

Does the Pandemic have Greater Impact on World's Stock Markets?

Swetadri Samadder¹, Amalendu Bhunia^{2,*}

¹Department of Mathematics, Fakir Chand College, West Bengal, India

²Department of Commerce, Dean, Faculty of Arts & Commerce, University of Kalyani, West Bengal, India

*Corresponding author: bhuniamalendu@gmail.com

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Abstract This study examines the pandemic impact on world's top forty-five stock markets along with memory analysis and leverage effect. The study is based on time-series data from January 1, 2020 to September 30, 2020 using scaling analysis by means of Hurst exponent and GARCH family models. Memory analysis suggests that all the stock markets are persistent in nature with a shade of uncertainty in the New Zealand stock market. GARCH family models show that volatility is present in some of the stock markets. Both EGARCH and TGARCH models clarified that the leverage effect is present in the BSE-India, Bangladesh, Egypt, Euronext Stock Exchange, New Zealand, and Canada stock markets; Negative information influences the stock market more than positive information for these stock markets. Nevertheless, in consideration of several limitations, an indicator to the future research is designated as well.

Keywords: International stock markets, memory analysis, volatility, leverage effect, GARCH models

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1. Introduction

The global economy has been affected by the pandemic-restrictions in the year 2020 about the movement of goods and services, travel restrictions, shutting down of industries with workers lessening in production, falling of demand with potential orders, disruption in supply chains, and hastens drop in stock market confidence [1,2]. Stock market indices around the globe suffered abrupt plummets because the pandemic generated economic uncertainty and produced fear among investors [3]. Researchers [4,5] found that the stock market's volatility has been increased around the globe in the first nine months of the year 2020 and adversely affect the global economic growth. The negative association between future market volatility and its fundamental market returns is in the interest of academicians, researchers, investors, and forecasters. There are two types of theories. One theory tells that the equity value of the firm turns into a small fraction of the entire firm value when the value of the firm shrinks. Then the equity shareholders accept the whole firms' risk, consequently the volatility of equity raises. The other theory shows that the future returns shrink when volatility reduces, subsequently, the current market returns will go down to hold the future beliefs [6,7,8]. Stock market volatility in 2020 has been raised notably through pandemic-induced economic downturn, uncertainty nearby government incentive measures, and a very arguable U.S. presidential election procedure [9]. Higher volatility

entails higher capital costs, increases the value of the option to wait, and interrupting investments. Stock market volatility has been increased extensively in 2020 by a mixture of macroeconomic indicators, a consequential economic downturn, uncertainty contiguous government incentive measures, and an extremely controversial U.S. presidential election procedure. At the same time, stock market volatility is usually related to investment risk. Modern portfolio theory tells that higher standard deviations designate bigger scatterings of stock market returns, together with enhanced investment risk [10].

The international economy is currently going into a downturn because of the tremendous volatility of the international financial market, huge capital outflows, and an extensive augment in the risk of public and private debt suffering. The market volatility in asset prices has been increased through the large risk of an international downturn and its shock on corporate profitability, structural market concerns, for example, strained sales by reason of deleveraging and fear and economic uncertainty. This shock is greatly reflected in the stock market performance by reason of the estimated losses as well as the volatility of stock markets, there is a call for both fiscal and monetary policy interferences and financial supports to guard human health, economic losses and protect the financial strength of the stock markets [11].

This study examines the impact of the Covid-19 pandemic on forty-five major stock markets. We test the scaling analysis through Hurst exponent to know the time series trends towards persistent behaviour. GARCH family models between these stock markets to find out the

diversification gains investors might receive. We also study the GARCH family models whether there exists any volatility and leverage effect in these stock markets.

The paper is designed in this way. Section 2 reviews the literature on volatility and leverage effect between global financial markets. Section 3 depicts the data and methodology. Section 4 presents the study's empirical results and Section 5 sums up our conclusions.

2. Literature Review

A lot of researches have been carried out to make out the stock market volatility during the year 2020. Most of the studies acknowledged the existence of stock market volatility and few of them acknowledged the non-existence of volatility. Bhunia & Ganguly [2] examined the volatility and leverage effect of the particular stock markets before and during the outbreak of the pandemic using daily time-series data between September 1, 2019 and April 30, 2020 with the application of GARCH models. The GARCH test results demonstrate that volatility and leverage effect existed and the pandemic has a greater influence on global stock markets. Bora & Basistha [12] observed the volatility of Indian stock market before and during the outbreak of the pandemic between September 3, 2019 and July 10, 2020 with the application of GJR-GARCH model. The result illustrates that the stock market particularly the BSE-Sensex turn into volatile in the pandemic period whereas there was no significant impact of the pandemic on the volatility of NSE stock market. Chaudhary et al. [11] observed the volatility of ten international stock markets before and during the period of pandemic between January 1, 2019 and June 30, 2020 with the application of GARCH models. The results show that the Covid-19 increased the volatility among international stock markets. Baek [13] investigated the shock of the pandemic on US stock market volatility based on daily index values of U.S. stock market and macroeconomic indicators between January 2, 2020 and April 30, 2020 using MS-AR(1) model. The results illustrate that changes in volatility are more responsive to pandemic information than macroeconomic indicators and the negative information concerning number of deaths is twice as impactful as positive information about recoveries signifying a negativity prejudice. The market response to the pandemic information shows a positive-negative irregularity. Małgorzata & Krzysztof [14] explored the association of US stock market returns with implicit volatility, understood correlation and liquidity using two-regime MS model. The result demonstrated close reliance of stock market returns with both implicit volatility and understood correlation but not with liquidity. Bai et al. [15] investigated the shock of infectious disease pandemic on international stock markets' volatility using an extensive GARCH-MIDAS model between January 2005 and April 2020. The empirical results demonstrated that infectious disease pandemic had a positive shock on the permanent volatility of global stock markets, even after controlling the persuades of precedent recognized volatility, worldwide economic policy uncertainty and the volatility leverage upshot. Chittineni [8] reviewed the association between India's implicit Volatility Index and

