IMPACT OF COVID-19 PANDEMIC ON THE INDIAN AND AMERICAN STOCK MARKETS: A COMPARATIVE STUDY ON DAILY RETURN DATA BASED ON VOLATILITY, RANDOMNESS, NONLINEARITY, AND CHAOS

Swetadri Samadder Department of Mathematics, Fakir Chand College, Diamond Harbour, South 24 Parganas, West Bengal, India, (Affiliated to University of Calcutta) swetadri.iitm@gmail.com

Abstract

In 2020, stock markets around the world, including India, experienced a massive collapse during the first wave of COVID-19. The second and third waves of COVID-19 struck in 2021. The objective of the present study is to search for the impact of the pandemic on prime Indian and American stock exchanges, namely, BSE SENSEX, NSE NIFTY, S&P 500, and Dow-Jones from January 1, 2020, to December 31, 2021. Nonlinearity, volatility, and chaos are measured by different techniques. The present study reveals that though all the indices are nonlinear, volatile, and non-chaotic, some structural changes are identified in this time frame.

Keywords: COVID-19, nonlinearity, GARCH, TGARCH, chaos

1. Introduction

The rapid spread of the unprecedented COVID-19 pandemic has put the world in jeopardy and changed the global outlook unexpectedly. Initially, the SARS-CoV-2 virus, which caused the COVID-19 outbreak triggered in Wuhan city, Hubei province of China in December 2019, and with time it spread all over the globe. This pandemic is not only a global health emergency but also a significant global economic downturn too. As many countries adopt strict quarantine policies to fight the unseen pandemic, their economic activities are suddenly shut down. Transports being limited and even restricted among countries have slowed down global economic activities. Most prominently, consumers and firms have prevented their usual consumption patterns due to the creation of panic among them and created market abnormality. Uncertainty and risk were created due to this pandemic, causing significant economic impact all over the globe affecting both advanced and emerging economies such as the United States, Spain, Italy, Brazil, and India etc.

The government of India announced Janata Curfew on March 22, 2020, and the lockdown policy to maintain social distancing practices to slow down the outbreaks from March 24, 2020. As the government announced such a lockdown policy, various economic activities have been stopped suddenly. The financial market of India is witnessed sharp volatility because of the disruption of the global market [1]. BSE SENSEX witnessed a drop of 13.2%, on March 23, 2020, which was the highest single they decline after the event of the Harshad Mehta Scam, on April 28, 1991 [2]. Similarly, Nifty has also fell to almost 29% during this period. Some economists have considered the impact of COVID-19 on the Indian stock market as a “black swan event,” that is, the occurrence of a highly unanticipated event with an extremely bad impact. USA Government imposed a lockdown one week before, on March 15, 2020. As an immediate consequence, Dow-Jones, S&P 500, and NASDAQ Composite indices slumped to 12.9%, 12% and 12.3% respectively. This was the worst decline since 1987 “Black Monday” market crash. Due to the lockdown policy adopted by the government, the factories have reduced the size of their labor force as well as production level which disrupted the supply chain. Again, because of the uncertainty prevailing among mankind, people also reduce their consumption habits leading to demand-side shock. Studies have also found that the entire previous pandemic had affected only the demand chain. But this COVID-19 pandemic has affected both the demand chain and supply chain.

The second wave of COVID-19 hit and cast a cloud of uncertainty on the stock markets in India. Roughly in the month of January 2021, the second wave of COVID-19 struck India, reaching its peak on May 03, 2021, and by the end of May, the active cases started to decline. The third wave in India is again hit at the end of 2021 [3]. USA scenario is much worse. The second wave in USA approached earlier; it lasted from mid-June 2020 to September end 2021. It reached its peak in the 4th

week of July [3]. 3rd wave in USA followed immediately in October, reached its peak on January 08, 2021, and persisted till the end of February 2021 [3]. In July 2021 4th wave started, it attains its maximum on August 27, 2021, and continued till November 2021 [3]. The fifth wave started to form in December 2021 [3]. So, it is evident that the COVID-19 pandemic seems to have become a periodic phenomenon over the last couple of years. In crisis-like situations such as pandemics, the financial performance of the stock market is expected to deteriorate due to public fears of declining economic activity, reduced disposable income, and investors' negative sentiments.

