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Responsiveness of Stock Market in US, UK and China to the Covid-19 Health Emergencies: Asymmetric and Impact Analysis

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Abstract
This work evaluates the behaviour of stock markets of US, UK and China in response to the financial crisis caused by Covid-19 virus between 2020 and 2023. Using the basic GARCH, EGARCH and TGARCH models, this study provides robust and extensive empirical evidence on volatility clustering, persistence and asymmetries in the investigated countries. Across the three markets, the existence of volatility persistence and leverage effects were established from the asymmetric estimates. Further it investigated the impact of Covid-19 cases and fatality on the volatility of the studied markets using Autoregressive Distributed Model (ARDL) and discovered that they have positive significant influence on the US and UK stock market returns respectively. China revealed non-significant effect. Our research recommend is that national health authorities, particularly in less developed countries should deepen their health institutions for robust, proactive and timely execution of emergencies to mitigate losses in event of similar occurrences in the future.
Keywords: *Stock Market; Asymmetric Analysis; USA; China; UK and GARCH*

1. INTRODUCTION

The identification of the COVID-19 virus happened in China in the last day of the month of 2019, before rapidly spreading to numerous countries. On March 11, 2020, the World Health Organization (WHO) officially declared it a global pandemic. Historical evidence from the literature indicates that various regions worldwide have previously encountered severe infectious disease outbreaks, including SARS in 2003, Dengue Fever and Avian Flu in 2006, Swine Flu in 2009, Cholera in 2010, MERS in 2013, Ebola and Measles in 2014, and Zika in 2016, all of which had significant economic effect in the affected regions. The COVID-19 pandemic represents the most profound and disruptive shock to the global economic system in recent history [1,2,3].

The six nations most severely impacted by the pandemic, as reported by [4], were the United States (1,219,487 cases), Brazil (711,380), India (533,570), Russia (402,756), Mexico (334,958), and the United Kingdom (232,112). During the fifteenth meeting of the International Health Regulations (IHR) Emergency Committee, on May 4, 2023, the WHO Director-General acknowledged the persistent presence of COVID-19 while recognizing a general decline in mortality rates and severe hospitalizations, declared that the pandemic no longer represents a health emergency.

The pandemic introduced significant uncertainty across economies and nations, triggering panic and disillusionment among investors [5]. This uncertainty adversely affected the global economy by disrupting economic activities [6] and destabilizing financial markets in developed and emerging economies [7]. According to [8] and [9], the economic effect of the pandemic surpassed the Global Financial Crisis in 2008 and all preceding pandemics [10].

Researchers such as [11] and [12] reported that as the pandemic persisted, the global financial markets experienced heightened volatility and adverse market reactions. The crisis led to a decline in the prices of shares, oil, and bonds [13]. On March 12, 2020, the global stock market experienced a major crash. As noted by Insaidoo et al. (2021), COVID-19 contributed to decreased stock returns and increased price volatility. For instance, the U.S. S&P 500 index reached its lowest levels in the month of March 2020 while according to [14] the Shanghai Stock Exchange plummeted by 8% on February 3, 2020. Similarly, the UK's FTSE 100 declined by 10.87% on March 12.

As a response to the crisis, rating bodies such as the IMF and OECD revised global economic growth projections downward from 6.3% to -3% and 1.5% respectively. Consequently, every economic assumption considered valid prior to the pandemic was reevaluated and revised downward.

Governments worldwide implemented administrative measures, including citywide lockdowns, restrictions on public gatherings, and international travel bans. Additionally, governments deployed both monetary and fiscal interventions to mitigate the economic fallout. However, these measures produced mixed outcomes. Some policies led to reduced production, weakened supply and demand, declining corporate earnings [15], and deteriorating stock market performance [16]. Others, however, yielded positive effects. [17] observed that monetary interventions contributed

positively to economic stability, whereas fiscal policies exacerbated stock market downturns.
This study focuses on the stock markets of the US, China, and the UK, given their substantial market capitalizations and distinct reactions following the outbreak. The choice of these countries is influenced by several factors. First, The United States and China hold the top two spots as the world's largest and second-largest economies. Understanding their market responses and resilience to COVID-19 shocks is critical. Second, these two nations share a significant historical connection to the pandemic: while China was the origin of the virus, the U.S. recorded one of the highest numbers of casualties. Third, the three countries host the largest stock markets within their respective continents, making them ideal candidates for examining the pandemic's financial implications.
At the time of this study, the COVID-19 pandemic was still evolving, and its effects continued to unfold. Most existing studies on the topic have focused on providing preliminary analyses of the pandemic's impact on financial markets. However, many of these studies relied on datasets covering only a few months in 2020, resulting in limited temporal scope. Consequently, much of the literature comprises predictions rather than definitive conclusions. For instance, [18] acknowledged that the long-term implications of the COVID-19 catastrophe remained uncertain. [3] projected which prolonged economic disruptions could lead to mass unemployment, business failures, and the collapse of numerous industries. [19] warned that global financial markets faced an unprecedented economic dilemma, which they referred to as "stagpression." However, the availability of an extensive dataset spanning from 2020 to 2023 offers this study a distinct advantage, enabling more precise estimates and reliable conclusions. [20] emphasized that the inclusion of larger datasets enhances the accuracy of financial research and improves decision-making processes. Similarly, [21] advocated for extended analyses of financial markets throughout the pandemic to produce more comprehensive insights.
This study makes value addition to existing literature by evaluating market volatility, asymmetric stock market reactions, volatility pooling as well as the impact of the pandemic through regression analysis. This aligns with [6] who emphasized that utilizing long-term COVID-19 data is essential for obtaining robust results. Furthermore, [22] stressed the need for continuous research on this subject, arguing that future studies should shift from analyzing market behavior during the pandemic to exploring its post-pandemic implications. Appraising the intertemporal impact of COVID-19 on the volatility of the investigated stock market can deliver useful perceptions on the reactive tendencies of investors to structural changes which may outlast the pandemic. Market participants and policymakers also will find utility in this study by shaping their adjustment and coping strategies to possible future economic disruptions.
The rest of the study is divided into four sections with section two presenting a brief review of literature; section three presents the methodology, the results and conclusions are respectively contained in sections four and five.