Nifty 50 Returns in the pandemic between March 2, 2009 and June 30, 2020 using linear regression analysis. The results showed that the Nifty 50 returns and volatility index were moving separately in the pandemic and there was no relationship between market size and the market shift. This implied that the Indian investors were not greatly concerned regarding the variation in the market size of the market in the pandemic period. Onally [16] assessed the shock of pandemic on the real economy and the USA, Italy, Spain, China, France, Iran and the UK capital markets agreeing to for changes in trading size and volatility beliefs in addition to day-of-the-week effects based on April 8, 2019 to April 9, 2020 using GARCH and VAR model. The GARCH model (1,1) test results indicated that the pandemic increased the volatility of the USA stock markets and VAR model showed that the death cases of Italy and France negatively affect the Dow Jones returns. Wang et al. [17] observed the vibrant change of volatility spillovers between numerous main global financial markets in the pandemic based on Diebold and Yilmaz's connectedness indices. The results indicated that the total volatility spillover arrived at its peak level of latest ten years. The USA and the UK stock markets are major spillover transmitters in the pandemic, whereas Chinese and Japanese stock markets are spillover receivers. Morales & Callaghan [18] observed the volatility and causality of global stock markets in the period of pandemic. They observed that the global stock markets are volatile except Chinese stock market. They also observed that the US and the EU had revealed insufficient reactions as well as a lack of commitment at the international level when global harmonization and global support is much required. Mishra & Mishra [19] found the volatility clustering in Asian stock markets because of the negative and fear reactions of investors, changes in crude oil prices and exchange rates. Christensen [20] and Piksina and Vernholmen [21] found that the pandemic news negatively impacted the market sentiment and increased the stock market volatility.

By and large, the literature demonstrates that stock market volatility exist among global markets because of location closeness. The pandemic undoubtedly influences stock market's volatility globally in most of the cases. Sketch on this, we study the scaling analysis as well as the stock market volatility and leverage effect in a sample of forty five major stock markets around the globe because this study is hardly available.

We find that most of the studies were concentrated on volatility persistence but they do not check the persistent behaviour. Based on the dimension of the study, we have considered the following research hypotheses.

(i) Selected stock markets have a long memory process in terms of persistent behaviour.

(ii) There does not exist any volatility and leverage effect in the selected stock markets.

3. Data and Methodology

For the present analysis, daily return of forty five main stock market indices across the world has been taken into consideration; namely, Abu Dhabi Securities Exchange (Saudi Arabia), Athens Stock Exchange (Greece),

Australia Securities Exchange (Australia), Bolsa De Valores De Columbia (Columbia), Bolsa Mexicana De Valores (Mexico), Bolsas Marcados Exchange (Spain), Bombay Stock Exchange (India), Borsa Istanbul Stock Exchange 100 (Turkey), Brasil Bolsa Balcao Exchange (Brazil), Bursa Malaysia (Malaysia), BVL Peru General Index TR (Peru), Dhaka Stock Exchange (Bangladesh), Dubai Financial Market (United Arab Emirates), Egyptian Exchange 30 (Egypt), Euronext Stock Exchange (Netherlands, Belgium, Ireland, Spain, UK and France), Hochimimh Stock Exchange (Vietnam), Hongkong Exchanges and Clearing (China), ISEQ All Share (Ireland), Jakarta Stock Exchange (Indonesia), Johannesburg Stock Exchange Limited (South Africa), KOSPI Composite Index (South Korea), London Stock Exchange (Great Britain), Moscow Exchange (Russia), MASI (Morocco), MERVAL (Argentina), Nasdaq (USA), NASDAQ OMX Nordic 120 (Sweden, Denmark, Finland and Iceland), Newyork Stock Exchange (USA), NIFTY50 (India), Nikkei 225 (Japan), NZX Limited (New Zealand), Oslo Stock Exchange (Norway), PSEI (Philippines), Qatar Stock Exchange (Qatar), Saudi Stock Exchange (Saudi Arabia), Shanghai Stock Exchange (China), Shenzhen Component (China), Singapore Stock Exchange (Singapore), Swiss Stock Exchange (Switzerland), Tel Aviv Stock Exchange (Israel), Thailand Stock Exchange (Thailand), The Deustach Borse Exchange (Germany), Toronto Stock Exchange Composite Index (Canada), Warsaw Stock Exchange GPW (Poland) and Wiener Boerse Stock Exchange (Austria).

The period of the study has been limited from January 1, 2020 to September 30, 2020. All the return values are converted to natural logarithm to reduce irregularity and heteroscedasticity of the data and entire analysis have been performed on these log return data of the stock indices. Persistency as well as memory of the data is analyzed measuring Hurst exponent. As main aim of our study is to gather information about volatility and leverage effect (if any) on the international stock market due to corona pandemic, GARCH (1,1), EGARCH (1,1) and TGARCH (1,1) model have been implemented.

