prices, equity values, and bond prices (Baret *et al*., 2020). The lockdowns and social distancing measures imposed to contain the spread of the virus have disrupted manufacturing and caused sharp declines in company revenue. The financial times stock exchange 100 index experienced its sharpest one-day decline since 1987 (BBC News, 2020) and the crisis has been deemed more dangerous than the global financial crisis of 2007-2008 by some experts (Georgieva, 2020).

Igwe (2020) predicted that the COVID-19 pandemic has caused significant volatility in financial markets worldwide, leading to economic downturns and negatively affecting the financial systems of many countries. Bekar *et al*. (2020) specifically focused on the US stock market and found that it reacted forcefully to the pandemic. Choi (2021) found that the connectedness between the volatility of South Korea, Japan, China, and the US varied over time, and the interdependence strengthened during the COVID-19 period. Al-Awadhi *et al*. (2020) found that the daily confirmed cases and death caused by COVID-19 significantly negatively impacted stock returns. He *et al*. (2020) examined the stock markets of several countries and found that COVID-19 had a negative but short-term impact and did not affect the stock markets of these countries more than the global average. The study of Basuony *et al*. (2021) highlights the asymmetric effect of COVID-19 on stock returns of various countries, with a more pronounced negative effect on stock markets with higher death rates. Alves (2022) also studied the chaotic behavior of different stock exchanges during the pandemic and observed that the degree of chaoticity increased for some stock exchanges while remaining unaltered or decreasing for others. Dima *et al*. (2021) did not find any affirmed evidence of a substantial change in VIX's efficiency in 2020. Tie *et al*. (2021) demonstrated that chaos in China's financial market intensified under the influence of the COVID-19 emergency. Overall, these studies suggest that the pandemic has significantly impacted stock markets globally, with varying degrees of impact on different countries and regions.

The existing studies on the influence of the pandemic on financial markets need further analysis using appropriate volatility models to measure the effect accurately. These models' consistency, reliability, and persistence should also be examined to make informed decisions during crises and formulate effective investment strategies. The analysis of the performance of major stock exchanges during this period can provide valuable insights for investors. The present study aims to analyze the statistical features of some major stock exchanges worldwide, namely, SENSEX (India), Dow-Jones (USA), NYSE Composite (USA), FTSE 100 (UK), SSE composite (China), Nikkei 225 (Japan), MOEX (Russia) and MASI (Morocco) during the COVID-19 pandemic using daily return data. The analysis will provide insights into how the stock markets responded to the pandemic and how this response can be measured using market volatility, non-linearity, and chaos measures. The study hopes to assist investors in developing effective investment strategies during crisis situations, and R-Studio software ((version 2022.07.2+576) will be used for the analysis.

Materials and Methods

Materials

The present study is performed on daily return data, which ranges between January 1, 2020, and December 31, 2021, which covers all the different waves of COVID-19 and, hence, is a reasonable choice for this study. It is important to note that the study is based on secondary data sources (Yahoo Finance, n.d.), and the quality and accuracy of the data may impact the analysis and conclusions. Return series is a suitable choice as they provide a complete and scale-free summary of investment opportunities for average investors. Additionally, return series are more likely to be stationary, which is a prerequisite for applying volatility models to the data (Campbell *et al*., 1997).

Methodology

TGARCH model of volatility

In the TGARCH model, the mean-corrected data or shock is assumed to follow a specific distribution and the conditional variance is modeled as a function of past variances and shocks, along with a threshold variable that distinguishes between positive and negative shocks. The threshold variable captures the asymmetric impact of positive and negative shocks on volatility, known as the leverage effect (Glosten *et al*., 1993). Assuming a_t representing the mean-corrected data of shock obtained from the time series $X_t, t = 1,2,...,n$ after fitting a properly ordered ARMA model, TGARCH (*m*, *n*) model is formulated as

$$a_t = \sigma_t \varepsilon_t,\ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{n} (\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2 \qquad (1)$$

where σ_t^2 is the implied volatility in a_t, $\{\varepsilon_t\}$ is a iid's with $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = 1$, a_t's are serially uncorrelated with $E(a_t) = 0$, $\alpha_0 > 0$ and $\alpha_i \geq 0$ for $i > 0$; $\beta_j \geq 0$ and $\sum_{k=1}^{\max(p,q)} (\alpha_k + \beta_k) < 1$. Moreover, $N_{t-i} = \begin{cases} 1 \text{ if } a_{t-i} < 0 \\ 0 \text{ if } a_{t-i} \geq 0 \end{cases}$

Therefore, N_{t-i} captures negative a_{t-i}. From (1), it is clear that the contribution of positive and negative σ_t^2 are $\alpha_i a_{t-i}^2$ and $(\alpha_i + \gamma_i) a_{t-i}^2$ respectively. Hence, for a positive γ_i, σ_t^2 is impacted more by negative shock compared with positive shock and a leverage effect exists. Threshold 0 is used to distinguish the effect of a positive and negative shock.