COVID-19 pandemic resulted in a large fall in the oil price and a large inclination in the gold price. Firzli has described this pandemic as "the greater financial crisis" [4]. The risk of global financial market has increased considerably in response to the pandemic [5]. Investors panicked to fear, & uncertainty, and their wealth was reduced a lot. The global stock market has struck out about US$6 trillion in a week from February 24, 2020, to February 28, 2020 [6]. The market value of the Bombay Stock Exchange (BSE) index declined almost 10,000 points within 15 days from March 6, 2020, to March 25, 2020, since the COVID-19 outbreak. S&P 500 had lost 34% of its valuation in August 2020 [7]. The stock market of Spain, Hong Kong, and China also witnessed a fall of 25.1, 14.75, and 12.1% in their price from March 8, 2020 to March 18, 2020 [8]. KOSPI is dropped below 1,600 in their history after 10 years [9].

Baret et al. [10] found that oil, equity, and bonds are affected badly during COVID-19 pandemic. The imposition of lockdown and social distancing largely hampered manufacturers and the company's revenue sharply decreased as a result, worldwide. The Financial Times Stock Exchange 100 index witnessed the sharpest 1-day decline since 1987 [11]. Georgieva [12] noted that for most of the developed and developing counties, the financial crisis due to COVID-19 pandemic is more hazardous in comparison with the Global Crises of 2007–2008.

Igwe [13] suggested that the shock from this pandemic can increase the volatility that can negatively affect the economic and financial system of every country. Bekar et al. examined and concluded that the US stock market reacted forcefully to COVID-19 [14]. Choi [15] found that the connectedness between the volatility of South Korea, Japan, China, and USA vary over time, and the interdependence increased during COVID-19 period. Al-Awadhi et al. [16] found that the increase in the daily confirmed cases and death caused by COVID-19 has a significant and negative impact on stock returns. He et al. [17] applied t-test and non-parametric Mann-Whitney test on the stock markets of China, Italy, South Korea, France, Spain, Germany, Japan and the United States of America and showed that COVID-19 has a negative, but short-term impact on the stock markets, but they found no evidence that COVID-19 negatively affects stock markets of these countries, more than it does the global average. Basuony et al. [18] investigated impact of COVID-19 pandemic on stock returns utilizing an asymmetric exponential generalized autoregressive conditional heteroscedasticity model, on stock market indices of Brazil, China, Italy, India, Germany, Russia, Spain, United Kingdom, and USA, from January 1, 2013, to December 31, 2020, and identified that unprecedented increases in conditional volatilities and the impact is asymmetric, with the negative effect of death being more pronounced. Alves [19] studies the change in chaotic behavior on different stock exchanges during COVID-19 pandemic and observed that the degree of chaoticity increases in the case of S&P 500, NASDAQ Composite, Euronext 100; unaltered for Nikkei 225, IBEX 35; decreases for SSE Composite Index. Dima et al. [20] found any no clear evidence of a substantial change in VIX's efficiency during 2020. Tie et al. [21] demonstrated that under the influence of an emergency (COVID-19), chaos in China's financial market intensified.

Though there are various studies regarding analyzing COVID-19 effect on stock markets, there lies a lack of in-depth analysis measuring suitable volatility models, stability of the model, and persistency of the effect of volatility. The present study explores the performance measurement analysis of prime Indian and American stock exchanges during the COVID-19 pandemic. The performance measurements are on daily return data of SENSEX, NIFTY (India), and S&P 500, Dow-Jones (USA). Comparative analysis on market volatility, non-linearity, and chaos is performed. This analysis can provide investors with additional information to formulate profitable investment strategies during crisis-like situations. This study helps us understand how the Indian and American market behaves when a pandemic hit them, and a comparative idea may be enriched among the investors. R-Studio version 2022.07.2+576 has been used for computational purposes.

2. Data and methodology
2.1 Data
The study is based on secondary sources of data. Data on the daily return of BSE SENSEX, NSE NIFTY, S&P 500, and Dow-Jones have been collected from January 1, 2020, to December 31, 2021 [22]. The reason for the choice of this time span is to incorporate all the different waves of COVID-19. Return series are taken into consideration as for average investors, the return of an asset is a complete and scale-free summary of the investment opportunity [23]. Moreover, the return series has more chance to be stationary which is a primary condition to apply the volatility model to the data.
2.2 Methodology
2.2.1 TGARCH Model Of Volatility
TGARCH (threshold generalized autoregressive conditional heteroskedasticity) model detects volatility present in data, in addition to the asymmetric nature of the volatility w.r.t positive and negative shock, known as the leverage effect [24]. Let a_t represents the mean-corrected data or shock obtained from the series $X_t, t = 1, 2, ..., n$ after fitting an ARMA model with proper order.
TGARCH (*m*, *n*) model is described as