2. LITERATURE REVIEW

US Stock Markets

The U.S. economy and stock market are closely linked and very connected. Stock markets have a significantly greater impact on the U.S. economy than on China's, influencing both individual investors and institutions. U.S. stock market activity is heavily influenced by large, institutional investors with a mix of local and international investors. The market capitalization of U.S. Stock Exchanges as at December 2023 was: NYSE, $25.56 trillion and Nasdaq, $23.41 trillion. Their respective number of listed companies were 2,272 and 3,432 which depend heavily on equity financing.

Measures Adopted to Contain the Pandemic in the US

[23] reported that the Dow Jones Industrial Average (DJIA) entered a bear market, reaching its lowest level in 11 years. Within a span of merely four trading days, the index plummeted by 6,400 points, representing an approximate 26% decline. [3] highlighted that the pandemic period introduced significant uncertainty, causing financial markets to follow an unpredictable trajectory. Notably, on 12 March 2020, the DJIA declined by 10%,while the NASDAQ declined by 9.4%, and the S&P 500 dropped by 9.5%.
In response to the extreme market volatility, Federal Reserve (FED) announced a zero-interest rate policy alongside an expansionary monetary policy. Specifically, on 16 March 2020, amid persistent financial instability, the FED introduced a zero-percent interest rate policy, eliminated reserve requirements, and initiated a quantitative easing (QE) program valued at a minimum of $700 billion. [3] observed that such Quantitative Expansion measures were unconventional monetary strategies that could exacerbate uncertainty and pose long-term economic risks. Similarly,

[24] argued that QE and zero-interest rate policies alone would be insufficient to facilitate market recovery during periods of deep recession and financial crisis, advocating instead for the adoption of a negative interest rate policy. Due to negative market reactions to these initial measures, the FED subsequently expanded its monetary stimulus, announcing an unlimited QE policy just eight days later.

China Stock Markets

China's capital market began to develop alongside the country's economic reforms. As the market economy evolved, the growing demand for more market-oriented resource allocation drove the gradual establishment and expansion of China's capital market. And currently its stock market has become the most important part of the Chinese economy. As of December 2023, its market capitalization had reached $10.89 trillion. China's largest stock exchange is the Shanghai Stock Exchange which as of December 202 had a record of $6.52 trillion as its market capitalization with 2,263 listed companies. While capitalization value and number of quoted firms of Shenzhen Stock Market in the corresponding period was $4.29 trillion and 2,853 respectively.

Although China's stock market has a large market capitalization, it is still small relative compared to the United States. Further, China's stock markets have often been dominated by retail investors who are more or less speculators than engaging in long-term sound investments. Foreign investors hold only a small percentage of the market capitalization.

Measures Adopted to Contain the Pandemic in China

Throughout February, China remained the epicenter of the COVID-19 outbreak prompting very swift and decisive responses from the government including the 23rd of January 2020, the lockdown of Wuhan. This event heightened uncertainty within capital markets, leading to increased market volatility. The Shanghai Stock Exchange dropped by 10% and the Shenzhen Stock Exchange by 6% [23].

People's Bank of China introduced a stimulus package of 1.2 trillion yuan which is around $174 billion in early February to maintain financial stability and support the economy. Additionally, the central bank reduced benchmark lending rates to stimulate business activity and investment [25]. [26] observed that China successfully contained the virus within three months, facilitating a rapid economic recovery in contrast to other nations, particularly the United States. They further noted that China ended the year 2020 with positive economic growth, followed by further improvements in 2021. Similarly, [27] emphasized that China appeared to lead the global recovery process. [28] also attributed China's swift economic rebound to the government's timely intervention through lockdown measures and other containment strategies, which effectively restored stability to Chinese financial markets.