Test for randomness: Runs test

The runs test (Bradley, 1968) is a non-parametric test used to detect if a time series follows a random process by examining the frequency of runs in the series. A run is specified as a sequence of consecutive observations of the same sign. The runs test checks whether the observed number of runs in a series is significantly different from the expected number of runs in a random series. If the observed number of runs is close to the expected number of runs, the series is considered to be random. If *x* and *y* denote numbers of positive and negative runs of a series, respectively, then the observed and expected number of runs are given by

$$R = x + y \qquad (2)$$

and

$$R' = \frac{2xy}{x+y} + 1 \qquad (3)$$

The test statistic is formulated as

$$Z = \frac{R - R'}{S_R} \qquad (4)$$

where

$$S_R^2 = \frac{2xy(2xy - x - y)}{(x+y)^2 (x+y-1)} \qquad (5)$$

If the test statistic falls outside of a critical range, the null hypothesis is rejected, indicating that the series is not random.

Non-linearity test

- *Keenan test*

Keenan (1985) proposes a non-linearity test based on a Fourier expansion of the time series. This test called the Keenan test, detects non-linearity by testing the null hypothesis of linearity against the alternative hypothesis of a specific form of non-linearity, i.e., quadratic non-linearity. It is a modified version of the RESET test (Ramsey, 1969, 1974), nullifying the effect of multi-collinearity between $\hat{X}_t^2$ and X_{t-1}. Keenan's assumed model is of the form:

$$\boldsymbol{X_t} = \mu + \sum_{u=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} \theta_{uv} a_{t-u} + \sum_{u=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} \theta_{uv} a_{t-u} a_{t-v} \qquad (6)$$

$$\sum_{u=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} \theta_{uv} a_{t-u} a_{t-v} \approx 0 \qquad (7)$$

reduces (6) to linear form. Keenan's test is based on the F-test principle. Optimal lag *p* is selected by applying any one of the standard information criteria, and X_t is regressed on $(1, X_{t-1}, \ldots, X_{t-p})$ to obtain the fitted values $(\hat{X}_t)$, the residuals set $\hat{a}_t$ and the residual sum of squares r. Then $\hat{X}_t^2$ is regressed on the same variable set $(1, X_{t-1}, \ldots, X_{t-p})$ to obtain the residuals set $(\hat{\zeta}_t)$. In last step,

$$\hat{\eta}_t = \frac{\sum_{t=p+1}^{n} \hat{a}_t \hat{\zeta}_t}{\sum_{t=p+1}^{n} \hat{\zeta}_t^2} \qquad (8)$$

and the test statistic

$$\hat{F} = \frac{(n-2p-2)\hat{\eta}^2}{(r-\hat{\eta}^2)} \qquad (9)$$

are computed.

Under the null hypothesis of linearity, i.e.

$$H_0: \sum_{u=-\infty}^{\infty} \sum_{v=-\infty}^{\infty} \theta_{uv} a_{t-u} a_{t-v} = 0 \qquad (10)$$

and with the assumption that (at) are i.i.d's and Gaussian, asymptotically $\hat{F} \sim F_{1,n-2p-2}$

Tsay test

Tsay (1986) test is a generalized form of Keenan test where general quadratic terms of the form $X_{t-i}X_{t-j}$, i,j = 1,…,p ; i< j, are taken under consideration. $X_{t-i}X_{t-j}$, i,j = 1,…,p ; i<j are regressed on $(1, X_{t-1}, \ldots, X_{t-p})$. Under null hypothesis of linearity,

$$\hat{F} \sim F_{m,n-m-p-1} \qquad (11)$$

Chaos test

- *0-1 Chaos test*

The 0-1 chaos test (Gottwald & Melbourne, 2004) is a binary test used to detect chaos in data, based on the idea that chaotic data will produce an erratic and unpredictable pattern of 0s and 1s. At the final stage, for non-chaotic data, 1 is assigned, and for chaotic data, the outcome is 0.

