ORIGINAL ARTICLE

The impact of the COVID 19 pandemic on stock market volatility: evidence from a selection of developed and emerging stock markets

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Abstract

This study examines the impact of the COVID 19 pandemic on the stock markets of China, India, Pakistan, the UK and the US using Generalised Autoregressive Conditional Heteroscedasticity (GARCH) and Threshold GARCH models with COVID 19 as an exogenous dummy variable in the variance equation. The sample period of 2016–2021 is divided into two sub-periods: the pre-COVID 19 period and the COVID 19 period. The results of the study indicate that there was persistent volatility in these markets and that this volatility increased as a result of the pandemic. In addition, the Threshold GARCH results indicate that the asymmetric term was significant in all markets indicating that bad news, such as the pandemic, had a stronger impact on the conditional variance of the returns as compared to good news. In addition, the results further confirm that the US market had no significant impact on the volatility of the Chinese market during the pandemic. The results have important implications for (1) international investors regarding portfolio management and investment risk minimisation in situations like the COVID 19 pandemic; and (2) policy-makers in terms of how they respond to any future pandemic.

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Introduction

This study investigates the impact of the COVID 19 pandemic on the stock market volatility of a selection of developed and emerging markets. Specifically, daily stock price data for the markets of China, India, Pakistan, the UK and the US are analysed over the period 1st January 2016 to 31st December 2021; this time frame covers the pre-COVID period (January 2016 to December 2019) as well as the COVID period (January 2020 to December 2021).[1]

The contagious Corona Virus (COVID 19) was first discovered in the city of Wuhan in China during November 2019; from there, it spread to the whole world within a relatively short span of time.[2] The World Health Organization (WHO) declared it a pandemic on 11th March 2020. According to a Congressional Research Service report, the pandemic evolved as a global public health emergency, which led to economic turmoil that affected the world economy far more than any crisis experienced in the last 70 years (CRS report 2021).[3] This pandemic posed a severe risk to human health alongside a financial threat to the world's economies. Investors and financial markets across the globe faced a high degree of uncertainty as a result of the slowdown in the different nations' economies. Due to the contagious nature of the virus, various measures were imposed by governments, including lockdowns and social distancing requirements, which had a negative effect on economic activities and a sizeable impact on government, company and household budgets. In particular, to reduce the transmission of the Corona Virus, many countries imposed restrictions on the movement of people in the form of lockdowns and quarantines, restrictions on mobility, the shutting down of manufacturing operations, the closure of educational institutions and limitations on cross-border traffic. These restrictions resulted in a dramatic reduction in the level of economic and social activity.[4] According to Basuony et al. (2021), the pandemic negatively affected the flow of goods and services across the world, resulting in an increase in commodity prices and an interruption to supply chains in major countries and regions including China, the US, the Eurozone and Japan.

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[1] The second wave of the COVID 19 pandemic caused unprecedented devastation in India due to the emergence of the Delta variant. This was a more highly transmissible and virulent strain than the original SARS-CoV-2 strain that hit the country during the first wave of the pandemic. The Delta variant was first detected in India in February 2021 (Brozak et al. 2021). At this time, India was the epicenter of the pandemic in the South Asian region. As a neighbor to both China and India, Pakistan is included in the sample since it was vulnerable to COVID 19 due to its close proximity to both of these countries. Since the virus was contagious, a flare up in these two countries could have had an impact on the Pakistani market as well.

[2] From China, the virus was transmitted to Italy in early March 2020 (Gherghina et al. 2021). In April 2020, COVID-19 was discovered in the US. By April 2021, Brazil, India, African and Asian nations were reported to be the central locations of the virus, with record infections and deaths. In the UK, the first case of COVID 19 was detected on 21st February 2020 (https://coronavirus.data.gov.uk/details).

[3] In terms of increased volatility, Cheng et al. (2022) argued that the COVID 19 shock was comparable to that of the Great Depression of 1929 and the Black Monday Crash of 1987; it even surpassed the volatility shock to the stock market from the 2008/09 Global Financial Crisis.

[4] These restrictions have had a devastating impact on the economies of emerging countries (Aktar et al. 2021).

With the spread of COVID 19 cases, investor risk aversion increased in the US. In March 2020, the US market experienced four regime shifts in a short period of only two weeks.[5] These circuit breakers had previously been introduced during the 1987 stock market crash (Gao et al. 2021). The major stock market indices (the Dow Jones, Nasdaq and SandP 500) plunged by 37.1, 30.1 and 31.9%, respectively; this US$ 10 trillion drop in market value was equivalent to more than 45.0% of US GDP in 2019 (Gao et al. 2021). In May 2020, the US Federal Reserve cut its key interest rate to zero and announced an easing of monetary policy to safeguard the liquidity of the stock market. Yousaf (2021) reported that, in March 2020, with the exception of Japan, all G7 stock markets hit a 20-year low within a short time frame of 24 h; the stock markets in these countries declined by between 12.0 and 19.0% during this time period.[6]

In general, the pandemic had a sizeable effect on the real economies of most countries, resulting in a reduction in trade, transportation and tourism, as well as food shortages. In addition to the real economy, the impact of the deadly pandemic on the world's financial markets was significant. This negative impact of the pandemic on financial markets has already been reported by various researchers (Al-Awadhi et al. 2020; Bai et al. 2020; Baker et al. 2020; He et al. 2020; Topcu and Gulal 2020). These researchers have documented that the COVID 19 pandemic was associated with negative returns for investors.