UK Stock Markets

Market capitalization of the London Stock Exchange was around 3.5 trillion British pounds in December 2023 with the number of companies listed at 1,977. This is a relatively small market compared to the Chinese and the United States though it is still larger than the other markets especially in emerging economies.

Measures Adopted to Contain the Pandemic in UK

The first cases of Covid-19 in the United Kingdom were reported on January 30, 2020, with the first confirmed death occurring on March 5, 2020. During this period, stock markets experienced significant declines. On March 12, 2020, the FTSE 100 index recorded its steepest drop since 1987, falling by more than 10%. Between February 19 and March 23, the FTSE All-Share Index plummeted by 33%. In April, UK consumer spending decreased by 36.5% [29], while the production index fell by 19.8% [30].

In administrative response, lockdown was announced on 23 March 2020. Additionally, in monetary terms, the Bank of England declared an interest rate cut, specifically on March 19, it announced a 15 basis points cut of overnight rate. Fiscal expansionary measures of 30 billion pounds and £200 billion purchases of government bonds which is a expansionary monetary policy measure.

Table 1: Average Daily Covid -19 Cases and Fatality Rates

		Year 2020		Year 2021		Year 2022		Year 2023	
Countries		Ave. Daily Cases	Ave. Daily Fatality	Ave. Daily Cases	Ave. Daily Fatality	Ave. Daily Cases	Ave. Daily Fatality	Ave. Daily Cases	Ave. Daily Fatality
US	51,755	940		90,379	1,287	129,132	733	12,102,	231
UK	6,423	248		28,028	235	31,738	107	1,935	

China	264 13	95 3	171,725, 91	45 101,033, 227

Source: Compiled by the authors from ourworldindata.org

Prior empirical have been done on the effect of COVID-19 on economies of the world, some jey empirical studies are summarized below:

Table 2: Summary of Key Empirical studies

S/No	Author(s)	Geography	Methodology	Findings
1	[31], [32] [3] and [6]	China	GARCH Family Models	The GARCH estimates confirmed the long-run persistence in the stock return volatility in the COVID-19 period.
2	[1]; [3], [33] and [34]	USA	GARCH Family Models and Impact Analyses	Stock market was found at a level that exceeded the October 1987, the 2008 financial crisis, and the Great Depression.
3	[35]	Six COVID most affected Countries	GARCH Family Models	Results showed an unprecedented level of volatility.
4	[18]	12 major equity markets	Generalized VAR	Disruptions in investors sentiment caused by uncertainties from the pandemic.
5	[36]	Pakistan and India	ARCH, GARCH models that applied regression,	Findings further support significant effects of COVID-19 on stock volatility in countries.
6	[37]	Sub-Saharan Africa	Event study Methodology and panel data regression	Their findings indicated that lockdown measures had an adverse effect on the performance of most sectors in sub-Saharan African markets.

Source: Author(s) Compilation

Prior studies in this area have been done with varied conclusions. In this study a review of studies done in not just the jurisdiction of interest but also in connected areas have been reviewed.

3. DATA AND METHODS

Data

We chose the S&P 500 index to represent the United States stock market. The FTSE 100 for the London Stock Exchange it is equivalent of S&P 500 while for China the Shanghai is used which is the largest stock market in China and also the Asia's biggest. The series are the important benchmark indices for the three countries which track the general movement of the stock exchanges. The data frequency is daily and high and hence can be used to capture the stylized fact inherent in the series to ensure credible results. The range is between January 1, 2020, and December 31 2023 (a total of 1003, 1005 and 1002 data points for US, UK and China respectively) which is sufficient enough to account for market bahaviour during the pandemic. The data were obtained from the websites of the three stock exchanges and www.investing.com. Covid -19 data were sourced from www.ourworldindata.org.

Table 2. List of Countries, Stock Market Indices and Sample Data Period

Countries	Stock Market Index	Data Period (Daily)
United States	S&P 500	1 Jan 2020 – 31 Dec 2023
United Kingdom	FTSE 100	1 Jan 2020 – 31 Dec 2023
China	Shanghai Composite Index	1 Jan 2020 – 31 Dec 2023

Data Transformation

The stock indices are logged to reduce the variance and smooth the wild fluctuations in price levels [38] and then are transformed to a compounded daily stock returns. We adopt the model as has been used by numerous authors such as [39], [40] respectively.

$$R_{mt} = LN\left(\frac{S_t}{S_{t-1}}\right)100 \qquad eq. 1$$

Where: R_{mt} = Daily returns for price indices for period (t).
S_t = Daily price indices for period (t).
S_{t-1} = Daily price indices for period $(t-1)$.

4. METHODS

Volatility clustering refers to a period of sustained high levels and low levels [11], it changes over time and is characterized with unusual jumps which must be appropriately modelled. Large number of scholars have corroborated that ARCH models are the most robust techniques to estimate volatility [See 41 and 42]. The autoregressive conditional heteroscedasticity model (ARCH) by [42] and its subsequent generalized version (GARCH) by [43] and [44] are robust for measuring volatility clustering. A key limitation of ARCH and GARCH models is their assumption of shock symmetry, meaning positive and negative effects have identical impacts on volatility. However, GARCH is preferable to ARCH as it is more parsimonious, reduces the risk of overfitting, and is less predisposed to the non-negativity constraints

ARCH (q) Model

The variance equation of the ARCH model of order q [42]

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-1}^2 \qquad eq. 2$$

The ARCH effect determines the heteroscedasticity, this occurs when a variable's variance follows a pattern.