From a data $X_t, t = 1,2,...,n$, a Fourier series p_n is constructed as

$$p_N = \sum_{t=1}^{N} x(t) e^{ikc} \text{ where } 1 \le N \le n \quad (12)$$

c, is a random number.

The smoothed mean square displacement $D_c(N)$ is measured as

$$D_c(N) = \frac{1}{n-m} \sum_{t=1}^{n-m} \left| p_{t+N} - p_t \right|^2 - \langle x \rangle^2 \frac{1-\cos Nc}{1-\cos c} \quad (13)$$

where $\langle x \rangle = (1/N) \sum_{t=1}^{N} x(t)$ and $n \le m \le N/10 \ll N$.

To add the possible presence of noise $D_c(N)$ is altered as $D_c^*(N)$

$$D_c^*(N) = D_c(N) + \alpha V_{damp}(N) \quad (14)$$

where $V_{damp}(N) = \langle x \rangle^2 \sin(\sqrt{2N})$ (15)

The asymptotic growth rate K_c for distinct c's is computed

$$K_c = corr(N, D_c^*(N)) \quad (16)$$

$$K = \text{median}(K_c) \quad (17)$$

the binary output takes values 0 and 1 for chaotic and non-chaotic data, respectively.

- *Lyapunov test*

Lyapunov test is a robust test to measure chaos. The Rosenstein method (Rosenstein *et al*., 1993) is a simple and computationally efficient method to estimate the largest Lyapunov exponent (McCaffrey *et al*., 1992; Bailey *et al*., 1997; BenSaïda & Litimi, 2013). The basic idea behind this method is to measure the average logarithmic rate of divergence of nearby trajectories in phase space (Eckmann & Ruelle, 1985).

For a time series $X_t, t = 1, 2, ..., n$, a trajectory $X = [X_1\ X_2\ \dots\ X_M]^T$ is reconstructed, $X_i = \left[x_i\ x_{i+j}\ \dots\ x_{i+(m-1)j}\right]$ being the state of the system at a time. Here *i*. *j* and *m* represent the lag and embedding dimension *m,* respectively.

Therefore, $M = N - (m - 1)J$ (18)

Closest neighbour of X_j, denoted by X_j is derived by

$$d_j(0) = \min_{\mathrm{X}_j} \left\| X_j - \mathrm{X}_j \right\| \quad (19)$$

Suppose the temporal separation between the closest neighbors is less than the mean period of the series. In that case, the two trajectories may not be close enough to accurately reflect the local dynamics, and the calculation of the Lyapunov exponent may not be reliable. So, the temporal separation between the closest neighbors must be greater than the mean period of the series.

The largest Lyapunov exponent λ_1 is estimated as the formulae suggested by Sato *et al*. (1987)

$$\lambda_1(i) = \frac{1}{i\Delta t} \cdot \frac{1}{M-i} \sum_{j=1}^{M-i} \ln \frac{d_j(i)}{d_j(0)} \quad (20)$$

Δt and $d_j(i)$ being the series period and the distance between the pair of closest neighbors after time $i\Delta t$.

The largest Lyapunov exponent abides by the power law

$$d(t) = Ce^{\lambda_1 t} \quad (21)$$

$d(t)$ being the average distance at time t and $C = d(0)$,

$$d_j(i) = C_j e^{\lambda_1 (i\Delta t)} \quad (22)$$

C_j being the initial separation.

(22) yields

$$\ln\left(d_j(i)\right) = \lambda_1 (i\Delta t) + \ln\left(C_j\right) \quad (23)$$

The largest Lyapunov exponent is estimated by applying the method of least square as

$$y(i) = \frac{1}{\Delta t} \left\langle \ln\left(d_j(i)\right) \right\rangle \quad (24)$$

Where $\langle . \rangle$ denotes the mean overall values of j.

$\lambda_1 > 0$ and $\lambda_1 < 0$ for chaotic and non-chaotic systems, respectively.

Results

ADF Unit Root Test Result

Augmented Dicky-fuller (ADF) unit root test (Dickey & Fuller, 1979) is applied on SENSEX, Dow-Jones, NYSE Composite, FTSE 100, SSE Composite, Nikkei 225, MOEX and *MASI*, for checking the stationarity condition, as it is a prerequisite condition to apply TGARCH model. Table 1 summarizes the result. The optimal lag of AR model is selected a by minimizing among the Akaike information criterion (AIC), Bayesian information criterion (BIC) & Hannan-Quinn information criterion (HIC).

