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STOCK MARKET VOLATILITY OF G-20 COUNTRIES BEFORE AND DURING THE COVID CRISIS

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Abstract *This research explores into the intricate dynamics and drivers of stock market volatility in both emerging and developed G20 economies. Empirical results from GARCH (1,1) and EGARCH (1,1) indicate the existence of both short-run and long-run symmetric and asymmetric volatility in the market returns of the G20 countries before and during the crisis and also captured the presence of information asymmetry. Argentina and China's markets experienced the highest symmetric short- and long-run volatility persistency during the pre-pandemic period, whereas the Russian market had the largest symmetric and asymmetric short- and long-run volatility persistency during the COVID-19 crisis among the other G20 countries. Consequently, the findings of this research contributed to the existing body of knowledge on stock market volatility, offering nuanced perspectives on the distinct characteristics and dynamics of emerging and developed economies, and paving the way for more informed decision-making in the global financial landscape.*

Keywords: *Market Volatility, G20 Economics, Emerging Countries, Developed Countries, GARCH Models*

INTRODUCTION

The COVID-19 epidemic triggered a significant amount of uncertainty for both developed and developing countries' economic policies and the resulting market meltdown. The USA and other developed stock markets witnessed a record decline during the first wave of COVID-19 while emerging markets such as Brazil, Mexico, and India experienced significant falls during the second phase of the pandemic, which was substantial compared to the 2007–08 financial crisis. Furthermore, the occurrence of several exogenous shocks soon after the pandemic's primary effects, such as a spike in inflation and high-interest rates, caused debt-liquidity crises at both the institutional and individual levels and further slowed down the recovery rate across various countries. Moreover, significant global events like the Russia-Ukraine war, supply disruptions in the energy and oil sectors, and other incidents created greater uncertainty in both domestic and international stock markets (Baker et al., 2020; Shankar & Dubey, 2021; Li et al., 2023). The crisis made it pertinent to understand the dynamics of volatility in the financial markets. The integrated global market emerged as a key factor in making domestic market volatility more noticeable during the crisis period; which raised concerns among international investors about the need for volatility forecasting to optimise portfolios, diversify risks, and hedge (Jeribi et al., 2022; Vijayakumar, 2020; Ezzat, 2012).

Volatility, a term used to describe the uncertain outcomes of stock prices, is negatively correlated with stock returns. FAMA (1969) defined volatility as a time-varying element that retains its memories. This leads to volatility clustering impact on stock price, i.e., a period of high (low) volatility in the financial market is followed by a period of low (high) volatility (Brooks, 2008). Another characteristic identified by Black (1976) is that volatility caused by negative news results more fluctuation in the stock price than the volatility generated by positive news of the same magnitude; this is known as the asymmetric volatility phenomenon in the stock returns. The behaviour theory explains that during uncertainty, investors' decision-making is often influenced by negative news due to the contagion effect of shocks, which raises asymmetric volatility in the stock returns. Further, in the literature, there are two explanations for asymmetric volatility those are the effect of the financial leverage and volatility feedback effect. Under the financial leverage effect, a fall in the current stock price enhances future volatility whereas, according to the volatility feedback effect the likelihood of higher volatility causes the stock price to drop (Banumathy & Azhagaiah, 2015; Goudarzi & Ramanarayanan, 2011; Ning et al., 2015; Horpestad et al., 2019; Desai & Joshi, 2021).

The world's most significant and systemically important economies are united under the G20. Its member nations

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account for nearly two-thirds of the entire world's populace, 85% of global GDP, and 75% of international trade. Due to trade, geopolitical relationships, and other associations, the occurrence of any financial crisis in G20 nations has a highly contagious impact on the world economy. Previous literature supports that the stock markets of the G20 countries were the biggest recipients of shocks during COVID-19 pandamic and the 2008 global financial crisis considering their market dominance and interdependence. Moreover, this serves as another impetus for the G20's establishment to counteract the crisis's consequences of such crises for the global economy. Preventing the global financial crisis from turning into a global depression was largely made possible by the international organisation of G20 countries (Bery et al., 2019; Phiri et al., 2023). The G20 consists of the majority of emerging and developed nations, furthermore, earlier studies reveal that the volatility of stock returns varies between developed and emerging stock markets even though the recovery experienced by the developed and emerging two markets is at a different pace and intensity. However, assessments of the dynamics of stock return volatility and its persistence over time among these markets were hardly available, this made the study more crucial. The study aims to identify whether, due to the asymmetric in the stock return volatility, the integrated world stock market experienced high volatility persistency before and during the crisis period. To account for the exogenous break in the financial series due to the outbreak of COVID-19 pandemic. Therefore, in order to evaluate the volatility persistence and leverage effect in the stock markets of the G20 countries before to and during COVID-19, the study period was split into two sections: the pre-crisis period, which ran from January 2016 to December 2019, and the crisis period, which ran from January 2020 to May 2023. There are four sections in this study. The first section provides a brief literature review, while the second section explains the data and methodology segment. In the third section of this study, the analysis of the empirical data is analysed, and in the fourth section, the conclusions from the study are offered.