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

where σ_t^2 is the implied volatility in a_t, $\{\varepsilon_t\}$ is a iid's having $E(\varepsilon_t) = 0$ 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 $\sum_{k=1}^{\max(p,q)} (\alpha_k + \beta_k) < 1$. Also,

$$N_{t-i} = \begin{cases} 1 \text{ if } a_{t-i} < 0 \\ 0 \text{ if } a_{t-i} \geq 0 \end{cases}$$

Hence, N_{t-i} catches negative a_{t-i}. (1) demonstrates that a positive a_{t-i} contributes $\alpha_i a_{t-i}^2$ on σ_t^2 where as a negative shock a_{t-i} contributes $(\alpha_i + \gamma_i) a_{t-i}^2$ on σ_t^2. So, for a positive γ_i, conditional variance σ_t^2 is influenced more by negative shock compared to positive shock and so, leverage effect exists. Threshold 0 is used to separate the effect of a positive and negative shock.

2.2.2 Test For Randomness: Runs Test
The runs test [25] is a non-parametric test to detect if a time series follows a random process. It is usually considered a linear test that searches for randomness of data by examining frequency of runs (a series of similar responses, either positive or negative). If a series is random, the actual number of runs in the series should be close to the expected number of runs, irrespective of the signs.

If *x* and *y* denote numbers of positive and negative runs of a series respectively, then the observed number of runs

$$R = x + y \tag{2}$$

The expected number of runs

$$R' = \frac{2xy}{x+y} + 1 \tag{3}$$

The test statistic

$$Z = \frac{R - R'}{S_R} \tag{4}$$

where the standard deviation of the number of runs is given by

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

follows the standard normal distribution, under the null hypothesis of no run (random nature).

2.2.3 Non-Linearity Test

2.2.3.1 Keenan Test

Keenan [26] proposes a nonlinearity test for time series that uses $\hat{X}_t^2$ only and modifies the second step of the RESET test [27-28] to keep off multi co-linearity between $\hat{X}_t^2$ and X_{t-1}. Keenan's assumed model of the series is of the form:

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

It is evident that,

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

reduces (6) to linear form, so Keenan's idea shares the principle of an *F* test. Firstly, optimal lag *p* is selected using any one of the standard information criterion, next 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 same variable set $(1, X_{t-1}, \ldots, X_{t-p})$ to obtain the residuals set $(\hat{\zeta}_t)$. In last step,

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

and the test statistic

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

are computed.

Under the null hypothesis of linearity, i.e.

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

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

2.2.3.2 Tsay Test

Tsay [29] test is a generalization of Keenan test which include general quadratic terms of the form $X_{t-i}X_{t-j}$, i,j=1,…,p ; i<j, in addition t $\hat{X}_t^2$, and $X_{t-i}X_{t-j}$, i,j=1,…,p ; i<j are regressed on $(1, X_{t-1}, \ldots, X_{t-p})$. Under null hypothesis of linearity,

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

2.2.4 Chaos Test

2.2.4.1 0-1 Chaos Test

0-1 chaos test [30] is one of the widely used test to detect chaos in the data. The outcome of this test is binary. It takes the value 0 if chaos is not detected and 1 if chaos is present. From a time series $X_t, t = 1, 2, \ldots, n$, a Fourier series p_n is 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 constructed 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 $n \le m \le N/10 = N$.

To incorporate the possible presence of noise $D_c(N)$ is modified as $D_c^*(N)$ as

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

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

The asymptotic growth rate K_c for distinct c's are computed as

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

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

is the binary output where *K=0* if the data is non-chaotic and *K=1* if the data shows the presence of chaos.

2.2.4.2 Lyapunov Test

Lyapunov test is a robust test to measure chaos. Chaos is identified from largest Lyapunov exponent, which describes the rate of separation of infinitesimally close trajectories in attracting manifold. trajectories diverge at an exponential rate for a chaotic attractor [31]. Numerous techniques are used to calculate the Lyapunov exponent [32-34]. In the present study, the method described by Rosenstein et al. (1993) is employed as it is favorable if the sample size is small.

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

So, M = N - (m -1)J (18)

Closest neighbour of X_j, denoted by $X_{\hat{j}}$ is obtained by

$$d_j(0) = \min_{X_{\hat{j}}} \left\| X_j - X_{\hat{j}} \right\| \quad (19)$$

$d_j(0)$ being the initial distance from X_j to its closest neighbour $X_{\hat{j}}$. Here temporal separation between the closest neighbours must be greater than the mean period of the series. This condition guarantees that each pair of neighbours are with almost the same initial conditions for different trajectories.