It is evident from Table 1 that all the return data are stationary in nature and fit for the volatility test.

Volatility Test Result

The TGARCH (1, 1) model is used to test for volatility during the COVID-19 period. The model is chosen because it incorporates the asymmetric effect of shocks on volatility. The appropriate lag for the ARIMA model is chosen based on the minimum Akaike information criterion (AIC), and the residuals from the ARIMA model are used as inputs to the TGARCH (1, 1) model to estimate the volatility of the return data. Table 2 summarizes the result.

Table 2 shows that all eight series are volatile due to significant GARCH components at the 5% significance level. This suggests that periods of high volatility tend to cluster together over time. The combined effect of ARCH and GARCH components is near 1 except NYSE composite and Nikkei 225, indicating that the volatile nature is persistent and clustering for maximum series. The stock markets also exhibit a positive and statistically significant leverage effect except for FTSE 100, indicating the market reacted more to

Table 1: ADF unit root test result

Name of the stock exchange	*AR Lag*	*Test statistic (p value)*
SENSEX	7	-6.63(0.01)*
Dow-Jones	7	-8.11(0.01)*
NYSE Composite	1	-4.81 (0.01)*
FTSE 100	7	-8.01 (0.01)*
SSE Composite	7	-8.67 (0.01)*
Nikkei 225	7	-8.00 (0.01)*
MOEX	7	-7.65 (0.01)*
MASI	7	-7.10 (0.01)*

*denotes rejection of the null hypothesis of the presence of unit root at 5% significance level.

Table 2: TGARCH (1,1) test result

Name of the stock exchange	α_0 *(Constant)*	α *(ARCH effect)*	β *(GARCH effect)*	$\alpha+\beta$	γ *(Leverage effect)*
SENSEX (ar lag = 7, ma lag = 5)	-0.18(0.00)*	-0.16(0.00)*	0.98(0.00)*	0.82	0.12(0.00)*
Dow-Jones (ar lag = 4, ma lag = 4)	-0.33(0.10)	-0.16(0.00)*	0.96(0.00)*	0.80	0.37(0.00)*
NYSE Composite (ar lag = 0, ma lag = 2)	-0.40(0.14)	-0.23(0.00)*	0.95(0.00)*	0.72	0.51(0.00)*
FTSE 100 (ar lag = 2, ma lag = 16)	-0.06(0.005)*	-0.14(0.00)*	0.99(0.00)*	0.85	-0.06(0.00)*
SSE Composite (ar lag = 2, ma lag = 2)	-0.73(0.00)*	-0.08(0.11)	0.92(0.00)*	0.84	0.22(0.00)*
Nikkei 225 (ar lag = 6, ma lag = 5)	-1.52(0.25)	-0.15(0.00)*	0.83(0.00)*	0.68	0.44(0.00)*
MOEX (ar lag = 4, ma lag = 4)	-0.22(0.00)*	-0.10(0.00)*	0.97(0.00)*	0.87	0.12(0.00)*
MASI (ar lag = 2, ma lag = 8)	-0.41(0.01)*	-0.02(0.72)	0.96(0.00)*	0.94	0.30(0.00)*

*denotes rejection of null hypothesis at 5% significance level. P-values are included in ( ) brackets.

Table 3: Weighted Ljung-box test result

Name of the stock exchange	*Weighted Ljung-Box test on standardized residuals*			*Weighted Ljung-Box test on standardized squared residuals*		
	Lag 1	Lag [2*(p+q)+(p+q)-1]	Lag [4*(p+q)+(p+q)-1]	Lag 1	Lag [2*(p+q)+(p+q)-1]	Lag [4*(p+q)+(p+q)-1]
SENSEX	0.23 (0.63)	11.38 (1.00)	26.65 (0.79)	0.38 (0.54)	1.71 (0.69)	2.97 (0.76)
Dow-Jones	0.43 (0.51)	4.21 (1.00)	10.88 (1.00)	0.33 (0.56)	0.79 (0.90)	1.48 (0.96)
NYSE Composite	0.00 (0.99)	0.01 (1.00)	0.04 (1.00)	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)
FTSE 100	0.35 (0.55)	21.96 (1.00)	44.53 (0.52)	0.26 (0.61)	1.86 (0.65)	3.29 (0.71)
SSE Composite	0.64 (0.42)	5.05 (0.95)	7.91 (0.81)	2.97 (0.08)	3.53 (0.32)	4.22 (0.55)
Nikkei 225	2.93 (0.09)	14.47 (1.00)	24.24 (0.80)	1.46 (0.23)	2.34 (0.54)	3.40 (0.69)
MOEX	0.004 (0.94)	5.62 (1.00)	12.12 (1.00)	0.03 (0.85)	2.42 (0.52)	5.41 (0.37)
MASI	2.17 (0.14	13.76 (0.98)	21.83 (0.80)	2.29 (0.13)	8.99* (0.02)	13.24* (0.01)