LITERATURE REVIEW

Numerous studies have been carried out to determine the volatility of stock markets in various nations, both during times of crisis and in the absence of one. Several of these studies confirmed that there was significant volatility in the stock markets of the chosen countries, in this part, emphasis is placed on the papers that examined the volatility persistency and the leverage effect experienced by the international stock markets during various crisis periods. Kishor and Singh (2017) discovered a considerable time-varying pattern of volatility in market returns of the BRICS countries during and after the global financial crisis. These variations in volatility were distinct to the respective markets and were not consistent. Additionally, it found that BRICS markets continued to experience volatility during the crisis (January 1, 2007 to December 31, 2008) and recovery (January 1, 2009 to December 31, 2010) periods. Aggarwal and Yadav (2020) predicted volatility in relation to five significant emerging countries— Brazil, China, Mexico India, and Indonesia—this study divided the study period into pre- and post-crisis periods, or January 2001–December 2008 and January 2009–December 2019. Throughout the entire study period, there was country-specific variation in return volatility of returns across the five emerging countries, and long-term shocks were more pronounced than short-term shocks.

Ganguly and Bhunia (2020) evaluated the impact of leverage and volatility on the global stock indices, this study compared data collected before and after the COVID-19 epidemic and divided the data accordingly. The leverage effect was detected through the empirical EGARCH test in both sub-periods, indicating a considerable contribution of the news pandemic to the volatility of the global stock market. Samadder and Bhunia (2021) addressed memory analysis and the leverage effect on the top 45 global stock markets during the COVID-19 pandemic that erupted between January 1, 2020 and September 30, 2020. The study clarified that the stock markets in Bangladesh, Egypt, India, Europe, and Canada all had leverage effects. Goudarzi and Ramanarayanan (2011) investigated volatility asymmetry in Indian (BSE500) stock indices during the global financial crisis using EGARCH and TGARCH models. This study clarified that more than good innovations, negative shocks raised the volatility of Indian stock indices. Bora and Basistha (2021) performed a GARCH test on the daily closing indices of Sensex and Nifty from September 3, 2019 to July 10, 2020, which revealed that the Indian stock market was more volatile in the pre-pandemic period than it was in the COVID-19 pandemic period. Mensi et al. (2021) identified asymmetric volatility spillover during COVID-19.

Singh and Tripathi (2016) demonstrated significant asymmetric volatility in daily return series from April 1, 2001, to March 31, 2016, in the Indian stock market. Chaudhary et al. (2020) discovered a negative average return during the COVID-19 period (January 2020 to June 2020) In the ten countries' indices—the US (S&P 500), UK (FTSE100), Japan (Nikkie, 225), Germany (Dax), China (Shanghai Composite), India (BSE-Sensex), France (CAC40), Canada (S&PTSX Composite) Italy (FTSE Italia All Share), and Brazil (IBX40). Furthermore, the analysis revealed that these market returns became increasingly volatile due to the COVID-19 pandemic. Horpestad et al. (2019) observed that, between January 3, 2000, and June 22, 2018, 19 equity indices from North America, Latin America, Europe, Asia, and Australia showed instances of volatility asymmetry. Amongst which US and European markets had the strongest asymmetric volatility impact. Daal et al. (2005) argued that volatility was higher in emerging Asian equity markets as compared to the US from July 5, 1995 through August 7, 2002. Siddiqui and Shamim (2024) cleared the presence of strong volatility persistence in the case of BRICS countries market except China. While a significant amount of existing literature focused on volatility persistence and the leverage effect on different international stock markets; whereas, many literatures gave emphasis to either develop or emerging nations. However, this study aimed to uncover volatility persistence and the leverage effect among the G20 stock markets, consisting of both developed and emerging nations, considering their substantial role in the global stock markets.

DATA AND METHODOLOGY

The daily closing price of 19 stock indices except the European Union because the European Union itself is an interconnected economy consisting of certain important nations like France, Germany, and Italy, which were treated individually in the G20 was obtained from Yahoo Finance (Zhang et al., 2020). The first instance of COVID-19 was reported for in China on 31st December 2019, and the WHO declared an end to the COVID-19 pandemic in May 2023. Henceforth, the period of the study was parted into two separate units that consist of the pre-crisis period, which began in January 01, 2016 and ended in December 31, 2019, and the crisis period, which ran from January 01, 2020 to May 31, 2023. The data were then converted into a natural log return $r_t = \ln (p_t/p_{t-1})$ in order to reduce the heteroscedasticity of the data. A natural logarithm automatically renders the return series stationary at the first difference, based on which the entire study has been conducted. Further, the closing price of stock indices was taken in the local currency of the respective countries.