Next, the largest Lyapunov exponent λ_1 is estimated as suggested by Sato et al. [36]

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

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

Largest Lyapunov exponent complies 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.

Taking logarithm to both sides of (23), we obtain

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

Largest Lyapunov exponent, estimated by applying method of least square is

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

where $\langle . \rangle$ denotes the mean over all values of *j*.

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

3. RESULTS

3.1 ADF Unit Root Test Result

ADF (Augmented Dicky-Fuller) [37] Unit Root test is implemented on SENSEX, NIFTY, S&P 500, and Dow-Jones, to check the stationarity of the series, which is an essential condition to test TGARCH on the series. The result is summarized in table 1. The optimal lag of AR model is selected taking a minimum between Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Information Criterion (HIC).

Table 1: Result of ADF unit root test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange	SENSEX	NIFTY	S&P 500	Dow-Jones
AR Lag	10	10	7	7
Test statistic (p value)	-6.51(0.00)*	-6.42(0.00)*	-7.99(0.01)*	-8.12(0.01)*

*****denotes rejection of the null hypothesis of the presence of unit root at 5% level of significance.
It is deduced from Table 1 that BSE return and NSE return data are stationary.

3.2 Volatility Test Result

The volatile nature of the stock exchanges is examined by TGARCH (1, 1) model. As all four series under the condition exhibit stationarity by table 1, TGARCH (1,1) is chosen. Firstly, ARIMA model with appropriate lag (based on minimum AIC) is computed on return data and then TGARCH (1,1) is fitted on the residual data. The result is stated in table 2.

Table 2: Result of TGARCH (1,1) on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange	SENSEX (ar lag=3, ma lag=5)	NIFTY (ar lag=9, ma lag=2)	S&P 500 (ar lag=7, ma lag=7)	Dow-Jones (ar lag=4, ma lag=4)
α_0 (Constant)	0.00(0.01)*	0.00(0.00)*	0.00(0.03)*	0.00(0.00)*
α (ARCH effect)	0.09(0.00)*	0.09(0.00)*	0.18(0.00)*	0.21(0.00)*
β (GARCH effect)	0.91(0.00)*	0.91(0.00)*	0.82(0.00)*	0.77(0.00)*
$\alpha+\beta$	1.00	1.00	1.00	0.98
γ (Leverage effect)	1.00(0.00)*	1.00(0.00)*	0.81(0.03)*	0.87(0.00)*

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

Table 2 indicates that all four series are volatile in nature as both ARCH and GARCH components are significant at 5% level of significance. As the combined effect of ARCH and GARCH components are near 1 for all the series, the volatile nature is stronger. Positive and statistically significant γ assures leverage effect in all the stock markets. Therefore, during COVID-19 pandemic, the market reacts more to negative shock in comparison to positive shock. Out of the total predicted squared variance, 9% is predicted by the latest squared error term and 91% is predicted by the square of the previous time periods in the case of Indian markets. The weightage of squared latest variance declines to 82% and 77%, respectively for S&P 500 and Dow-Jones, whereas the weightage of squared error term increases to 18% and 21% respectively, for them. Hence, the ARCH effect is stronger in American markets and the GARCH effect has more impact on Indian markets.

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

Weighted Ljung-Box Test [38] is applied on both the standardized residuals and standardized squared residuals series to check if TGARCH (1,1) model is successful to remove the serial dependence of standardized residuals and standardized squared residuals, with the null hypothesis of no autocorrelation at lag k>0. Table 3 demonstrates the test result.

Table 3: Result of Weighted Ljung-Box Test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

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	0.04 (0.84)	6.64 (1.00)	14.49 (0.96)	0.85 (0.36)	1.72 (0.69)	2.59 (0.82)
NIFTY	0.00 (0.95)	14.81 (1.00)	28.96 (0.34)	0.27 (0.60)	0.86 (0.89)	1.97 (0.91)
S&P 500	0.01 (0.90)	14.26 (1.00)	28.07 (0.95)	6.39* (0.01)	6.94 (0.055)	7.49 (0.16)
Dow-Jones	0.00 (0.99)	10.00 (1.00)	23.55 (0.99)	0.01 (0.90)	4.24 (0.22)	7.61 (0.15)

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

Table-3 shows that there is no serial auto-correlation among the standardized residuals and standardized squared residuals except S&P 500 with lag 1. It may be interpreted that conditional mean and conditional variance models of TGARCH (1,1) are adequate to remove autocorrelation among standardized residuals and standardized squared residuals.