*denotes rejection of null hypothesis of no autocorrelation at 5% significance level. *p-values* are included in ( ) brackets.

negative shocks than positive shocks during the COVID-19 pandemic. The leverage effect is most in NYSE composite, followed by Nikkei 225 and Dow Jones. Past volatility has a significant impact on future volatility for all the markets. The weightage of squared latest variance are much in all the markets, but Nikkei 225 suggests comparatively less volatility.

Next, some additional tests regarding model consistency, reliability, and stability are executed.

The weighted Ljung-Box test ((Ljung & Box, 1978) is used on standardized residuals and standardized squared residuals to check if the TGARCH (1,1) model removes the serial dependence of the residuals. The test checks for autocorrelation at lag k>0 and the null hypothesis is that the residuals are independently and identically distributed. Table 3 describes the test result.

Table 3 shows that for almost all the series, the null hypothesis of no autocorrelation at lag k>0 cannot be rejected at the 5% significance level, indicating that the TGARCH (1,1) model is successful in removing serial dependence in both the standardized residuals and standardized squared residuals. However, for MASI, the null hypothesis is rejected at the 5% significance level for lag 49, which hints for some residual serial correlation and needs further inspection. Nonetheless, the overall results suggest that the TGARCH (1,1) model adequately captures the volatility dynamics of the return series.

The weighted ARCH-LM test (Kostov *et al.*, 2006) is used to determine if there is any residual ARCH effect present after fitting the TGARCH model. The test's null hypothesis

Table 4: Weighted ARCH-LM test result

Name of the stock exchange	*Weighted ARCH-LM Test on standardized residuals*		
	Lag 3	Lag 5	Lag 7
SENSEX	0.38(0.53)	0.46(0.90)	1.69(0.78)
Dow-Jones	0.00(0.93)	0.85(0.78)	1.02(0.91)
NYSE Composite	0.00 (1.00)	0.00 (1.00)	0.00 (1.00)
FTSE 100	1.50(0.22)	2.59(0.35)	3.03(0.51)
SSE Composite	0.18(0.67)	0.35(0.93)	0.48(0.98)
Nikkei 225	0.03(0.85)	1.71(0.54)	2.34(0.64)
MOEX	0.02(0.89)	0.36(0.92)	3.19(0.48)
MASI	4.56(0.03)*	11.68(0.00)*	12.70(0.004)*

*denotes rejection of null hypothesis presence of ARCH effect at 5% significance level. P-values are included in ( ) brackets.

is that no residual ARCH effect is present after the model is fitted. Table 4 demonstrates the result.

Table 4 supports the findings in Table 3, indicating that it has not been any evidence of the ARCH effect in the standardized squared residuals for all indices except MASI. This implies that the TGARCH (1,1) model successfully removes autocorrelation among almost all the standardized residuals and squared residuals. However, it is significant to note that, as hinted in Table 3, the presence of a statistically significant ARCH effect in the standardized residual of MASI may suggest that all ARCH effects may not be eliminated after fitting the TGARCH (1,1) model. Nevertheless, the overall conclusion is that the TARCH (1,1) model is a reliable choice to study the series under consideration.

The Nyblom stability test (Nyblom, 1989) is used to examine the stability of the parameter estimates in a time series model. The null hypothesis is that the parameter estimates are constant over time, while the alternative hypothesis is that they are not. The test is based on the martingale difference sequence and checks whether the parameter estimates are statistically significant at different lags. If the test statistic is significant, the null hypothesis is rejected, indicating that the parameter estimates are unstable over time. In the context of the current study, the Nyblom stability test can be used to examine whether the parameter estimates of the TGARCH (1,1) model are stable over time for the four indices under consideration. The test result is produced in Table 5.