Emerging Countries			Developed Countries		
No.	**Country**	**Stock Index**	**No.**	**Country**	**Stock Index**
1	India	Nifty 50	10	UK	FTSE100
2	China	SSE	11	Germany	DAX
3	Argentina	Merval	12	Japan	Nikkei
4	Indonesia	IDX	13	France	CAC40
5	Brazil	BOVESPA	14	Saudi Arabia	Tadawul
6	Mexico	IPC	15	Canada	S&P composite
7	Russia	MOEX	16	Australia	ASX 200
8	Turkey	BIST100	17	Italy	FTSE MIB
9	South Africa	FTSEJSE	18	Korea	KOSPI
19	USA	DJIA			

Source: MSCI, 2022.

Modelling Volatility

Volatility modelling is one of the crucial aspects of the estimation of risk involved in financial assets An important element of measuring volatility is the standard deviation or variance of assets, which cannot be measured through a traditional econometric model because of its time-varying nature which suggests a strong deviation from a normal distribution (Epaphra, 2017; Lakshmanasamy, 2021). The OLS property deals with the white noise process of the residual i.e. it is assumed to have a constant mean and variance, and further no auto-correlation. If we run OLS with the financial series having time-varying variances such as both the auto-correlation and heteroscedasticity, the result will not be conclusive. The unconditional variance $(\sigma^2) = \frac{1}{n} \sum_i^n = (Xi - X)^2$ does not vary with time, and it would not be useful for investors who want to buy assets at t and sell it at t+1. Furthermore, the main drawback of using the traditional ARMA model to measure the conditional variance is that the MA term gives equal weightage to all the previous lag values but in reality, as we can see the recent lag value has more impact over the current price in compare to the former lag values.

To evade this problem Robert Engle (1982) introduced the Auto-Regressive Conditional Heteroscedasticity (ARCH) model, which explains heteroscedasticity and volatility clustering. The ARCH-LM or Auto-Regressive Conditional Heteroscedasticity-Lagrange Multiplier test is conducted to assess the presence of heteroscedasticity or arch effect in residual series the conditional variance $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots\ldots\ldots + \alpha_p u_{t-p}^2$ Here the conditional variance (σ_t^2) of error term u_t depends on the squared of past error terms to capture the autocorrelation in the series and the correlation between u_t^2 and u_{t-1}^2 is likely to be positive. Moreover, $\alpha_0 \geq 0, \alpha_1 \geq 0 \ldots\ldots \alpha_p \geq 0$. Since the conditional variance is α_t^2 the value of conditional variance is assumed to be positive (Abbas et al., 2013; Yıldırım & Çelik, 2020).

The null hypothesis: H_0: $\alpha_1 = 0$; $\alpha_2 = 0$ …... $\alpha_p = 0$

H_α: If any co-efficient (β) ≠ 0, it means there is an ARCH effect. This implies that previous information contributes toward present volatility and these results in volatility clustering.

GARCH (1,1) Model

Bollerslev (1986) developed the generalised ARCH or GARCH (p, q) model to remove the constraint in adopting ARCH which has been regarded as the base model for examining the volatility of financial time series. He argued that conditional variance is not only the function of the squared-lagged error but also a function of squared-lagged conditional variance.

Where, $\alpha_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

$\alpha_1 u_{t-1}^2$ is the ARCH effect which considers the short-term volatility persistency mainly caused by recent news, $\beta_1 \sigma_{t-1}^2$ is the GARCH effect which explains the long-term volatility persistency generated from previous news on financial series. The significant GARCH term implies that previous volatility contributes to the present volatility. If sum of α_1 and β_1 more than one, the volatility persists for a relatively longer period.

EGARCH Model

The EGARCH model measures the asymmetric impact of good and bad news on conditional variance. Both the good and bad news create volatility in financial assets, whereas the model states that bad news or negative shocks produce more uncertainty about future volatility than the good news of the same magnitude, which reflects a leverage effect (Brooks, 2008). This asymmetry is assessed by γ. If γ = 0 then positive news of the equal magnitude has the same effect as a negative shock, whereas γ < 0 implies that positive (good) news generates lower volatility on market return than negative (bad) news. Hence, to have leverage effect γ must be negative and significant.

Log $\alpha_t^2 = \alpha_0 + \beta_1 \log \sigma_{t-1}^2 + \alpha_1| + u_{t-1}| \sigma_{-1}| \gamma u_{t-1} / \sigma_{t-1}$

In the above equation, $\beta_1 \log \sigma_{t-1}^2$ is the GARCH effect; $\alpha_1| + u_{t-1}| \sigma_{-1}|$ is the ARCH effect; $\gamma u_{t-1} / \sigma_{t-1}$ is the Leverage effect. This model has considered the log of conditional variance to eliminate the non-negative restrictions of coefficients.

EMPIRICAL TEST

Descriptive Statistics

The study was initiated with descriptive statistics, which enabled us to observe the distribution of the data through the parameters of mean, standard deviation, skewness, kurtosis, and normality.