3.1. Scaling Analysis and Estimation of Hurst Exponent

Scaling analysis is useful to check to check the memory of the time series. Hurst exponent is a useful measure for scaling analysis of a time series. It can be obtained using Standard Deviation Analysis (SDA) [22] which is one of the finest forms of Finite Variance Scaling Method (FVSM) [22-27].

Given a time series $\{x(t_n)\}$ (where $n = 1, 2, \dots, N$ and t represents time), a sequence of cumulative standard deviations $D(t_j)$ associated with the partial time series $\{x(t_n)\}$ ($n = 1, 2, \dots, j$) is generated by the following manner:

$$D(t_j) = \left[\frac{\sum_{i=1}^j x^2(t_i)}{j} - \left(\frac{\sum_{i=1}^j x(t_i)}{j} \right)^2 \right]^{\frac{1}{2}} \quad (1)$$

for $j=1, 2, \dots, N$.

$D(t)$ follows a power law by

$$D(t) \propto t^H \quad (2)$$

Here, H is the Hurst exponent which can be estimated from the slope of the best fitted straight line in the log-log plot of $D(t)$ versus t . H ranges between 0 and 1. $H=0.5$ indicates a random nature or Brownian motion of the time series. $0 < H < 0.5$ implies that the time series has anti-persistent behaviour and is governed by a short memory process. $0.5 < H < 1.0$ indicates the tendency of the time series towards persistent behaviour and the process will be long memory process. In limiting cases, $H=0$ and $H=1$ is obtained for a white noise and a smooth time series respectively.

3.2. GARCH Model

Volatility is an important statistical measure to analyze stock market return. It detects the phenomenon when standard deviation of a time series changes over a period of time, i.e.; it basically it explains conditional heteroscedasticity. Stock market volatility is time dependent and 'volatility clustering' occurs when periods of high volatility follow periods of low volatility and vice versa. In situations of financial turmoil and the corresponding negative shocks, the leverage effect is taken in consideration, and time varying volatility models are required to capture asymmetry in volatility arisen due to positive and negative shocks [28].

ARCH (Auto Regressive Conditional Heteroscedasticity) model was introduced by Engle [29] where conditional values of shock a_t corresponding to a log return r_t was given by

$$a_t = \sigma_t \varepsilon_t \quad (3)$$

Where implied volatility σ_t^2 depends on lagged values of the precedent shocks by

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \dots + \alpha_m a_{t-m}^2 \quad (4)$$

with m as the order of the model, $\{\varepsilon_t\}$ as a sequence of independent and identically distributed random variables with $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = 1$, a_t 's are not serially correlated with $E(a_t) = 0$, $\alpha_0 > 0$ and $\alpha_i \geq 0$ for $i > 0$.

Bollerslev [30] proposed an extended version of ARCH model, namely, generalized auto regressive conditional heteroscedasticity (GARCH) model where precedent conditional variances also were taken into consideration in addition with lagged precedent shocks while estimating σ_t^2 . A GARCH (m, n) model was described by $a_t = \sigma_t \varepsilon_t$,

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^m \alpha_i a_{t-i}^2 + \sum_{j=1}^n \beta_j \sigma_{t-j}^2 \quad (5)$$

Where in addition to $\{\varepsilon_t\}$ as a sequence of iid random variables with zero mean and unit variance, a_t 's are not serially correlated with $E(a_t) = 0$, $\alpha_0 > 0$ and $\alpha_i \geq 0$ for

$$i > 0; \beta_j \geq 0 \text{ and } \sum_{k=1}^{\max(m,n)} (\alpha_k + \beta_k) < 1.$$

3.3. EGARCH Model

Though leptokurtic distribution and volatility clustering is captured by GARCH model, asymmetric behaviour of the volatility with respect to positive and negative shock is not recognized by this model as σ_t^2 is dependent on the square of the lagged values of the shocks and so does not count their sign. To overcome this problem, Nelson [31] introduced exponential auto regressive conditional heteroscedasticity (EGARCH) model considering asymmetric effect between positive and negative return which is known as leverage effect. Leverage effect is a negative correlation between the past return and future volatility return. When a positive shock has less effect on the conditional variance compared to negative shock, then leverage effect is present, i.e.; a good news or shock generates less variance or volatility compared to depressing news in presence of leverage effect.

Nelson [31] established that negative shocks are more influential for predicting volatility than positive shocks and an EGARCH (m, n) model was formulated by $a_t = \sigma_t \varepsilon_t$,

$$\ln \sigma_t^2 = \omega + \sum_{i=1}^n \alpha_i \left\{ \frac{a_{t-i}}{\sigma_{t-i}} \right\} + \sum_{i=1}^n \gamma_i \left\{ \frac{a_{t-i}}{\sigma_{t-i}} \right\} + \sum_{j=1}^m \beta_j \ln(\sigma_{t-j}^2) \quad (6)$$

Equation (6) incorporates the positive and negative effect of a_t to have different effect on volatility. This model is asymmetric as coefficient of a_{t-i}/σ_{t-i} is captured as γ_i in the model. As γ_i 's are negative in general, negative or downward shocks have more influence on volatility of the return than positive or

upward shock. γ_i is called leverage effect. Hence, stock market is more sensitive to negative news than compared to positive news in presence of leverage effect.