Weighted ARCH-LM Test [39] measures if any ARCH effect is present in the standardized residual after fitting the TGARCH model. The null hypothesis is that no ARCH effect is present after fitting the model. Table 4 summarizes the result.

Table 4: Result of Weighted ARCH-LM Test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange	Weighted ARCH-LM Test on Standardized Residuals		
	Lag 3	Lag 5	Lag 7
SENSEX	0.61(0.43)	1.07(0.71)	1.61(0.80)
NIFTY	0.11(0.74)	0.29(0.94)	1.48(0.82)
S&P 500	0.24(0.62)	1.09(0.71)	1.36(0.85)
Dow-Jones	0.28(0.60)	7.78(0.02)*	8.90(0.03)*

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

Table 4 emphasizes the result described in table-3 as there is no hint of the presence of the ARCH effect in standardized squared residuals, except for Dow-Jones, with lag 5 and lag 7. From table 2, it is evident that the ARCH effect is most on Dow-Jones, in comparison to the other 3 indices. Therefore, for Dow-Jones, all the ARCH effects may not be eliminated after fitting the TGARCH (1,1) model. This is a possible explanation for the presence of a statistically significant ARCH effect in Dow-Jones standardized residual. Overall, TARCH (1,1) model is a reliable choice to study the series under our study.

Nyblom stability test [40] examines structural change within a time series model, i.e., if the parameter values are dependent on time or not. The null hypothesis is parameter values are constant, i.e., of zero variance, against the alternate hypothesis that parameters follow the martingale process. The test result is reported in Table 5.

Table 5: Result of Nyblom Stability Test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange	α_0 (Constant)	α (ARCH effect)	β (GARCH effect)	γ (Leverage effect)	Asymptotic critical value

SENSEX	0.26	0.40	0.33	0.27	0.47 (5%) 0.75(1%)
NIFTY	0.51	0.60	0.58	0.11	
S&P 500	0.67	0.84	0.91	0.47	
Dow-Jones	0.35	0.31	0.51	0.71	

It is clear from table-5 that most of the parameter values, are below critical values, except S&P 500 ARCH and GATCH coefficients. This indicates the stability of the parameter values. Hence, it may be inferred that almost all the parameters are constant (stable) over time and TGARCH (1,1) is proved to be a stable model for forecasting.

Sign bias tests [41] check the misspecification of the conditional volatility model. They examine whether the standardized squared residuals are foreseeable by the means of dummy variables significative of certain information. Sign bias test uses a dummy variable that tests the influence of positive and negative shocks on volatility not predicted 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 reports the result of sign bias test.

Table 6: Result of Sign Bias Test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange	Sign bias	Negative sign bias	Positive sign bias	Joint effect
SENSEX	1.04(0.30)	1.11(0.27)	0.80(0.42)	1.94(0.58)
NIFTY	2.21(0.03)	1.43(0.15)	1.27(0.20)	5.37(0.15)
S&P 500	0.46(0.65)	0.06(0.95)	0.21(0.83)	0.28(0.96)
Dow-Jones	0.78(0.44)	0.77(0.44)	0.03(0.98)	0.91(0.82)

P-values are included in ( ) brackets.

It is evident from table 6 that all outcomes of sign bias tests are in favor of clear specification of the TGARCH (1,1) model. It strengthens the fact that the TGARCH (1,1) model has captured all asymmetric volatility present in the data, and hence, the adequacy of the model is established.

Adjusted Pearson Goodness-of-Fit Test [39] is performed to compare the empirical distribution of the standardized residual with the theoretical distribution. In our study, four choices (20, 30, 40, 50) of the number of cells denote a sensible range, covering the optimum choice. The outcome is briefed in Table 7.

Table 7: Result of Adjusted Pearson Goodness-of-Fit Test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange / Group	SENSEX	NIFTY	S&P 500	Dow-Jones
	Statistic (P value)	Statistic (P value)	Statistic (P value)	Statistic (P value)
20	32.23(0.03)	25.29(0.15)	28.25(0.08)	33.34(0.02)
30	4001(0.08)	37.95(0.12)	36.94(0.15)	37.54(0.13)
40	51.42(0.09)	48.03(0.15)	18.49(0.14)	53.90(0.06)
50	56.62(0.21)	52.69(0.34)	52.96(0.32)	54.16(0.28)

Table 7 states that the empirical distribution of the standardized residual with the theoretical distribution matches the theoretical distribution, for higher cell numbers. Therefore, the goodness of the model fit is higher, which supports the valid choice of the TGARCH (1,1) model.