Table 1: Descriptive Statistics

(a) Before the period of COVID-19 (01/01/2016 to 31/12/2019)

Variables	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB (Prob)
India	0.0004	0.0005	0.0518	-0.0337	0.0081	0.1991	5.6912	0.0000
China	0.0000	0.0005	0.0544	-0.0730	0.0113	-1.0047	10.0387	0.0000
Russia	0.0006	0.0004	0.0388	-0.0871	0.0091	-0.8693	12.2731	0.0000
Argentina	0.0013	0.0020	0.0973	-0.4769	0.0267	-5.9524	108.51	0.0000
South Africa	0.0001	0.0000	0.0364	-0.0362	0.0089	-0.1686	4.2400	0.0000
Indonesia	0.0003	0.0007	0.0281	-0.0408	0.0080	-0.3721	5.1522	0.0000
Mexico	0.0000	0.0001	0.0336	-0.0598	0.0085	-0.6047	7.6931	0.0000
Brazil	0.0010	0.0013	0.0638	-0.0921	0.0137	-0.3117	6.0625	0.0000
Turkey	0.0004	0.0007	0.0406	-0.0734	0.0125	-0.5030	5.3805	0.0000
USA	0.0005	0.0007	0.0486	-0.0471	0.0082	-0.6833	7.8770	0.0000
Germany	0.0002	0.0007	0.0344	-0.0706	0.0098	-0.5263	0.5059	0.0000
UK	0.0001	0.0002	0.0351	-0.0351	0.0079	-0.1539	5.4171	0.0000
France	0.0002	0.0004	0.0406	-0.0838	0.0094	-0.7846	10.5057	0.0000

Variables	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB (Prob)
Italy	0.0001	0.0007	0.0491	-0.1333	0.0129	-1.0874	15.2062	0.0000
Korea	0.0001	0.0004	0.0347	-0.0454	0.0077	-0.6870	5.7250	0.0000
Japan	0.0002	0.0006	0.0691	-0.0825	0.0119	-0.4504	9.8081	0.0000
Canada	0.0002	0.0005	0.0289	-0.0249	0.0061	-0.2717	5.3806	0.0000
Australia	0.0002	0.0007	0.0328	-0.0325	0.0073	-0.5548	5.1764	0.0000
Saudi Arabia	0.0002	0.0006	0.0535	-0.0551	0.0106	-0.2951	6.6510	0.0000

(b) During the period of COVID19 (01/01/2020 to 31/05/2023)

Variables	Mean	Median	Max	Min	SD	Skewness	Kurtosis	JB (Prob)
India	0.0005	0.0012	0.0840	-0.1390	0.0131	-1.7490	23.30	0.0000
China	0.0020	0.0001	0.0555	-0.0803	0.0106	-0.7642	8.9427	0.0000
Russia	0.0000	0.0012	0.1836	-0.4046	0.0215	-6.9902	144.16	0.0000
Argentina	0.0028	0.0030	3.0093	-2.8920	0.1429	0.1306	424.2653	0.0000
South Africa	0.0002	0.0001	0.0726	-0.1022	0.0135	-0.7883	11.0530	0.0000
Indonesia	0.0001	0.0003	0.0970	-0.0680	0.0109	-0.0564	14.3835	0.0000
Mexico	0.0001	0.0001	0.0418	-0.0663	0.0113	-0.3799	5.6114	0.0000
Brazil	4.15e-07	0.0002	0.1302	-0.1599	0.0183	-1.4600	21.1351	0.0000
Turkey	-0.0028	0.0029	0.0942	-4.6020	0.1521	-29.7445	899.5767	0.0000
USA	0.0001	0.0004	0.1076	-0.1384	0.0146	-0.9282	21.3309	0.0000
Germany	0.001	0.0005	0.1041	-0.1305	0.0145	-0.6835	15.1755	0.0000
UK	1.89e-05	0.0006	0.0866	-0.1151	0.0122	-1.1472	16.9708	0.0000
France	0.0002	0.0009	0.0805	-0.1309	0.0143	-0.9939	14.9289	0.0000
Italy	0.0002	0.0012	0.0854	-0.1854	0.0158	-2.2597	27.8052	0.0000
Korea	0.0001	0.0007	0.0825	-0.0876	0.0128	-0.1617	9.2062	0.0000
Japan	0.0003	0.0008	0.0773	-0.0627	0.0130	0.0427	6.2146	0.0000
Canada	0.0001	0.0010	0.1129	-0.1317	0.0129	-1.6387	33.83145	0.0000
Australia	5.93e-05	0.0009	0.0676	-0.1020	0.0121	-1.2226	15.2419	0.0000
Saudi Arabia	0.0002	0.0009	0.0683	-0.0868	0.0108	-1.6586	16.8074	0.0000

Source: Authors calculations from the data of Yahoo.Finance.