GARCH (p, q) Model**.**

$$\sigma_t^2 = \omega + \textstyle\sum_{i=1}^{q} \alpha_i\, \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_i\, \sigma_{t-j}^2 \qquad eq. 3$$

p is the order of the GARCH terms $\boldsymbol{\sigma}^2$,

q represents is the order of the ARCH terms ε^2.

$\boldsymbol{\sigma}_t^2$ is volatility

ε_t^2 is the error term.

ω is the intercept.

$\alpha_1, \alpha_2, \ldots, \alpha_q$ are the parameters of ARCH processes,

and $\beta_1, \beta_2, \ldots, \beta_p,$ are the GARCH descriptions.

Exponential GARCH (EGARCH) following [45], Power GARCH (PGARCH) by [46] and Threshold GARCH (TGARCH) proposed by [47] are some of the extensions of the basic GARCH model designed to overcome its inherent limitations and account for asymmetries. This is premised on the fact that good news (positive shocks) and Bad news (adverse shocks) elicit different reactions from the market and accounting for these differentials increases the accuracy of the estimation.

Following [45] we modelled the exponential GARCH (EGARCH) which accounts for asymmetry in volatility and is not vulnerable to the non-negative constraint to obtain positivity, stationarity and finite kurtosis. This is achieved by using the log value of volatility as an outcome variable, [48]. The equation is presented thus:

$$\log(\sigma_t^2) = \omega + \sum_{j=1}^{q} \beta_i \log(\sigma_{t-1}^2) + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \qquad eq.4$$

Here, γi is the parameter for the leverage effect, while ω represents the intercept value, the ARCH and GARCH terms are as earlier defined. The hypothesis for the test of leverage effect is stated thus:

$\boldsymbol{\gamma}_i < 0$, the impact is asymmetric, and it is otherwise if $\boldsymbol{\gamma}_i \neq 0$.

Hence it presumes that the negative effect is greater [20].

Threshold GARCH Model (TGARCH).

Following [47], TGARCH evaluates the negative movements in volatility usually overrides the positive movements [40]. Just like EGARCH, TGARCH is without parameter restrictions, and it ensures the positivity of the conditional variance. However, to ensure stationarity and absence of kurtosis, the parameters of the model must be restricted.

$$\sigma_t^\delta = \omega + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^\delta + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 r_{t-k} \qquad eq.5$$

ω = intercept, $\varepsilon_{t-1}$is the ARCH term and $\boldsymbol{\sigma_{t-1}^2}$ is the GARCH term; αi, and the impact of negative news = $\alpha_i + \gamma_i$. based on prior assumptions, it is expected that $\gamma_i > 0$, meaning that negative shocks intensify volatility, this implies that the market has leverage impact.

5. RESULTS AND DISCUSSIONS

Preliminary Results.

Table 3: Descriptive Statistics and Unit Root Tests

Return Index (Panel A)

Panel 1.	**Mean**	**Std.Dv.**	**Max.**	**Min**	**Kurtosis**
USA	8.2761	0.1423	8.4756	7.7130	3.9005
UK	8.8579	0.0916	8.9889	8.5159	3.4552
China	8.0885	0.0701	8.2202	7.8861	2.4158
Volatility Index (Panel B)					
USA	2.0593	4.3484	55.38924	0.2016	66.3681
UK	1.3798	2.2400	24.66759	0.2296	51.2826