3.3 Run Test Result

Run test is executed on all considered datasets to examine the randomness of the data and the outcome is briefed in Table 8.

Table 8: Result of Run Test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange	Test Statistic (P value)
SENSEX	236(0.24)
NIFTY	228(0.06)
S&P 500	273(0.07)
Dow-Jones	275(0.04)

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

Table 8 explains that though the return series of SENSEX, NIFTY, and S&P 500 are random in nature, Dow-Jones return is non-random. Hence, Dow-Jones return data may be governed by some underlying factors, during COVID-19 pandemic period.

3.4 Nonlinearity Test Result

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

Table 9: Result of Nonlinearity test on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

Name of the stock exchange	Optimal AR lag	Type of test	Test statistic (P value)	Type of test	Test statistic (P value)
SENSEX	10	Keenan test	5.71(0.02)*	Tsay test	7.42(0.00)*
NIFTY	10		4.83(0.03)*		7.13(0.00)*
S&P 500	7		12.69 (0.00)*		9.09(0.00)*
Dow-Jones	7		12.38(0.00)*		10.74(0.00)*

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

It may be observed from table 9 that, all the examined series are non-linear in nature as described by both Keenan test and Tsay test.

3.5 Chaos Test Result

The chaotic nature of Indian and American markets during COVID-19 pandemic is investigated using 0-1 chaos test and rechecked by Lyapunov test. The result and corresponding graphs are shown in table 10. Optimal embedding dimension, required in Lyapunov test is computed using BIC.

Table 10: 0-1 Chaos test and Lyapunov test results on SENSEX, NIFTY, S&P 500, and Dow-Jones daily return

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	0.997	Lyapunov test	-0.40	5	-70.11* (0.00)
NIFTY		0.997		-0.31	5	-77.93* (0.00)
S&P 500		0.995		-0.57	2	-360.90* (0.00)
Dow-Jones		0.995		-0.58	2	-441.79* (0.00)

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

According to the 0-1 chaos test (see table 10), test statistic value of all the series under our study is close to 1, exhibiting non-chaotic nature. This is confirmed by the largest Lyapunov exponent test, as the mean largest Lyapunov exponent is significantly negative for all the series.

4. Discussion

The paper explores whether the recent COVID-19 pandemic has any impact on the Indian (SENSEX, NIFTY) and American (S&P 500, Dow-Jones) stock markets. The return series of all the markets are found to be stationary. Thus, overall, the basic nature of the markets is not that much affected during COVID-19. All but Dow-Jones support randomness in this 2 years pandemic time span. Hence, the future prediction may be subtle. Dow-Jones investors may think that the price action movement is impacted by some underlying variable and may gain insight into possible future price action and profitable trading opportunities. Nonlinear behavior for all the markets is confirmed during COVID-19 pandemic. Therefore, the interrelation between different variables and factors in the market may show nonlinear association. Though most of the markets are random and nonlinear, the presence of chaos is not detected. Hence, forecasting may be possible with suitable accuracy, in this time period. All four markets in our study show volatile behavior. Moreover, volatility is asymmetric. It means the stock market reacts more toward bad or negative speculation, compared to good or positive information. Negative shocks, causing higher volatility in the market, may be argued as an outcome of the panic and economic uncertainty created by COVID-19 on investors. This tendency of stock markets being influenced more by negative news is more in Indian stock markets compared to American stock markets. The possible explanation in this regard may be that, as American markets exhibit non-randomness (Dow-Jones) and anti-persistent asymmetric volatility (S&P 500), underlying factors may be identified, and the consequence of COVID-19 pandemic may be faded away in a relatively shorter period. Asymmetrical volatility is persistent except in the case of S&P 500. It means that, whether the nature of the shock is, it has a long-term effect on the volatility in Indian markets. This is a thing of concern, as long-term asymmetric volatility may create economic instability in the market. Proper precautions and measures should be taken to reduce the leverage effect.