3.4. TGARCH Model

Another volatility model to cope up with both positive and negative shock is threshold GARCH (TGARCH) model developed by Glosten et al. [32]. It was described by $a_t = \sigma_t \varepsilon_t$,

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^n (\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j=1}^m \beta_j \sigma_{t-j}^2 \quad (7)$$

Where N_{t-i} is an indicator of negative a_{t-i} , i.e.;

$$N_{t-i} = \begin{cases} 1 & \text{if } a_{t-i} < 0 \\ 0 & \text{if } a_{t-i} \geq 0 \end{cases} \text{ and } \alpha_i, \gamma_i \text{ and } \beta_j \text{ are nonnegative}$$

integers satisfying same restrictions as they follow in GARCH model. It is clear from equation (7) that a positive shock a_{t-i} has impact $\alpha_i a_{t-i}^2$ on conditional variance 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 , negative shock has larger impact on conditional variance compared to positive shock and we conclude that leverage effect exists. This model uses threshold 0 to differentiate the impact between positive and negative shock.

4. Empirical Results and Analysis

4.1. Scaling Analysis Test Results

Table 1. Memory Profile

Name of the Stock Exchange	HEV	Name of the Stock Exchange	HEV
Abu Dhabi Securities Exchange	0.86	MASI	0.71
Athens Stock Exchange	0.65	MERVAL	0.69
Australia Securities Exchange	0.82	Nasdaq	0.82
Bolsa De Valores De Columbia	0.57	NASDAQ OMX Nordic 120	0.70
Bolsa Mexicana De Valores	0.74	Newyork Stock exchange	0.86
Bolsas Marcados Exchange	0.75	NIFTY50	0.79
Bombay Stock Exchange	0.81	Nikkei 225	0.61
Borsa Istambul Stock Exchange 100	0.62	NZX Limited	0.52
Brasil Bolsa Balcao Exchange	0.61	Oslo Stock Exchange	0.81
Bursa Malaysia	0.65	PSEI	0.68
BVL Peru General Index TR	0.78	Qatar Stock Exchange	0.79
Dhaka Stock Exchange	0.87	Saudi Stock Exchange	0.77
Dubai Financial Market	0.81	Shanghai Stock Exchange	0.66
Egyptian Exchange 30	0.67	Shenzhen Component	0.57
Euronext Stock Exchange	0.74	Singapore Stock Exchange	0.62
Hochiminh Stock Exchange	0.60	Swiss Stock Exchange	0.71
Hongkong Exchanges and Clearing	0.60	Tel Aviv Stock Exchange	0.63
ISEQ All Share	0.77	Thailand Stock Exchange	0.77
Jakarta Stock Exchange	0.81	The Deustach Borse Exchange	0.78
Johannesburg Stock Exchange	0.70	Toronto Stock Exchange	0.86
KOSPI Composite Index	0.68	Warsaw Stock Exchange GPW	0.67
London Stock Exchange	0.74	Wiener Boerse Stock Exchange	0.73
Moscow Exchange	0.78		

Table 1 summarizes the profile of scaling analysis for log return data corresponding to forty five different stock market indices, i.e.; whether they possess short-term (anti-persistent) memory, long-term (persistent) memory or no memory. It is evident that Hurst exponent value (HEV) in all the stock market indices are greater than 0 suggesting long or persistent memory which indicates essential dependence between the present and past data. Also it is noticed that Hurst

exponent value for NZX Limited is slightly greater than 0.5 which leads a leaning towards randomness interpreting a more uncertain behaviour in terms of future predictability.

4.2. Test Result for GARCH (1,1) Model

Table 2 interprets GARCH (1,1) test result for corresponding stock markets.