China	0.9820	0.5963	4.495040	0.4636	11.7354

Source: Extracted from the EViews

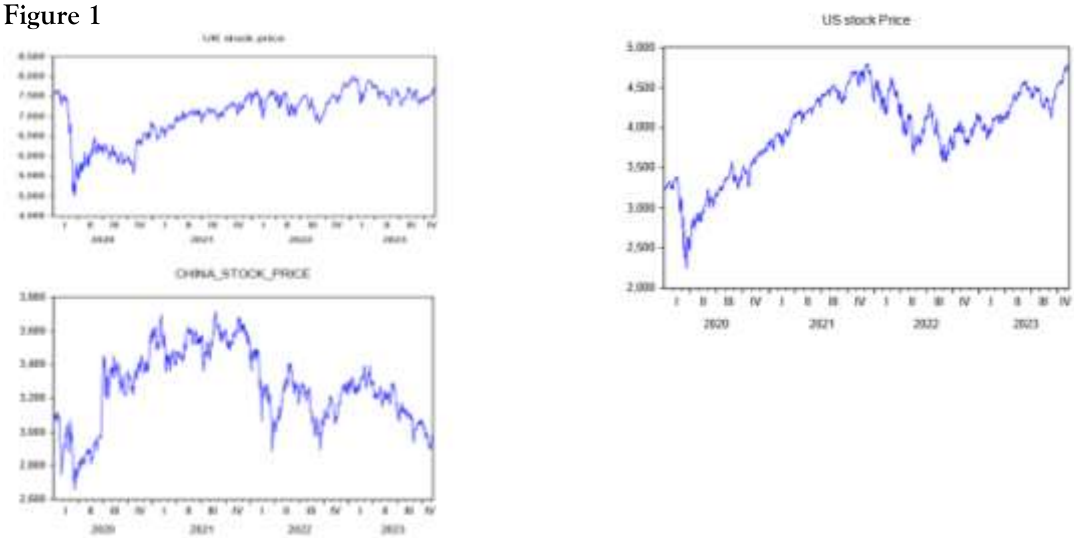
Table 2 displays the summary statistics of the returns and volatility indexes. In the first panel, the mean values for all the countries' stock returns are positive. While the average value of US stock returns for the study period is 8.2761, UK is 8.8579, whereas China has 8.0885. The results indicate that standard deviation is greater in US, followed by UK and then China and this reveals the risk and volatility level in the various stock markets. We detect high kurtosis in all the series hence existence of leptokurtosis in the distributions.
In the volatility index panel, the risk earlier shown in panel A is confirmed here; the large difference between the minimum and the maximum values of the volatility index indicates presence of high volatility in these stock markets. within the period of investigation, US records the highest investor panic ,55% whereas china has the lowest with 4%.

Table 4: ADF and PP Tests for Stock Return Index

	ADF			**PP**		
Countries	**(Trend and Intercept)**			**(Trend and Intercept)**		
	ADF Stat	Critical Value (0.05)	Order of integration	PP Stat	Critical Value (0.05)	Order of integration
USA	-9.3702	-2.8642	I(1)	-38.0714	-2.8642	I(1)
UK	-32.1550	-2.8642	I(1)	-32.1667	-2.8642	I(1)
China	-31.0027	-2.8642	I(1)	-31.0455	-2.8642	I(1)

Source: Extracted from the EViews.
In table 4, the stationarity of the variables was robustly tested with ADF and PP frameworks. All the series attained stationarity after first differencing, that is at order one.
The Stock Price Time-Series Plot.
A significant fall is observed in the stock prices in 2020 in the US and UK and subsequent slight rising and falling in the remaining part of the investigation period. This reflects the impact of the surge of the outbreak. However China after a steep fall in price in the first quarter of 2020 witnessed a considerable rise and then steep fall when the second wave of the virus occurred. Generally, it is visible that the sudden incidence of the pandemic disrupted the equity market prices of these countries. However the expansionary fiscal and monetary decisions of the governments prompted the recovery trends in the stock market prices. This has further indicated that investors always display prompt response to government policies. The descriptive and the graphic time series plot are the first evidence of the effects of the pandemic on the studied stock markets.

Figure 1



Test of Arch Effect

For robustness and proper application of the ARCH family models, the determination of a possible ARCH effect is necessary. This means confirmation of the non-constant variance of the return series. We employed two methods of testing the existence of this ARCH effect: plotting of the residuals of the stock returns in equation 6 and the statistical arch test in equation 7.

$$Y_t = \mathrm{K} + \xi_t \qquad eq.6$$

y_t is the return series, ĸ, the constant while ξ_t is the plot of residuals.t-

$$\xi_t^2 = \psi_0 + \left(\sum_{i=1}^{q} \pi_i\, \xi_{t-1}^2\right) + \mu_t \qquad eq.7$$

ξ_t^2 depicts the Ho of no ARCH, that is Ho: π_ι = 0 at 5% significant level up to order q. Arch effects are present in the three markets as evidenced in table 5 wherein the probabilities of US (133.2673), UK (39.68378) and China (22.7323) F-Statistics are non-significant at 0.0000. Corroborating, it is also obvious that in figures 3 Where market returns show evidence of volatility clustering, fluctuating around zero (mean reverting). It changes between the positive and negative values. Therefore, we can adopt non-linear models, specifically ARCH models.

Table 5: Arch Effect Test

Countries	F-statistic	Prob. F(1,1002)
United States	133.2673	0.0000
United Kingdom	39.68378	0.0000
China	22.7323	0.0000