Table 1(a) contains the descriptive statistics of the daily return series of 19 G20 countries' stock markets. The time frame was divided into two sections: the pre-COVID phase, which ran from January 2016 to December 2019, and the COVID-19 period, which ran from January 2020 to May 2023. According to the test, out of 19 countries, Argentina (merval) yielded the highest average returns at 0.0013 during the pre-COVID period followed by Brazil (bvsp) at 0.0010, Russia (moex) at 0.0006, and finally the USA (djia) at 0.0005, whereas in contrast, Chinese market showed a negative mean value of -7.98e-05 during the pre-COVID period. Furthermore, Argentina and Brazil's markets were the most volatile from January 2016 to December 2019, having the highest standard deviation of 0.0267 and 0.0137, respectively, and the least deviation was observed in Canada (s&p) and Australia (asx), with a comparatively low standard deviation of 0.0061 and 0.0073, respectively. The descriptive statistics presented in Table 1(b) revealed an intriguing trend: during the pre-COVID-19 and COVID-19 periods, Argentina experienced comparatively high average market returns with significant market variances. Notably, both the return and standard deviation increased from 0.001 to 0.0029 and from 0.02 to 0.15, respectively for Argentina. Russia and Turkey witnessed a negative return at -0.56e-06 and -0.0028 with a large standard deviation of 0.0216 and 0.15 respectively, whereas the Indian market showed a steady rise in average return during COVID-19, with a mean value at 0.0005, followed by Japan (Nikkei) at 0.0003 A marginal rise in the average return was seen in some of the G20 countries during the COVID-19 pandemic; these included Mexico, Japan, Italy, South Africa, China, Argentina, and India. When it comes to the returns on Chinese stocks, a distinct market recovery was noted. The majority of developed nations experienced a fall in their average return during the period of January 2020 to May 2023 compared to emerging

G20 markets. However, during the COVID-19 crisis, all the G20 market, except China, witnessed a substantial rise in market fluctuation, which was represented by the value of the standard deviation. All the return series showed negative skewness except for India during pre-COVID and Argentina and Japan during COVID-19. Also, the G20 return series showed a leptokurtic and non-normal distribution.

GARCH (1,1) Test

Table 2: GARCH (1,1) Test Results

(a) Before the period of COVID-19 (01/01/2016 to 31/12/2019)

Variables	(Constant)		α (Arch Effect)		β (Garch Effect)		α+β
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	
India	1.6	0.01	0.07	0.00	0.90	0.00	0.97
China	7.72	0.00	0.05	0.00	0.94	0.00	0.99
Russia	6.42	0.00	0.08	0.00	0.84	0.00	0.92
Brazil	1.24	0.00	0.08	0.00	0.85	0.00	0.93
Argentina	5.25	0.00	0.45	0.00	0.55	0.00	1.00
Turkey	9.88	0.00	0.06	0.00	0.88	0.00	0.94
South Africa	2.06	0.00	0.06	0.00	0.91	0.00	0.96
Indonesia	1.12	0.00	0.05	0.00	0.93	0.00	0.98
Mexico	6.62	0.00	0.15	0.00	0.76	0.00	0.91
USA	3.87	0.00	0.20	0.00	0.75	0.00	0.95
UK	4.86	0.00	0.15	0.00	0.74	0.00	0.89
Italy	5.80	0.00	0.12	0.00	0.84	0.00	0.96
Germany	4.69	0.00	0.10	0.00	0.85	0.00	0.95
Japan	7.68	0.00	0.14	0.00	0.80	0.00	0.94
France	5.34	0.00	0.18	0.00	0.77	0.00	0.95
Saudi Arabia	7.60	0.00	0.14	0.00	0.78	0.00	0.92
Canada	1.82	0.00	0.14	0.00	0.81	0.00	0.95
Korea	4.18	0.00	0.06	0.00	0.87	0.00	0.93
Australia	2.07e-06	0.00	0.09	0.00	0.86	0.00	0.95

(b) During the period of COVID19 (01/01/2020 to 31/05/2023)

Variables	(Constant)		α (Arch Effect)		β (Garch Effect)		α+β
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	
India	1.75	0.00	0.11	0.00	0.88	0.00	0.99
China	1.05	0.00	0.15	0.00	0.77	0.00	0.92
Russia	3.91	0.00	0.18	0.00	0.84	0.00	1.02
Brazil	1.10	0.00	0.10	0.00	0.85	0.00	0.95
Argentina	0.01	0.00	0.14	0.00	-0.01	0.98	0.13
Turkey	0.00	0.00	-0.00	0.97	0.00	0.00	0.97
South Africa	1.31	0.00	0.12	0.00	0.79	0.00	0.91
Indonesia	6.23	0.00	0.17	0.00	0.77	0.00	0.94
Mexico	5.15	0.01	0.09	0.00	0.87	0.00	0.96
USA	5.54	0.00	0.17	0.00	0.79	0.00	0.96
Japan	1.04	0.00	0.10	0.00	0.82	0.00	0.92

Variables	(Constant)		α (Arch Effect)		β (Garch Effect)		α+β
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	
Germany	9.47	0.00	0.16	0.00	0.79	0.00	0.95
Korea	9.10	0.00	0.19	0.00	0.77	0.00	0.96
Saudi Arabia	4.10	0.00	0.16	0.00	0.80	0.00	0.96
Italy	1.40	0.00	0.18	0.00	0.76	0.00	0.94
France	1.19	0.00	0.17	0.00	0.77	0.00	0.94
Canada	5.98	0.00	0.25	0.00	0.69	0.00	0.94
Australia	5.47	0.00	0.16	0.00	0.79	0.00	0.95
UK	7.37	0.00	0.15	0.00	0.79	0.00	0.94

Source: Authors calculations from the data of Yahoo.Finance.