Table 3. GARCH (1,1) Test Results

	ADSE-Saudi	Greece	Australia	Columbia	Mexico	Spain	BSE-India
ω (constant)	0.58 (0.20)	0.00 (0.94)	0.00 (0.95)	0.00 (0.96)	0.20 (0.25)	0.09 (0.055)	0.00 (0.82)
α (ARCH effect)	-0.12 (0.07)	0.61* (0.01)	2.59* (0.00)	2.01* (0.00)	-0.12* (0.03)	-0.06* (0.00)	2.59* (0.00)
β (GARCH effect)	0.39 (0.48)	0.54* (0.00)	0.01 (0.37)	0.15* (0.02)	0.87* (0.00)	1.04* (0.00)	-0.002 (0.69)
$\alpha + \beta$	0.27	1.15	2.60	2.16	0.75	0.98	2.59
	Turkey	Brazil	Malaysia	Peru	Bangladesh	UAE	Egypt
ω (constant)	0.50 (0.41)	1.13* (0.03)	0.67 (0.41)	0.00 (0.99)	0.00 (0.97)	0.54 (0.46)	0.00 (0.22)
α (ARCH effect)	-0.07* (0.00)	0.35 (0.06)	-0.08* (0.00)	2.42* (0.00)	1.14* (0.01)	-0.07* (0.00)	1.25* (0.00)
β (GARCH effect)	0.59 (0.32)	-0.21 (0.52)	0.58 (0.34)	0.02 (0.21)	0.33* (0.00)	0.54 (0.43)	0.00 (0.98)
$\alpha + \beta$	0.52	0.14	0.50	2.44	1.47	0.47	1.25
	Euronext SE	Vietnam	Hongkong	Ireland	Indonesia	South Africa	South Korea
ω (constant)	0.75 (0.30)	0.53* (0.00)	0.43 (0.32)	0.81 (0.69)	0.30 (0.17)	0.00 (0.97)	0.64 (0.54)
α (ARCH effect)	-0.05* (0.00)	0.64* (0.00)	-0.09* (0.00)	-0.05 (0.14)	1.34* (0.00)	2.50* (0.00)	-0.05 (0.21)
β (GARCH effect)	0.23 (0.78)	-0.10 (0.15)	0.53 (0.36)	0.12 (0.96)	-0.04 (0.40)	0.02 (0.12)	0.54 (0.50)
$\alpha + \beta$	0.18	0.54	0.44	0.07	1.30	2.52	0.49
	Great Britain	Russia	Morocco	Argentina	Nasdaq	NASDAQ	NSE-USA
ω (constant)	0.069 (0.09)	0.48 (0.41)	0.75* (0.01)	0.54* (0.01)	0.26 (0.10)	0.60 (0.33)	0.13 (0.09)
α (ARCH effect)	-0.08* (0.00)	-0.09 (0.07)	0.90* (0.00)	0.66* (0.00)	-0.09* (0.00)	-0.11* (0.00)	-0.08* (0.00)
β (GARCH effect)	1.03* (0.00)	0.64 (0.22)	0.04 (0.34)	-0.10 (0.29)	0.76* (0.00)	0.60 (0.24)	0.97* (0.00)
$\alpha + \beta$	0.95	0.55	0.94	0.56	0.67	0.49	0.89
	NSE-India	Japan	New Zealand	Norway	Philippines	Qatar	SSE-Saudi
ω (constant)	0.01 (0.08)	0.49 (0.38)	-0.014 (0.88)	0.00 (0.79)	0.80 (0.38)	0.36 (0.47)	0.0005 (0.89)
α (ARCH effect)	1.98* (0.00)	-0.07 (0.19)	0.60* (0.01)	2.60* (0.00)	-0.06* (0.00)	-0.06* (0.00)	2.76* (0.00)
β (GARCH effect)	-0.003 (0.53)	0.55 (0.35)	0.55* (0.00)	-0.0003 (0.87)	0.53 (0.37)	0.54 (0.43)	0.02 (0.12)
$\alpha + \beta$	1.98	0.48	1.15	2.60	0.47	0.48	2.78
	China	Shenzhen	Singapore	Switzerland	Israel	Thailand	Germany
ω (constant)	0.28* (0.004)	0.02* (0.01)	0.72 (0.31)	0.02 (0.07)	0.36* (0.01)	0.00 (0.97)	0.16 (0.09)
α (ARCH effect)	0.68* (0.008)	-0.06* (0.00)	0.07* (0.00)	-0.06* (0.00)	1.18* (0.00)	2.51* (0.00)	1.45* (0.00)
β (GARCH effect)	-0.14 (0.23)	1.02* (0.00)	0.54 (0.30)	1.06* (0.00)	-0.30 (0.14)	0.06 (0.08)	-0.02 (0.69)
$\alpha + \beta$	0.54	0.96	0.61	1.00	0.88	2.57	1.43
	Canada			Poland		Austria	
ω (constant)	0.03 (0.18)			0.00 (0.97)		0.21 (0.13)	
α (ARCH effect)	-0.08* (0.00)			1.10* (0.004)		-0.18* (0.006)	
β (GARCH effect)	1.05* (0.00)			0.42* (0.00)		0.87* (0.00)	
$\alpha + \beta$	0.97			1.52		0.69	

*denotes significant at the 5%. P-values are included in () brackets.

All the parameters in GARCH (1,1) model is not statistically significant at 5% significance level. GARCH effect is significant and positive for Greece, Columbia, Mexico, Spain, Bangladesh, Great Britain, Nasdaq-USA, NSE-USA, New Zealand, Shenzhen-China, Switzerland, Canada, Poland, and Austria stock markets. So, GARCH effect is highest in Switzerland and lowest in Columbia due to varying conditional variance over time and their effect on unconditional variance. Determination of volatility is quantified by sum of α and β and we observed that $\alpha + \beta$ is statistically significant at 5% significance level for Greece, Australia, Columbia, BSE-India, Peru, Bangladesh, Egypt, Indonesia, South Africa, NSE-India, New Zealand, Norway, Saudi Arabia,

Switzerland, Thailand, Germany, and Poland stock markets. Hence, BSE-India has strongest combined ARCH and GARCH effect due to higher ARCH component (2.59). It also reveals that volatility of these stock markets can be indicated by precedent volatility which is persistent over time.

4.3. Test Result for EGARCH (1,1) Model

As some of the stock markets are volatile, we want to investigate if there is any leverage effect governing the stock markets. EGARCH (1,1) model has been implemented to check this. Table 3 summarizes EGARCH test result.