Source: Summary of the ARCH effect estimates

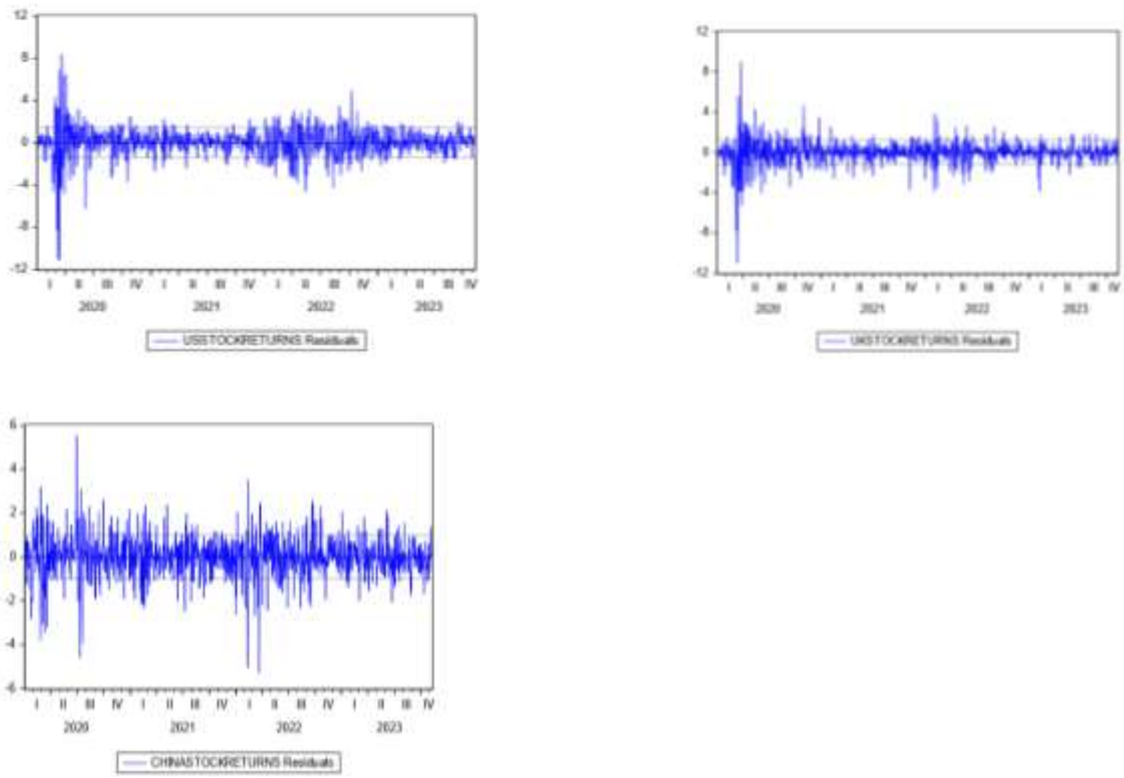


Figure 2: Volatility Clustering of UK, US and China Daily Return Series.

Table 6: Stock Returns Estimates Using GARCH Family Models

Models	Equations	Model Parameters	Coefficients	Z- stat	P-value
USA (S&P 500)					
	Mean	Intercept	0.0753	2.432	0.015
GARCH (1, 1)		AR	-0.0572	-1.6774	0.0935
		Intercept	0.0526	4.3552	0
	Variance	ARCH	0.1627	6.4264	0
		GARCH	0.8096	29.619	0
	Mean	Intercept	0.028	0.8536	0.3933
		Intercept	-0.179	-7.5606	0
EGARCH		ARCH	0.2472	7.8341	0
(1,1)	Variance	Asymmetric	-0.1137	-6.4799	0
		GARCH	0.9532	105.2401	0
	Mean	Intercept	0.0573	1.7708	0.0766
		Intercept	0.0558	5.4212	0
TGARCH	Variance	ARCH	0.0517	3.0811	0.0021
(1,1)		Asymmetric	0.1818	5.1314	0
		GARCH	0.8228	37.199	0
UK (FTSE 100)					
	Mean	Intercept	100.0289	3228.579	0
GARCH (1, 1)		AR	103.79	-1.0801	0.2801
		Intercept	0.0682	5.4313	0
	Variance	ARCH	0.1492	7.6159	0
		GARCH	0.7948	30.6854	0

	Mean	Intercept	99.9918	3517.7	0
		Intercept	-0.1118	-7.1465	0
EGARCH		ARCH	0.1478	7.287	0
(1,1)	Variance	Asymmetric	-0.1664	-9.9598	0
		GARCH	0.9628	170.5006	0
	Mean	Intercept	102.5255	29.3112	0
TGARCH		Intercept	0.0539	7.6192	0
(1,1)		ARCH	0.0061	2.7625	0.04
	Variance	Asymmetric	0.2029	7.4807	0
		GARCH	0.8445	47.3053	0
CHINA (SHANGHAI STOCK EXCHANGE)					
		Intercept	0.0019	0.0683	0.9455
GARCH (1, 1)	Mean	AR	-0.0055	-0.1564	0.8757
		Intercept	0.0512	4.0466	0.0001
	Variance	ARCH	0.0921	7.6549	0
		GARCH	0.8556	43.2441	0
	Mean	Intercept	-0.014	-0.4889	0.6249
		Intercept	-0.1875	-8.5011	0
EGARCH		ARCH	0.2366	8.7677	0
(1,1)	Variance	Asymmetric	-0.0708	-3.935	0.0001
		GARCH	0.911	44.2334	0
	Mean	Intercept	-0.012	-0.4117	0
		Intercept	0.0719	4.0375	0.0001
TGARCH	Variance	ARCH	0.0639	6.8388	0
(1,1)		Asymmetric	0.0809	3.3138	0
		GARCH	0.8204	30.6986	0