5. Conclusions

In conclusion, the present study argues that, during the COVID-19 pandemic, the basic stationary nature of the return data of Indian and American stock markets is preserved and chaos does not affect them. Indian stock market is more volatile in comparison to American stock markets. Moreover, Indian markets are more impacted by negative shocks in comparison to American markets and this leverage effect is persistent. Higher volatility combined with the leverage effect leads to hindering investors' confidence. Thus, it is advisable for investors to be careful and take proper measures while investing in this market. Short-term investments are avoidable. Long-term investment may be suggested as there is no evidence of chaos.

References

[1] Raj Ram, A. (April 21, 2020). COVID-19 and stock market crash. *Outlook Money*. https://www.outlookmoney.com/equity/covid-19-impact-on-stock-market-4666
[2] Mandal, S. (April 06, 2020). Impact of Covid-19 on Indian stock market. *Adamas University*. https://adamasuniversity.ac.in/impact-of-covid-19-on-indian-stock-market
[3] World Health Organisation. (2021, June 15). https://covid19.who.int/region/searo/country/in
[4] Weltman, J. (March 20, 2020). ECR risk experts contemplate another financial crisis. *Euromoney*. https://signal2forex.com/2020/03/22/ecr-risk-experts-contemplate-another-financial-crisis/
[5] Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, Article 101528. https://doi.org/10.1016/j.frl.2020.101528
[6] Ozili, P., & Arun, T. (2020). *Spillover of COVID-19: Impact on the global economy*. Munich Personal RePEc Archive (MPRA paper no. 99850). https://mpra.ub.uni-muenchen.de/99850/
[7] Statista Research Department (January 11, 2022). S&P 500 performance during major crashes as of August 2020. https://www.statista.com/statistics/1175227/s-and-p-500-major-crashes-change/
[8] Shehzad, K., Xiaoxing, L., & Kazouz, H. (2020). COVID-19's disaster are perlous than global financial crisis: A rumor or fact? *Financial Research Letters*, *36*, Article 101669. https://doi.org/10.1016/j.frl.2020.101669

[9] Loon, L. (November 03, 2022). COVID-19 impact on the stock market South Korea 2021. *Statista*. https://www.statista.com/statistics/1103184/south-korea-coronavirus-impact-on-stock-market/
[10] Baret, S. Celner, A., O'Reilly, M., & Shilling, M. (2020). COVID-19 potential implications for the banking and capital market sector. *Maintaining Business and Operational Resilience*. London, England: Deloitte insights.
[11] BBC News (March 12, 2020). Coronavirus: FTSE 100, Dow, S&P 500 in worst day since 1987. https://www.bbc.com/news/business-51829852
[12] Georgieva, K. (2020). IMF Managing Director Kristalina Georgieva's statement following a G20 Ministerial Call on the coronavirus emergency. https://www.imf.org/en/News/Articles/2020/03/23/pr2098-imf-managing-director-statement-following-a-g20-ministerial-call-on-the-coronavirus-emergency
[13] Igwe, P. A. (2020). Corona virus with looming global health and economic doom. *African Development Institute of Research Methodology*, *1*(1), 1–6.
[14] Bekar, S.R., Bloom, N., Davis, S. J., Kost, K.J., Sammon, S.C., & Viratyosin, T. (2020). *The Unprecedented Stock Market Impact Of Covid-19* (Working Paper No. 26945). Working Paper Series. NATIONAL BUREAU OF ECONOMIC RESEARCH. http://www.nber.org/papers/w26945
[15] Choi, S. (2021). Volatility spillovers among Northeast Asia and the US:Evidence from the global financial crisis and the COVID-19pandemic. Analyses of topical policy issues, 73, 179-193. https://doi.org/10.1016/j.eap.2021.11.014
[16] Al-Awadhi, A. M., Khaled, A., Ahmad, A., & Salah, A. (2020). Death and contagious infectious diseases: Impact of the Covid-19 virus on stock market returns. *Journal of Behavioral and Experimental Finance*, *27*, Article 100326.
[17] He, Q., Liu, J., Wang, S. & Yu, J. (2020). The impact of COVID-19 on stock markets, *Economic and Political Studies*, *8*(3), 275-288. https://doi.org/10.1080/20954816.2020.1757570
[18] Basuony M.A.K., Bouaddi ,M., Ali, H., & EmadEldeen ,R. (2021).The effect of COVID-19 pandemic on global stock markets: Return, volatility, and bad state probability dynamics. *Journal of Public Affairs*, Article e2761. https://doi.org/10.1002/pa.2761
[19] Alves, P.R.L. (2022). Quantifying chaos in stock markets before and during COVID-19 pandemic from the phase space reconstruction. *Mathematics and Computers in Simulation*, *202*, 480-499. https://doi.org/10.1016/j.matcom.2022.07.026
[20] Dima, B., Dima, S.M., & Ioan, R. (2021). Remarks on the behaviour of financial market efficiency during the COVID-19 pandemic. The case of VIX. *Finance Research Letters*, *43*, Article 101967. https://doi.org/10.1016/j.frl.2021.101967
[21] Tie, L.,Huang, B., Pan, B., & Sun, G.. (2021). Using Big Data to Discover Chaos in China's Futures Market Du ring COVID-19, *Cmc-Computers Materials & Continua*, *69*(3), 3095-3107.
[22] Yahoo Finance. (n.d.). Retrieved July 15, 2022, from https://finance.yahoo.com/
[23] Campbell, J.Y., Lo, A.W., & MacKinlay, A.C. (1997). *The Econometrics of Financial Markets*. Princeton University Press.
[24] Glosten, R.T., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, *48*, 1779–1801.
[25] Bradley, J.V. (1968). *Distribution-Free Statistical Tests*. Prentice-Hall, Englewood Cliffs, New Jersey.
[26] Keenan, D.M.A. (1985). Tukey nonadditivity-type test for time series non-linearity. *Biometrika*, *72*(1), 39–44. https://doi.org/10.1093/biomet/72.1.39
[27] Ramsey, J. B. (1969). Tests for Specification Errors in Classical Linear Least Squares Regression Analysis. *Journal of the Royal Statistical Society, Series B, 31* (2). 350–371.
[28] Ramsey, J. B. (1974). Classical model selection through specification error tests. In Zarembka, Paul (Ed.). *Frontiers in Econometrics* (pp. 13–47). Academic Press, New York.
[29] Tsay, R.S. (1986). Nonlinearity tests for time series. *Biometrika*, *73*(2), 461–466. https://doi.org/10.2307/2336223