To assess symmetric volatility over the long and short terms, as well as its persistence across the period, the GARCH (1,1) model was used. The long-term volatility in the market return, which was brought on by past market volatility or lagged values of volatility, was recognised by the GARCH (β) parameter, while the ARCH (α) parameter measured short-term volatility, or volatility in the market return caused by news and information. The aforementioned GARCH (1,1) table demonstrates that all ARCH (α) and GARCH (β) parameters were highly significant at the 1% level of significance before and during the COVID-19 era rejecting the null hypothesis that the return series had no symmetric short- and long-term volatility (Table 2). This suggested the existence of both short- and long-term volatility in the market returns of the G20 countries. A notable exception to this was Argentina (merval) throughout the COVID-19 period, where the GARCH (β) parameter was insignificant at a 5% level of significance. Additionally, the larger GARCH (β) and smaller arch (α) coefficients in the conditional variance equation support the hypothesis that the volatility in the G20 countries' market return was due to long-term shocks than recent news and information, implying that the market retains its memories for longer than one period of time (Aggarwal & Yadav, 2020). The volatility persistency was measured in each of the market returns by the sum of the ARCH (α) and GARCH (β) parameters. If the absolute value of α + β is close to one, implying that volatility at t time will take time to die out. The above GARCH (1,1) table demonstrated that, the sum of the ARCH (α) and GARCH (β) coefficients were less than 1for all the stock indices during the pre-COVID period, except Argentina (merval) and also during the COVID-period which showed the probability of the mean-reversion except Russia (moex) (Chaudhary et al., 2020). Also, volatility tended to be explosive for Argentina (merval) in the pre-COVID period and for Russian (moex) stock indices in the case of the COVID period since it was greater than 1. Notably, before COVID-19, the developed markets' volatility persistency ranged from 0.95 to 0.89, whereas that of the emerging G20 market returns ranged from 1 to 0.91. On the other hand, during COVID-19, it varied between 1.02 and 0.91 for the emerging G20 markets and between 0.96 and 0.92 for the developed ones, which revealed an increase of volatility during the COVID-19 crisis. In addition, there was a rise in news and information driven volatility during the crisis period as compared to the pre-crisis period, as shown by the ARCH coefficients. Henceforth, the volatility and its persistence among the G20 countries (both emerging and developed) were sensitive to the crisis.

EGARCH Test

Table 3: EGARCH Test Results

(a) Before the period of COVID-19 (01/01/2016 to 31/12/2019)

Variables	(Constant)		α (ARCH Effect)		γ (Leverage Effect)		β (GARCH Effect)		α+β
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	
India	-0.53	0.00	0.08	0.00	-0.14	0.00	0.96	0.00	1.04
China	-0.17	0.00	0.12	0.00	0.00	0.58	0.99	0.00	1.11
Russia	0.39	0.00	0.09	0.00	-0.04	0.10	0.97	0.00	1.06
Brazil	-0.50	0.00	0.14	0.00	-0.03	0.10	0.95	0.00	1.09
Argentina	-1.61	0.00	0.68	0.00	0.05	0.14	0.85	0.00	1.53

Variables	(Constant)		α (ARCH Effect)		γ (Leverage Effect)		β (GARCH Effect)		α+β
	Coefficient	P- Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	
Turkey	-0.29	0.00	0.07	0.00	-0.06	0.00	0.97	0.00	1.04
South Africa	-0.26	0.00	0.04	0.03	-0.11	0.00	0.98	0.00	1.02
Indonesia	-0.54	0.00	0.13	0.00	0.09	0.00	0.95	0.00	1.08
Mexico	0.75	0.00	0.24	0.00	-0.04	0.03	0.94	0.00	1.18
USA	-0.75	0.00	0.20	0.00	-0.17	0.00	0.94	0.00	1.14
UK	-0.63	0.00	0.13	0.00	-0.12	0.00	0.94	0.00	1.07
Italy	-0.38	0.00	0.16	0.00	-0.10	0.00	0.97	0.00	1.13
France	-0.59	0.00	0.19	0.00	-0.16	0.00	0.95	0.00	1.14
Saudi Arabia	-0.76	0.00	0.24	0.00	-0.10	0.00	0.94	0.00	1.18
Korea	-0.75	0.00	0.07	0.00	-0.11	0.00	0.93	0.00	1.00
Japan	-0.80	0.00	0.17	0.00	-0.19	0.00	0.93	0.00	1.10
Germany	-0.33	0.00	0.07	0.00	-0.12	0.00	0.97	0.00	1.04
Canada	-0.48	0.00	0.14	0.00	-0.12	0.00	0.96	0.00	1.10
Australia	-0.37	0.00	0.09	0.00	-0.12	0.00	0.97	0.00	1.06