Extracted from the EViews

6. DISCUSSION OF RESULTS

The findings indicated leverage effect across the three major stock markets during the period of Covid-19 Disease. EGARCH and TGARCH are very much in agreement and similar with this revelation. In EGARCH estimates, the coefficients of asymmetry are significantly negative in US (-0.1137), UK (-0.1664) and China (-0.0708). Further the TGARCH asymmetric parmeters are positive in the three markets, US (0.1818), UK (0.2029), and China (0.0809). All of them are in consonance with the models a priori expectations. It all means that the investigated markets respond more to bad news than they do to good news of equal magnitude The implication is that the scaring news of Covid-19 with its associated lock downs sent market participants panicky and jittery and hence their resorting to actions antithetical to market fundamentals. This investors' pessimism towards corona pandemic is a significant factor in swaying the activities in stock market indices. It explains the sudden plunge in the prices of the stocks and negative effect of the outbreak in the markets. This is in agreement with the proposition by Yousfi et al, (2021) when they stated that bad news would spike U.S. stock market volatility.

The volatility persistence of stock market returns is represented by the Arch and Garch terms in the models. The two terms illustrate the Time-varying volatility and the presence of volatility clustering in the markets' returns during the pandemic. Persistence occurs when the two parameters are close to one (1). Drawing from the estimates, it is evident that there is high volatility persistence in the three stock markets. In Table 6, the majority of the persistence parameters are close to 1. (Garch, 0.96), (Egarch, 1.2) and (Tgarch, 0.82) for US. And for UK the estimates are (Garch, 0.93), (Egarch, 1.1) and (Tgarch, 0.84). Whereas Chinese markets persistence disclosures across the three models are as follows (Garch, 0,94), (Egarch, 1.1) and (Tgarch, 0.9). In the results, Egarch model, across all the three markets shows explosive volatility persistence as the estimates are greater than 1. Remarkebly, all the parameters show statistical significance. The consequence of all these is that the volatility of one period would cross over to another period; simply implying that shock to the market dies out very slowly. Except Egarch, all these results satisfy the stability condition of the Garch (1,1) model, that is, the sum of Arch effect and Garch effect is less than 1.

Diagnostic Check

Our paper also conducted test to determine if there is any remaining ARCH effect using ARCH-LM test. This is necessary in determining the efficiency of the conditional variance model. Hence, the expectation is that at 5% significance level of the null hypotheses will not be rejected.

Table 7: Diagnostic Test

Countries	EGARCH		TGARCH	
	F-stat (p.value)	ObsR^2 (p.value)	F-stat (p.value)	ObsR^2 (p.value)
US	0.2085 (0.6480)	0.2089(0.6476)	0.3124(0.5763)	0.3129 (0.5759)
UK	0.1451 (0.7033)	0.1454 (0.7029)	0.0033 (0.9536)	0.0033 (0.9535)
China	0.3540(0.5520)	0.3546(0.5515)	0.0155(0.9007)	0.0156(0.9006)

Source: Extracted from the EViews Diagnostic estimates. In parenthesis are p-values

The probabilities of the F-statistics and the observed R^2 in both models exceed the 0.05 significance level, hence the homoscedasticity test results agrees that the models is suitable for estimating volatility implying that the ARCH effect has been properly addressed.

Impact Analysis

To ascertain the direction and magnitude of the relationship between Covid pandemic, we adopted the autoregressive distributed lag model (ARDL) framework specified as:

$$\mathcal{Y}_t = \alpha + \sum_{i=1}^{p} \Upsilon_j \mathcal{Y}_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q} X_{j,\ t-i}{}' \beta_{j,\ i} + \xi_t \qquad 8$$

Where $\mathcal{Y}_t$ is a vector; $\mathbf{X}_t$ is regressor which can be I(1) or I(0); $\boldsymbol{\beta}$ and Υ are parameters; α is the intercept; k, p, q are optimal lag orders, ξ_t is a vector of the residual.

Substituting our variables in ARDL we derive a model for impact estimates.

$$\Delta SV_t = \alpha_{01} + \sum_{i=1}^{p} \alpha_{1i} \Delta SV_{t-i} + \sum_{i=1}^{q} \alpha_{2i} \Delta CC_{t-i} + \sum_{i=1}^{q} \alpha_{3i} \Delta CD_{t-i} + \lambda ECT_{t-} i + \xi_t \qquad 9$$

where α is the constant term, SV is the stock market volatility, CC is the number of Covid Cases, and CD the number of Covid Death. While ξ_t = is a white noise phenomenon for capturing the effects of other exogenous factors on stock market volatility. Additionally λ estimates the speed of reestablishment of equilibrium. But before then the stationarity of the variables were explored to ensure that there is no any with unit roots.