Table 3. EGARCH (1,1) Test Results

	ADSE-Saudi	Greece	Australia	Columbia	Mexico	Spain	BSE-India
ω (constant)	0.29* (0.02)	0.73* (0.00)	-2.12* (0.00)	-0.75* (0.04)	-2.07* (0.00)	2.52* (0.00)	-1.97* (0.00)
α (ARCH effect)	-0.33* (0.00)	0.94* (0.00)	2.68* (0.00)	1.27* (0.00)	1.71* (0.00)	-1.37* (0.00)	0.12 (0.59)
β (GARCH effect)	0.86* (0.00)	1.01* (0.00)	0.85* (0.00)	0.61* (0.00)	-0.37* (0.02)	0.05 (0.81)	0.58* (0.00)
$\alpha + \beta$	0.53	1.95	3.45	1.88	1.44	-1.32	0.70
γ (leverage effect)	0.34* (0.00)	0.35* (0.03)	0.93* (0.00)	-0.10* (0.59)	0.25 (0.19)	0.72* (0.00)	-2.67* (0.00)
	Turkey	Brazil	Malaysia	Peru	Bangladesh	UAE	Egypt
ω (constant)	-1.39* (0.00)	-1.30* (0.00)	1.17* (0.00)	-1.06* (0.00)	-0.02 (0.87)	0.50* (0.00)	-2.42* (0.00)
α (ARCH effect)	1.25* (0.00)	1.66* (0.00)	-1.87* (0.00)	1.48* (0.00)	-0.05 (0.76)	-0.70* (0.00)	1.42* (0.00)
β (GARCH effect)	-0.57* (0.00)	0.57* (0.00)	-0.19 (0.12)	0.01 (0.96)	0.90* (0.00)	0.72* (0.00)	0.95* (0.00)
$\alpha + \beta$	0.68	2.13	-2.06	1.49	0.85	0.02	2.37
γ (leverage effect)	0.23 (0.00)	0.26 (0.16)	-1.55* (0.00)	0.78 (0.00)	-0.54* (0.00)	0.40* (0.00)	-0.64* (0.00)
	Euronext SE	Vietnam	Hongkong	Ireland	Indonesia	South Africa	South Korea
ω (constant)	0.12 (0.70)	-0.26 (0.29)	0.72* (0.00)	-1.33* (0.00)	-0.70 (0.10)	-2.22* (0.00)	0.78* (0.00)
α (ARCH effect)	-1.46* (0.00)	0.30 (0.29)	-1.40* (0.00)	0.61* (0.00)	0.91* (0.01)	2.67* (0.00)	-0.83* (0.00)
β (GARCH effect)	-0.56* (0.00)	0.76* (0.00)	0.26 (0.12)	-0.81* (0.00)	-0.67* (0.00)	0.70* (0.00)	0.62* (0.00)
$\alpha + \beta$	-2.02	1.06	-1.14	-0.20	-0.24	3.37	-0.21
γ (leverage effect)	-1.10* (0.00)	0.50 (0.00)	0.36 (0.00)	0.26 (0.00)	0.47 (0.01)	0.28 (0.20)	1.06 (0.00)
	Great Britain	Russia	Morocco	Argentina	Nasdaq-US	NASDAQ	NSE-USA
ω (constant)	0.14 (0.08)	-0.98* (0.00)	0.15 (0.75)	-1.90* (0.00)	0.62* (0.02)	0.19 (0.21)	-0.85* (0.02)
α (ARCH effect)	-0.18 (0.09)	1.14* (0.00)	0.93* (0.00)	1.31* (0.00)	-1.58* (0.00)	-0.22* (0.00)	0.47* (0.00)
β (GARCH effect)	0.97* (0.00)	0.80* (0.00)	-0.63* (0.00)	-0.55* (0.00)	0.00 (0.98)	0.92* (0.00)	-0.87* (0.00)
$\alpha + \beta$	0.81	1.94	0.30	0.76	-1.58	0.70	-0.40
γ (leverage effect)	0.13 (0.12)	0.36 (0.03)	0.12 (0.43)	0.89 (0.00)	0.99 (0.00)	-0.09 (0.21)	0.30 (0.01)
	NSE-India	Japan	New Zealand	Norway	Philippines	Qatar	SSE- Arabia
ω (constant)	-2.43* (0.00)	0.74* (0.00)	-0.44 (0.08)	0.38* (0.01)	-1.87* (0.00)	-1.18* (0.00)	-2.08* (0.00)
α (ARCH effect)	-1.14* (0.00)	-1.05* (0.00)	0.53* (0.05)	-0.49* (0.02)	1.83* (0.00)	1.19* (0.00)	2.10* (0.00)
β (GARCH effect)	0.13 (0.16)	0.59 (0.00)	1.13 (0.00)	0.78 (0.00)	-0.31 (0.10)	0.53 (0.01)	-0.25 (0.09)
$\alpha + \beta$	-1.01	-0.46	1.66	0.29	1.52	1.72	1.85
γ (leverage effect)	2.72 (0.00)	0.55 (0.00)	-1.17* (0.00)	0.71 (0.00)	0.38 (0.06)	0.27 (0.16)	0.35* (0.00)

	China	Shenzhen	Singapore	Switzerland	Israel	Thailand	Germany
ω (constant)	-3.20* (0.00)	-0.15 (0.35)	0.24* (0.00)	-0.82* (0.00)	-2.12* (0.00)	-0.67* (0.00)	-1.16* (0.00)
α (ARCH effect)	2.16* (0.00)	-1.48* (0.00)	-0.31* (0.00)	1.08* (0.00)	2.32* (0.00)	0.81* (0.00)	1.26* (0.00)
β (GARCH effect)	-0.11 (0.14)	-0.07 (0.44)	0.93* (0.00)	0.77* (0.00)	-0.07 (0.73)	0.81* (0.00)	0.55* (0.00)
$\alpha + \beta$	2.05	-1.55	0.62	1.85	2.25	1.62	1.81
γ (leverage effect)	-0.28 (0.15)	-1.39* (0.00)	-0.11 (0.07)	0.66* (0.00)	0.49* (0.04)	0.42* (0.02)	0.30 (0.11)
	Canada	Poland	Austria	*denotes significant at the 5%. P-values are included in () brackets.			
ω (constant)	0.55* (0.00)	-0.97* (0.01)	0.90* (0.00)				
α (ARCH effect)	-0.93* (0.00)	0.57 (0.09)	-1.99* (0.00)				
β (GARCH effect)	0.65* (0.00)	-0.73* (0.00)	0.05 (0.74)				
$\alpha + \beta$	-0.28	-0.16	-1.94				
γ (leverage effect)	-0.54* (0.00)	1.81* (0.00)	0.18 (0.33)				