(b) During the period of COVID-19 (01/01/2020 to 31/05/2023)

Variables	(Constant)		α (ARCH Effect)		γ (Leverage Effect)		β (GARCH Effect)		α+β
	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value	
India	-0.35	0.00	0.16	0.00	-0.10	0.00	0.97	0.00	1.13
China	-1.78	0.00	0.32	0.00	-0.15	0.00	0.83	0.00	1.15
Russia	-0.55	0.00	0.27	0.00	-0.15	0.00	0.96	0.00	1.23
Brazil	-0.40	0.00	0.16	0.00	-0.10	0.00	0.97	0.00	1.13
Argentina	-0.76	0.00	0.14	0.28	-0.64	0.00	0.89	0.00	1.03
Turkey	-3.71	0.00	-0.69	0.23	0.05	0.93	0.02	0.15	-
South Africa	-0.57	0.00	0.13	0.00	-0.16	0.00	0.94	0.00	1.07
Indonesia	-0.62	0.00	0.25	0.00	-0.09	0.00	0.95	0.00	1.20
Mexico	-0.34	0.00	0.14	0.00	-0.07	0.00	0.97	0.00	1.11
USA	-0.52	0.00	0.25	0.00	-0.12	0.00	0.96	0.00	1.21
UK	-0.46	0.00	0.14	0.00	-0.17	0.00	0.96	0.00	1.10
Italy	-0.57	0.00	0.17	0.00	-0.18	0.00	0.95	0.00	1.14
France	-0.37	0.00	0.09	0.00	-0.15	0.00	0.96	0.00	1.05
Saudi Arabia	-0.53	0.00	0.21	0.00	-0.11	0.00	0.96	0.00	1.17
Korea	-1.09	0.00	0.33	0.00	-0.14	0.00	0.90	0.00	1.23
Japan	-0.62	0.00	0.16	0.00	-0.10	0.00	0.94	0.00	1.10
Germany	-0.53	0.00	0.17	0.00	-0.17	0.00	0.95	0.00	1.12
Canada	-0.62	0.00	0.22	0.00	-0.20	0.00	0.95	0.00	1.17
Australia	-0.49	0.00	0.19	0.00	-0.12	0.00	0.96	0.00	1.15

Source: Authors calculations from the data of Yahoo.Finance.

In this study, the EGARCH (1,1) model was used to explain the asymmetric effect of good and bad news on the volatility of market returns of G20 countries before and during COVID-19, which is referred to as the leverage effect (Table 3). To study period was divided into two parts. The first part was the period before the COVID-19 pandemic, i.e., January 2016 to December 2019, and the second covered the period during the pandemic, i.e., January 2020 to May 2023.

The model indicated the existence of volatility asymmetry and a leverage effect if γ was statistically significant and had a negative value. The EGARCH (1,1) test results showed the presence of a leverage effect during the pre-pandemic period in all the G20 countries market returns, except the stock indices of the China (sse), Brazil (bvspa), Argentina (merval) and Russia (moex), as the value of γ was not significant at the 5% level of significance. On the other hand, these indices attained statistical significance during the COVID-19 pandemic, together with a negative value of γ. Additionally, all G20 stock indices had a negative sign of γ and were statistically significant at a 5% significance threshold throughout the pandemic, which rejects the null hypothesis that the return series had no information asymmetries and leverage effect. This further revealed the strong existence of the leverage effect, except for BIST (Turkey). This finding indicated that negative news about the crisis would be more likely to cause uncertainty in the market returns of the G20 countries than positive news at the same level. Furthermore, the ARCH and GARCH terms were non-negative and significant for all G20 countries stock indices before and during the period of the pandemic, except for BIST (Turkey), which had neither any leverage effect nor any Arch and GARCH effect. This highlighted the existence of volatility asymmetry in the short-term as well as the long-term, before and throughout the COVID-19 crisis. However, the small ARCH and bigger GARCH terms imply that the market return was more influenced by the long-term asymmetric volatility that was present; volatility was likely to be carried out by the previous day's asymmetric volatility than the asymmetric volatility generated by the recent news. Further, the EGARCH (1,1) test revealed the volatility persistence, which was calculated by the sum of α and β, ranging from 1.00 to 1.18 before the period of the pandemic, along with high volatility persistency across the specified period in the Saudi Arabian (Tadawul) and USA (djia) markets. However, during the period of the pandemic, ranging from 1.03 to 1.23, indicating high volatility and persistency in the Russian (moex), South Korean (kospi), and USA (djia) market returns. Moreover, all markets exhibited high volatility persistence both before and during the pandemic. Interestingly, during the pandemic, there was an increase in the ARCH effect, which led to an increase in the value of the conditional variance during this period. This suggests the asymmetric news relating to COVID-19 crisis enhanced the rate of uncertainty in the market returns of the G20 countries.