[30] Gottwald, G.A., & Melbourne, I. A. (2004). A new test for chaos in deterministic systems. *Proceedings of the Royal Society A, 460*, 603–611. https://doi.org/10.1098/rspa.2003.1183
[31] Eckmann, J.P. & Ruelle, D. (1985). Ergodic theory of chaos and strange attractors. *Reviews of Modern Physics*, *57*, 617.
[32] Bailey, B.A., Ellner, S.P., & Nychka, D.W. (1997). Chaos with Confidence: Asymptotics and Applications of Local Lyapunov Exponents. In Cutler, C.D., Kaplan, D.T. (Eds.), *Nonlinear Dynamics and Time Series: Building a Bridge Between the Natural and Statistical Sciences* (pp. 115–133). American Mathematical Society. https://doi.org/10.1090/fic%2F011%2F08
[33] BenSaïda, A., & Litimi, H. (2013). High level chaos in the exchange and index markets. *Chaos Solitons Fractals*, *54*, 90–95.
[34] McCaffrey, D., Ellner, S., Gallant, A., & Nychka, D. (1992). Estimating the Lyapunov exponent of a chaotic system with nonparametric regression. *Journal of the American Statistical Association*, *87*, 682–695.
[35] Rosenstein, M. T., Collins, J. J., & De Luca, C. J. (1993), A practical method for calculating largest Lyapunov exponents from small data sets, *Physica D*, *65*(1), 117–134.
[36] Sato, S., Sano, M., & Sawada, Y. (1987). Practical methods of measuring the generalized dimension and the largest Lyapunov exponent in high dimensional chaotic systems, *Progress of Theoretical Physics*, *77*(1), 1-5. https://doi.org/10.1143/PTP.77.1
[37] Dickey, D.A., & Fuller, W.A. (1979). Distribution of the estimates for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427.
[38] Ljung, G. M., & Box, G. E. P. (1978). On a Measure of a Lack of Fit in Time Series Models. *Biometrika*. *65* (2), 297–303. https://10.1093/biomet/65.2.297
[39] Kostov, P., Wu, Z., & McErlean, S. (2006). Do Chinese Stock Markets Share Common Information Arrival Processes. In J. Chen, & S. Yao (Eds.), *Globalisation, Competition and Growth in China* (pp. 77-93). Taylor and Francis.
[40] Nyblom, J. (1989). Testing for the Constancy of Parameters Over Time. *Journal of the American Statistical Association*, *84*(405), 223-230.
[41] Engle, R.F., & Ng, V.K. (1993). Measuring and Testing the Impact of News on Volatility. *Journal of Finance*, *48*, 1749-1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x