Table 3 points out that the sum of α and β is statistically significant at 5% level of significance for Greece, Australia, Columbia, Mexico, Brazil, Egypt, South Africa, Russia, New Zealand, Qatar, Switzerland, Thailand and Germany stock markets, which indicates that volatility is existed in those stock markets. As more the sum of α and β , more the effect of ARCH and GARCH, Australia has strongest existence of ARCH and GARCH component. A negative and statistically significant γ confirms the presence of leverage effect implying positive information has lesser effect on conditional variance and negative information has higher impact on conditional

variance. Among forty five stock markets considered in our study, BSE-India, Malaysia, Bangladesh, Egypt, Euronext Stock Exchange, Shenzhen-China, and Canada has negative γ at 5% significance level. So, bad news produces higher volatility than good news in those stock markets and leverage effect in BSE-India stock market is very much higher compared to all other stock markets. This indicates, BSE-India is very much sensitive to bad news.

4.4. Test Result for TGARCH (1,1) Model

Table 4 describes the TGARCH (1,1) results.

Table 4. TGARCH (1,1) Test Results

	ADSE-Saudi	Greece	Australia	Columbia	Mexico	Spain	BSE-India
ω (constant)	0.24 (0.14)	0.00 (0.95)	0.00 (0.90)	0.00 (0.98)	0.38 (0.30)	4.20 (0.13)	0.05* (0.00)
α (ARCH effect)	0.07 (0.70)	1.81* (0.01)	2.68* (0.00)	0.07 (0.25)	0.05 (0.80)	-0.09 (0.60)	-0.0005 (0.99)
β (GARCH effect)	0.76* (0.00)	0.35* (0.00)	0.00 (0.92)	0.59* (0.00)	0.60 (0.16)	0.45 (0.35)	-0.06 (0.74)
$\alpha + \beta$	0.83	2.16	2.68	0.66	0.65	0.36	-0.06
γ (leverage effect)	-0.21 (0.21)	-1.28 (0.08)	-0.51 (0.74)	1.12 (0.055)	-0.18 (0.38)	-0.33 (0.14)	0.90* (0.02)
	Turkey	Brazil	Malaysia	Peru	Bangladesh	UAE	Egypt
ω (constant)	0.41 (0.12)	0.93* (0.02)	0.73 (0.35)	1.34* (0.00)	0.00 (0.67)	0.48 (0.44)	0.05* (0.01)
α (ARCH effect)	0.19* (0.00)	0.80 (0.05)	-0.19 (0.06)	0.58 (0.00)	-0.13 (0.00)	-0.05 (0.84)	-0.08 (0.61)
β (GARCH effect)	0.59* (0.00)	-0.07 (0.81)	0.57 (0.32)	-0.12 (0.24)	0.82* (0.00)	0.57 (0.96)	0.45* (0.00)
$\alpha + \beta$	0.78	0.73	0.38	0.46	0.69	0.52	0.37
γ (leverage effect)	-0.26* (0.01)	-0.72 (0.08)	0.11 (0.24)	-0.56* (0.00)	0.55* (0.00)	-0.01 (0.34)	0.60* (0.01)
	Euronext SE	Vietnam	Hongkong	Ireland	Indonesia	South Africa	South Korea
ω (constant)	0.24 (0.11)	0.31 (0.19)	0.45 (0.27)	0.56 (0.17)	0.66 (0.30)	0.00 (0.99)	0.62 (0.48)
α (ARCH effect)	-0.25* (0.02)	0.33 (0.10)	0.00 (0.98)	0.17 (0.18)	0.17 (0.13)	3.30* (0.00)	0.03 (0.90)
β (GARCH effect)	0.76* (0.00)	0.56* (0.03)	0.54 (0.37)	0.94* (0.00)	0.41 (0.48)	0.01 (0.10)	0.52 (0.46)
$\alpha + \beta$	0.51	0.83	0.54	1.11	0.58	3.31	0.55
γ (leverage effect)	0.34* (0.01)	-0.42 (0.06)	-0.14 (0.28)	-0.26* (0.04)	-0.21* (0.04)	-1.20 (0.33)	-0.09 (0.74)