CONCUSION

The study tested the GARCH (1.1) and EGARCH (1,1) models to evaluate the effect of the COVID-19 crisis on the volatility of stock returns in the G20 countries as well as the extent of symmetric and asymmetric volatility persistence therein. Thus, the whole period was divided into two sub-periods: the pre-COVID period, while extended from January 2016 to December 2019, and the COVID-19 crisis which covered the period from January 2020 to May 2023. This literature uncovered some captivating material that showed how the pattern shifts when a crisis approaches. Descriptive statistics revealed that there had been an increase in market deviation throughout the COVID-19 era compared to the pre-COVID-19 phase for all the G20 stock markets, except for the Chinese market, where the variability was larger prior to the COVID-19 crisis. All the markets had a positive return during the period from January 2020 to May 2023, with the exception of Russia and Turkey, which saw a negative average market return. This demonstrated that following the crisis's initial phase, the market began to recover (Rajput & Sufiya, 2022; Singh et al., 2020).

Additionally, the GARCH and EGARCH models indicated that the crisis has led to a rise in volatility in the market returns of G20 nations. The GARCH (1,1) model was run to capture the symmetric volatility pattern in the market returns of the G20 countries which indicated the existence of both short- and long-term symmetric volatility in the market returns of the G20 countries before and during the crisis. The model further demonstrated that in COVID-19, emerging G20 markets had higher levels of symmetric volatility persistency than developed G20 markets. The model also suggested that the market retained its memories for longer than one period of time. The conditional variance was less than 1 showing the probability of the mean-reversion except Russia and Argentina. Notably, Russia had the largest persistent volatility during the aforementioned time, with a negative average return. The increasing average return in the Indian market, however, indicated that there was room for growth despite the ongoing high volatility, which runs counter to the findings of Banumathy and Azhagaiah (2015). Furthermore, the asymmetric impact of positive and negative news on the volatility of the market returns of G20 nations before and during COVID-19 was measured using the EGARCH (1,1) model. The leverage effect was witnessed by the model in both the pre-pandemic and pandemic periods in all G20 market returns, except of the stock indices of the China, Brazil, Argentina, and Russia during the period before the crisis and; with the exception of Turkey, which had no information asymmetry or short- and long-run asymmetric volatility for the period of crisis. Hence the results concluded that negative news about the crisis created uncertainty in the market returns of the G20 countries than positive news at the same level. The model also demonstrated that asymmetric volatility, both short- and long-term i.e., ARCH and GARCH effect, existed before and throughout the COVID-19 pandemic.

All of the markets experienced persistently high volatility before and during the pandemic, as indicated by the value of conditional variance greater than one and was obtained using the EGARCH (1,1) model. Remarkably, compared to the time before the crisis, there was an increase in the ARCH effect or news impact during the pandemic, which raised the value of the conditional variance. This showed the symmetric and asymmetric news relating to the COVID-19 crisis increased the rate of uncertainty in the G20 countries' market returns. Henceforth, the volatility of G20 market returns was sensitive to the crisis. The Argentina and Chinese markets witnessed the highest symmetric short- and long-run volatility persistence during the pre-pandemic period, whereas the Russian market had the largest symmetric and asymmetric short- and long-run volatility persistency during the COVID-19 crisis among the other G20 countries**.** Thus, it became evident that the respective country's economic conditions and regulatory policies as well as geo-political tensions in the region had a significant impact on their stock markets. The market was still extremely unpredictable despite the fact that it had started to rebound (Chaudhary et al., 2020). The findings significantly contribute to helping global investors to make informed decisions regarding their portfolio diversification, considering the different dynamics and circumstances impacting volatility in market returns.

The study has certain limitations. Since the study basically focuses on the period before and during the COVID-19 crisis might not capture the full impact, especially given the ongoing and potentially long-term effects of the pandemic on stock markets. As a result, the study might only provide a snapshot rather than a comprehensive view of the volatility. Additionally, G-20 countries implemented varied fiscal and monetary policies during the crisis, which could have affected stock market volatility in different ways. These differences make it challenging to generalise findings across all countries or isolate the effects of COVID-19 from other factors.

The policy implications of stock market volatility in G-20 countries during COVID-19 can help financial regulators develop policies to stabilise markets, prevent panic, and enhance investor confidence in future crises. Also, the findings could highlight the need for coordinated economic responses among G-20 countries during global crises. A better understanding of stock market behaviour could facilitate more effective policy coordination and economic support measures.

Future research could extend the time frame to include the post-COVID-19 period, examine how stock markets recover and whether volatility patterns observed during the crisis persist or change over time. Future studies could compare the effectiveness of various volatility models in predicting stock market behaviour during crises.

Finally, this study provides a comprehensive analysis of stock market volatility specifically during the COVID-19 crisis, contributing to the limited literature that examines the impact of pandemics on financial markets. Unlike previous studies that have focused on more traditional crises, this research adds new insights into how a global health crisis affects market behaviour across major economies.

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