Table 5 shows that most of the parameter values are below the critical values, which supports the stability of the parameter values. The only exception is the Dow Jones constant and GARCH coefficients, which are above the 5% critical values though well below 10% critical value, suggesting some instability in those parameters. However, the overall inference is that the TGARCH (1,1) model is stable for forecasting.

Sign bias tests (Engle & Ng, 1993) are used to check the misspecification of the conditional volatility model. The test examines whether the standardized squared residuals are foreseeable by the means of dummy variables significant of certain information. The sign bias test uses a dummy variable that tests the influence of positive and negative shocks on volatility not accounted for by the model. The negative sign bias test concentrates on the effect of negative shocks, whereas the positive sign bias test focuses on the impact of positive shocks. The null hypothesis is additional parameters related to the additional dummy variables = 0. It emphasizes the specification of the conditional volatility model. Table 6 briefs the result of sign bias test.

The results from Table 6 indicate that the TGARCH (1,1) model is well-specified, as nearly all outcomes are in favor of the null hypothesis that the additional parameters related to the dummy variables are zero, indicating that the model has captured all asymmetric volatility present in the data. For SENSEX and MASI, it is evident that, the model does not predict effect of some positive shocks on volatility, though joint effect of positive and negative shocks on volatility is forecasted. Therefore, the TGARCH (1,1) model is adequate and reliable for forecasting the volatility of the stock markets under study.

Adjusted Pearson Goodness-of-Fit Test (Kostov *et al.*, 2006) is a statistical test used to determine whether a sample of data comes from a population with a specific probability distribution. The test statistic is based on the difference

Table 5: Nyblom stability test result

Name of the stock exchange	α_0 *(Constant)*	α *(ARCH effect)*	β *(GARCH effect)*	γ *(Leverage effect)*	*Asymptotic critical value*
SENSEX	0.19	0.21	0.16	0.17	0.47 (5%) 0.75(1%)
Dow-Jones	0.66*	0.31	0.57*	0.12	
NYSE composite	0.41	0.25	0.35	0.45	
FTSE 100	0.10	0.10	1.34	0.09	
SSE composite	0.45	0.15	0.46	0.15	
Nikkei 225	0.46	0.04	0.38	0.12	
MOEX	0.10	0.25	0.10	0.10	
MASI	0.34	0.34	0.32	0.43	

*denotes violation of critical value at 5% significance level.

Table 6: Sign bias test result

Name of the stock exchange	*Sign bias*	*Negative sign bias*	*Positive sign bias*	*Joint effect*
SENSEX	1.82(0.06)*	1.50(0.13)	1.90(0.06)*	6.04(0.11)
Dow-Jones	0.95(0.34)	0.32(0.75)	0.08(0.94)	1.22(0.75)
NYSE Composite	1.23(0.22)	0.00(1.00)	1.10(0.27)	2.10(0.55)
FTSE 100	0.67(0.50)	0.66(0.51)	0.70(0.48)	0.93(0.82)
SSE Composite	0.45(0.65)	1.69(0.09)	0.55(0.58)	3.18(0.36)
Nikkei 225	0.07(0.94)	0.38(0.71)	1.46(0.14)	2.76(0.43)
MOEX	0.99(0.32)	1.27(0.21)	1.41(0.16)	3.76(0.29)
MASI	0.83(0.40)	0.73(0.46)	2.22(0.03)*	5.48(0.14)

p-values are included in ( ) brackets.

Table 7: Adjusted Pearson Goodness-of-Fit test result

Name of the stock exchange		*SENSEX*	*Dow-Jones*	*NYSE Composite*	*FTSE 100*
		Statistic (*p-value*)	Statistic (*p-value*)	Statistic (*p-value*)	Statistic (*p-value*)
Group	20	22.56 (0.26)	30.72* (0.04)	31.00* (0.04)	17.26 (0.57)
	30	33.20 (0.27)	35.87 (0.18)	48.26* (0.01)	24.96 (0.68)
	40	37.58 (0.53)	48.49 (0.14)	61.08* (0.01)	36.23 (0.60)
	50	52.60 (0.34)	56.94 (0.20)	57.90 (0.18)	51.34 (0.38)
Name of the stock exchange		*SSE Composite*	*Nikkei 225*	*MOEX*	*MASI*
		Statistic (*p-value*)	Statistic (*p-value*)	Statistic (*p-value*)	Statistic (*p-value*)
Group	20	13.02 (0.84)	21.74 (0.30)	22.63 (0.25)	23.28 (0.22)
	30	30.09 (0.41)	25.73 (0.64)	35.35 (0.19)	25.07 (0.67)
	40	31.21 (0.81)	43.22 (0.70)	39.44 (0.45)	38.77 (0.48)
	50	40.17 (0.81)	65.85 (0.05)	50.60 (0.41)	45.56 (0.61)

between the observed and expected frequencies in each cell of a frequency table.