Table 8 ADF and PP Tests

			ADF (Trend and Intercept)			PP (Trend and Intercept)		
Countries		**Variables**	ADF Stat	Critical Value (0.05)	Order of integration	PP Stat	Critical Value (0.05)	Order of integration
	SV I(0)		-5.0410	-2.9266	I(0)	-5.0579	-2.9266	
US	CC I(0)		-12.0241	-2.9266	I(0)	-10.0470	-2.9251	
	CD I(0)		-6.2655	-2.9314	I(1)	-3.2002	-2.9281	

	SV I(0)	-4.4866	-2.92662	I(0)	-4.5064	-2.9266
UK	CC I(0)	-5.4360	-2.9266	I(0)	-5.0245	-2.9266
	CD I(0)	-3.5905	-2.9369	I(0)	-6.2385	-2.9297
China	CC I(0)	-4.2656	-2.9281	I(0)	-4.5702	-2.9266
	CC I(1)	-7.4698	-2.9266	I(1)	-7.4331	-2.9266
	CD I(1)	-6.2337	-2.9314	I(1)	-6.61189	-2.9314

Source: Computed by the authors.

The figures in the table above display that the series are with mixed order of integration, I(0) and I(1). Also considering the number of our observation, 48, the ARDL model is suitable to produce robust and credible results.

Table 9: ARDL Test

Panel 1	EStimates	Prob. Value
USA		
SV(-1)	0.3759	0.0000
Covid Cases	0.5077	0.0225
Covid Deaths	0.8661	0.0100
ECM(-1)	-0.6240	0.0000
Panel 2		
UK		
SV(-1)	0.1112	0.3256
Covid Cases	0.0631	0.8645
Covid Deaths	0.6072	0.0016
ECM(-1)	-0.8887	0.0000
Panel 3		
CHINA		
SV(-1)	0.2910	0.0677
Covid Cases	-0.0284	0.5522
Covid Deaths	0.1000	0.1239
ECM(-1)	-0.7089	0.0000

Source: Extracted from the ARDL estimates in EViews

Table 9 displays the three regression results. Generally, we can see that market volatility and COVID-19 crisis are positively connected in respect to US and UK. Specifically, in UK only Covid cases is statistically significant at a 5% level. While in US both indicators of Covid 19 explained the rise in the market oscillation. It implies that the virus outbreak in the two countries has raised the stock market uncertainty. This caused an adverse yield to the equity market and raised more concern about portfolio and risk diversification. However, China reveals a different result; whereas Covid cases shows negative relationship with the market volatility, Covid deaths exhibits positive attribute. But none of them are significant. It can be stated that in some degree the Chinese market did not feel the full impact of the disease. The outcome suggests that the uncertain period of first quarter of 2020 with exponentially increasing COVID-19 deaths might have slightly disrupted the investors' sentiments in China in short-term. Perhaps this is because China quickly exited the pandemic and during the second wave its government and investors might have adequately provided hedges against the consequential adverse effect on the market. The country with the highest impact of Covid-19 cases and deaths on stock market is US with 51% and 87% respectively.

7. CONCLUSIONS

We examine the behaviour of US, UK and China stock markets during the turbulence time of the Covid- 19. GARCH family models of basic GARCH, and asymmetric GARCH (EGARCH and TGARCH) were employed to unravel if these markets exhibited volatility clustering and asymmetry amidst the pandemic. The three stock markets manifested the two attributes of equity markets whenever the market is hit with disorders, shocks and instabilities. This research work established the appearance of volatility clustering and dominance characteristics across the examined markets. The pessimistic and panic sentiments of the market investors are very critical and contributing here. Though the degree of volatilities is different across countries based on the severity of the pandemic. Further our study revealed that there is existence of volatility persistence amongst the market. This implies that the market shock is slow in dying off. This work also engaged ARDL model to investigate the impact of Covid cases and deaths on market volatility and found that US was severely affected the most, the two indicators were significant even with high coefficient levels of 51 and 87 percent. The UK was next with only Covid cases influencing the outcome variable. However in the case of China, the market seemed to be immune to the Covid cases and deaths. Most probable, this regression result may have produced different results particurlarly on China if this study have employed more variables such as governments' responsiveness to the pandemic, fear index and other social and political factors. Stock prices reflect expectations of future profits, and investors perceive the disease as inhibiting economic activity and decreasing profits.

This study has presented a considerable extensive empirical analysis of the responsiveness of stock markets to the effects of COVID-19 using data for the period of 2020- 2023. Greater number of previous researches dwell largely on data in the early stage of the health crisis. This lends more credence and robustness to our work. Further, this work corroborates the findings of [49] who observed that the nosedives in China stock market was relatively lower than that in the USA and UK, including other countries. The study findings demonstrate that the volatility in the affected countries increased as a result of the outbreak. And this is in consistent with some earlier research works such as [50] and [3]. Our research therefore recommends to the national health authorities particularly in less developed countries to deepen their health institutions for robustness and proactive initiative so as to timely execute emergencies in the event of a similar occurrences in future. More than that, composed and calculated financial and macroeconomic approaches devoid of pressure will also help to alleviate financial and economic losses. Portfolio managers can also take advantage of the research findings in creating a superior portfolio to mitigate losses. It will also help in moderating herd bahaviour among investors in similar scenario.

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