	Great Britain	Russia	Morocco	Argentina	Nasdaq	NASDAQ	NSE-USA
ω (constant)	0.1 (0.46)	0.46 (0.45)	0.94* (0.00)	0.24 (0.08)	0.41 (0.31)	1.01 (0.23)	0.58 (0.44)
α (ARCH effect)	-0.1* (0.00)	0.07 (0.72)	0.90 (0.07)	1.08* (0.00)	0.05 (0.83)	-0.08 (0.12)	-0.02 (0.85)
β (GARCH effect)	1.01* (0.00)	0.58 (0.30)	-0.07 (0.21)	0.40* (0.01)	0.54 (0.28)	0.22 (0.78)	0.52 (0.46)
$\alpha + \beta$	0.91	0.65	0.83	1.48	0.59	0.14	0.50
γ (leverage effect)	0.02 (0.46)	-0.15 (0.37)	-0.20 (0.71)	-1.13 (0.00)	-0.14 (0.53)	-0.03 (0.54)	-0.07 (0.63)
	NSE-India	Japan	New Zealand	Norway	Philippines	Qatar	SSE-Arabia
ω (constant)	0.03* (0.00)	0.54 (0.44)	-0.02 (0.74)	0.51 (0.61)	0.55* (0.00)	0.33 (0.51)	1.30* (0.00)
α (ARCH effect)	1.47* (0.00)	-0.01 (0.46)	0.07 (0.44)	0.07 (0.34)	0.66* (0.02)	0.04 (0.81)	0.31 (0.09)
β (GARCH effect)	-0.02 (0.08)	0.47 (0.52)	0.68* (0.00)	0.55 (0.06)	0.34* (0.04)	0.54 (0.46)	-0.14 (0.38)
$\alpha + \beta$	1.45	0.46	0.75	0.62	1.00	0.58	0.17
γ (leverage effect)	-1.42 (0.00)	-0.06 (0.78)	1.01* (0.02)	-0.13 (0.04)	-0.74 (0.01)	-0.11 (0.58)	-0.44 (0.01)
	China	Shenzhen	Singapore	Switzerland	Israel	Thailand	Germany
ω (constant)	0.20* (0.01)	0.16 (0.21)	0.75 (0.19)	0.00 (0.98)	0.16 (0.10)	0.00 (0.99)	0.00 (0.85)
α (ARCH effect)	0.56 (0.16)	-0.20 (0.18)	-0.07* (0.00)	1.07* (0.00)	-0.12* (0.00)	4.71* (0.00)	5.30* (0.00)
β (GARCH effect)	-0.05 (0.62)	0.79 (0.00)	0.56 (0.17)	0.80 (0.00)	0.72 (0.00)	0.06 (0.11)	0.02 (0.20)
$\alpha + \beta$	0.51	0.59	0.49	1.87	0.60	4.77	5.32
γ (leverage effect)	0.46 (0.37)	0.17 (0.24)	-0.15 (0.17)	-1.14 (0.00)	0.81* (0.01)	-3.92 (0.02)	-4.13 (0.02)
	Canada	Poland	Austria	*denotes significant at the 5%. P-values are included in () brackets.			
ω (constant)	0.36 (0.10)	0.04* (0.01)	0.35 (0.30)				
α (ARCH effect)	-0.27* (0.01)	0.03* (0.00)	-0.07 (0.76)				
β (GARCH effect)	0.70* (0.01)	1.02* (0.00)	0.60 (0.20)				
$\alpha + \beta$	0.43	1.05	0.53				
γ (leverage effect)	0.27* (0.01)	-0.17 (0.00)	-0.09 (0.72)				

The sum of ARCH and GARCH coefficient is statistically significant at 5% level of significance for Greece, Australia, Ireland, South Africa, Argentina, NSE-India, Philippines, Switzerland, Thailand, Germany, and Poland stock markets, which indicates that volatility is existed in those stock markets. Positive and statistically significant γ confirms leverage effect in TGARCH model. γ is positive and statistically significant at 5% level of significance for BSE-India, Bangladesh, Egypt, Euronext Stock Exchange, New Zealand, Israel, and Canada stock markets. So, negative shock produces more fluctuation in those stock markets compared to positive shock. Leverage effect in New Zealand stock market is highest compared to other stock markets.

5. Conclusions

Our study aimed to analyze the market volatility world's forty five largest stock exchanges from January 1, 2020 to September 30, 2020. Scaling analysis result shows that memory of all the stock market are persistent and so they possesses long term memory which diminish the chance of random fluctuation or turmoil in stock market.

Only New Zealand stock market has chance to behave randomly and to have no memory at all. So, chance of volatility is less in all the considered stock market. GARCH (1,1) model shows that all the stock markets are not volatile which supports the claim from the result obtained by memory analysis of the stock markets. Greece, Columbia, Mexico, Spain, Bangladesh, Great Britain, Nasdaq-USA, NSE-USA, New Zealand, Shenzhen-China, Switzerland, Canada, Poland, and Austria stock markets are volatile. Volatility of these stock markets can be designated by precedent volatility which is persistent over time. EGARCH (1,1) model points out that leverage effect exist in BSE-India, Malaysia, Bangladesh, Egypt, Euronext Stock Exchange, New Zealand, Shenzhen-China, and Canada stock markets. So, bad news produces higher volatility than good news in those stock markets. So, the bad information in these stock markets has a larger impact on conditional volatility in contrast to impacts produced by the good information. TGARCH (1,1) model shows that leverage effect exist in BSE-India, Bangladesh, Egypt, Euronext Stock Exchange, New Zealand, Israel, and Canada stock markets. So, negative shock has more added contribution in market volatility in those stock markets compared to positive shock.

Our findings will help international investors to get an overall idea about market volatility worldwide and to think where to invest. As most of the stock markets are volatile, diversification is possible also. It is recommended that the other international stock markets which do not have significant leverage effect should be careful and take necessary steps in order to avoid market turmoil.

The study is not free from some limitations. We have not considered all the stock markets of the globe, stock market returns, and market capitalization. At the same time, we have not examined the causal relationship among the selected stock markets. If these variables and methods are measured in a future research, there may be other motivating results in this perspective.

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