This study uses the test to compare the empirical distribution of the standardized residuals with the theoretical distribution. The number of cells in the frequency table varies from 20 to 50, and the test is performed for each value of the number of cells. The results of the test are summarized in Table 7.

Table 7 shows that the *p-values* are greater than 0.05 for nearly all values of the number of cells, except Dow-Jones (number of cells = 20) and NYSE composite (number of cells = 20 and 30), indicating that the null hypothesis of the standardized residuals following a normal distribution cannot be rejected. This suggests that the TGARCH (1,1) model adequately fits the data.

Table 8: Run test result

Name of the stock exchange	*Number of runs*	*Test Statistic (p-value)*
SENSEX	234	-1.39(0.16)
Dow-Jones	275	-1.964(0.049)
NYSE Composite	259	0.49(0.62)
FTSE 100	288	3.02(0.00)*
SSE Composite	262	1.68(0.09)
Nikkei 225	260	1.40(0.16)
MOEX	252	0.00(1.00)
MASI	206	-3.86(0.00)*

*denotes rejection of null hypothesis of randomness at 5% significance level. P-values are included in ( ) brackets.

Run Test Result

The outcome of run test is stated in Table 8. Table 8 suggests that the return series of FTSE 100 and MASI during COVID-19 pandemic period may have been influenced by some underlying factors that caused a non-random pattern to emerge, while the return series of SENSEX, Dow-Jones, NYSE composite, SSE composite, Nikkei 225 and *MOEX* did not exhibit any such pattern.

Non-linearity Test Result

Keenan test and Tsay test are performed to examine the presence of nonlinear dependence in the considered stock exchange indices Table 9.

Nonlinear measures of the considered series are performed using Keenan test and Tsay test and the result is displayed in Table 9.

Table 9 suggests that both the Keenan test and Tsay test indicate that SENSEX, Dow-Jones and *MASI* are nonlinear. FTSE 100, SSE composite and Nikkei 225 show non-linearity by the Tsay test, but linearity by the Keenan test. NYSE composite has a linear trend.

Chaos Test Result

Both 0-1 chaos test and the Lyapunov test are used to investigate the chaotic nature of Indian and American markets during the COVID-19 pandemic. The result is shown in Table 10. Different embedding dimensions are tried in the Lyapunov test, and the one with the lowest BIC is chosen as the optimal embedding dimension.

The 0-1 chaos test (see Table 10) result suggests that test statistic value of all the series under our study is close to 1, indicating non-chaoticness in all the series. The largest Lyapunov exponent test reasserts this, as the mean largest Lyapunov exponent is significantly negative for all the series.

Table 9: Non-linearity test result

Name of the stock exchange	*Optimal AR lag*	*Type of test*	*Test statistic (p-value)*	*Type of test*	*Test statistic (p-value)*
SENSEX	7	Keenan test	7.86(0.005)*	Tsay test	8.16(0.00)*
Dow-Jones	7		12.38(0.00)*		10.74(0.00)*
NYSE Composite	1		0.21(0.65)		0.40(0.52)
FTSE 100	7		0.10(0.76)		6.56(0.00)*
SSE Composite	7		0.15(0.69)		1.61(0.03)*
Nikkei 225	7		0.31(0.58)		4.29(0.00)*
MOEX	7		2.24(0.13)		7.50(0.00)*
MASI	7		6.89(0.001)*		18.78(0.00)*

*denotes rejection of null hypothesis of linearity at 5% significance level. P-values are included in ( ) brackets.

Table 10: Chaos test result

Name of the stock exchange	*Type of test*	*Test statistic (p-value)*	*Type of test*	*Largest Lyapunov Exponent*	*Optimal embedding dimension m)*	*Test statistic (p-value)*
SENSEX	0-1 chaos test	0.996	Lyapunov test	-0.54	5	-74.01(0.00)*
Dow-Jones		0.996		-0.58	2	-418.33(0.00)*
NYSE Composite		0.995		-1.66	1	-565.54 (0.00)*
FTSE 100		0.996		-3.62	1	-202.17 (0.00)*
SSE Composite		0.997		-3.10	1	-241.98 (0.00)*
Nikkei 225		0.996		-3.30	1	-1274.60(0.00)*
MOEX		0.997		-3.45	1	-220.09(0.00)*
MASI		0.998		-0.75	3	-105.01(0.00)*

*denotes rejection of the null hypothesis of chaos at 5% significance level. P-values are included in ( ) brackets.

Discussion

The paper has thoroughly analyzed the effects of COVID-19 pandemic on eight major global stock markets. The study found that the return series of all markets were stationary, indicating that the COVID-19 pandemic time span did not significantly impact the basic nature of the markets. This suggests that some underlying variables or factors are affecting the market. This provides an opportunity for investors to gain insights and potentially identify profitable trading opportunities based on their understanding of these underlying factors. However, the fact that the markets except FTSE 100 and MASI did support randomness which means that future predictions for those markets may be more subtle and difficult to make with a high degree of accuracy. Some underlying law might govern FTSE 100 and MASI and easier to forecast. The study found evidence of nonlinear behavior in all markets, excluding the NYSE Composite during the COVID-19 pandemic. This means that the association between different variables and factors in the market may not be linear, and there may be complex interactions between these variables. This can make it more difficult to predict future market behavior using traditional linear models. The absence of chaos in the markets indicates that there is a certain degree of predictability and regularity in their behavior. While the markets may exhibit nonlinear behavior, they are not completely chaotic, meaning that their future behavior can be predicted with a certain degree of accuracy. The study found that all eight markets exhibited volatile behavior during the COVID-19 pandemic, as expected. This volatility was asymmetric, meaning the markets reacted more strongly to negative news and speculation than to positive information. This may have been due to the panic and economic uncertainty created by the pandemic, which led investors to be more cautious and risk-averse. Volatility is less persistent in the NYSE composite and Nikkei 225, though they may be more influenced by negative shocks compared to other markets due to the differences in their market characteristics. The effect of asymmetric volatility is absent FTSE 100, indicating that there may be identifiable underlying factors that can help mitigate the impact of negative news. The possible explanation of this lies in its non-random nature. SENSEX and MOEX exhibit a lower leverage effect, suggesting their resilience in the face of adverse information and signaling a more stable response to negative news. SSE composite and MASI show a notable amount of volatility with a leverage effect. This characteristic may present opportunities for traders seeking to capitalize on market fluctuations, but it also implies a higher level of risk and potential for amplified price movements.

Asymmetric volatility is a concern as it may lead to economic instability in the market, especially if it persists in the long term. The paper suggests that proper precautions and measures should be taken to reduce the leverage effect. This may include implementing regulatory measures to limit excessive borrowing and leverage by market participants, improving transparency in the financial markets, and encouraging diversification of investment portfolios to minimize risks. Additionally, investors and traders should carefully monitor market conditions and adjust their trading strategies accordingly to manage risk and avoid excessive losses during periods of high volatility. Overall, the findings of the paper highlight the importance of understanding the nature of volatility in financial markets and taking appropriate measures to mitigate its impact on the economy.

Conclusion

In conclusion, the present study argues that, during the COVID-19 pandemic, the basic stationary nature of the return data of major global stock markets is preserved and chaos does not affect them. Except for NYSE composite, all markets show non-linearity. This characteristic positions it as a potentially less risky investment option, suggesting a more stable and predictable performance than markets with asymmetric volatility. Investors may find the FTSE 100 appealing for its perceived reliability and lower susceptibility to sudden and extreme market movements. Asymmetric volatility is more alarming in the NYSE composite and Nikkei 225, which means that negative shocks have a greater impact on volatility. This heightened asymmetry raises concerns about the potential for a market crash, as negative events seem to substantially influence the overall market dynamics in these indices. This can be a cause for concern for investors as it may affect their level of trust in the market. Moreover, due to the higher volatility and leverage effect in the NYSE composite, investors should exercise caution and consider long-term investment strategies instead of short-term investments, which are more susceptible to market fluctuations. Taking proper measures, such as diversifying investments, keeping a balanced portfolio, and keeping abreast of market developments, can help mitigate risks and increase investor confidence. Long-term investment may be a more suitable strategy for investors in the markets considered in the present study during the COVID-19 pandemic, as there is no evidence of chaos and the basic stationary nature of the return data is preserved. However, it is important for investors to carefully analyze and consider the persistent leverage effect and higher volatility and take proper precautions and measures while investing.

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