The aim of the current study is to investigate the more recent impact of the COVID 19 pandemic on the stock market volatility of equity indices for a selection of emerging and developed markets. As information is a key driver of volatility, it will have an influence on investor trading behavior which, in turn, will affect stock prices. These price changes have significant implications for international investors, fund managers and policy-makers (Gajurel and Chawla 2022). In addition, according to Khan et al. (2022), an investigation of transmission mechanisms explains how the stability and interdependence amongst markets change after an unexpected crisis event. Furthermore, the degree of volatility transmission indicates the extent of market integration and has important implications for portfolio diversification (Mukherjee and Mishra 2010).

The present study aims to contribute significantly to the existing literature on several fronts. First, it analyses the impact of COVID-19 on return volatility across a sample comprising both developed and emerging markets. Specifically, the study examines the indices of five markets: the US (SandP 500), the UK (FTSE 100), China (SSE Shanghai Composite), India (BSE Sensex), and Pakistan (KSE 100). This selection was guided by the intention to include the country where the virus originated (China) and to assess the sensitivity of two emerging markets (India and

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[5] According to Mazur et al. (2021), in only four trading days in March 2020, the Dow Jones Industrial Average (DJIA) plunged 6,400 points, an equivalent of roughly 26 per cent. They identified these days as March 9, 12, 16 and 23, 2020. In addition, Hong et al. (2021) argued that the four consecutive triggers of the key market-wide circuit breaker occurred on March 9th, 12th, 16th and 18th, 2020.

[6] The study analysed the stock markets of Canada (SandP/TSX), France (CAC 40), Germany (DAX), Italy (FTSE MIB), Japan (Nikkei 225), the UK (FTSE 100) and the US (SandP500).

Pakistan) as well as two developed markets (the UK and the US) to ascertain if their responses to volatility varied. Notably, the emerging markets under consideration are two of the region's most densely populated countries where the virus spread was particularly severe (Rasul et al. 2021).

Second, the study not only examines the magnitude of spillovers amongst the selected markets but also investigates their directional aspects, a dimension often overlooked in previous research. Specifically, the current study examines if the normal direction of any spillover changed during a pandemic period as the reactions of investors in densely populated countries (India and Pakistan) with less developed health systems lead the responses of investors in the UK and the US. Third, this study examines cross-market variance spillovers to identify both the risk transmitters and recipients across these markets during the COVID-19 crisis period. Such an analysis is crucial in identifying the leading markets (risk transmitters) both before and during the pandemic, thereby aiding investors in formulating appropriate trading strategies. Additionally, from a policy-maker's standpoint, identifying the sources of risk may assist in mitigating systemic risk during crisis periods.

Furthermore, while most existing studies have focused on the impact of COVID-19 on stock market volatility transmissions during the initial waves of the pandemic, this study extends its scope to encompass a more comprehensive period of the health crisis, including the timeframe up to the later waves of COVID-19, which persisted until late 2021.[7]

Finally, the current paper draws on the observations of Wang and Wu (2018), which acknowledged that investors and policy-makers are not solely concerned with volatility but also with asymmetric volatilities; they want to know if the responses of stock markets to 'good' and 'bad' news is different for an extreme event. To address this aspect, the current study employs asymmetric GARCH models to investigate the asymmetric volatility transmissions among the markets, a factor that holds significant implications for stock pricing, risk management, trading strategies, and diversification benefits within these markets.

Overall, the current study has important implications for policy-makers and portfolio managers. In particular, it is critical to examine the volatility of financial assets and the consequences of volatility spillovers across various stock markets during the COVID 19 crisis as knowledge of this important issue may be useful in terms of learning for future pandemics. This point is especially important as the COVID 19 crisis was an expensive pandemic from a policy-maker perspective so learning from this might reduce costs in the future in the event of another pandemic. Furthermore, evidence on volatility and spillovers in relation to the pandemic may help market participants to form hedging strategies that mitigate against downside risk in their investment portfolios. Not all asset classes (Bouri et al. 2021), sectors (Alomari et al. 2022) or countries (Shrestha et al. 2020) were equally impacted by the COVID 19 crisis. In addition, spillovers across asset classes and countries were impacted differently by this pandemic (Le et al. 2021). The results from the study emphasise

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[7] As per Vo (2023), the Omicron variant surfaced in early December 2021. The author referred to this period as the third wave, a distinction largely overlooked by prior studies.

the importance of holding a broad-based portfolio that consists not just of stocks but one that also contains safe-haven assets such as bonds and gold. They suggest that investors and regulators need to consider volatility spillovers associated with a pandemic such as COVID 19 in order to protect their portfolios and markets from turbulence in another country's security market adversely impacting their own nation's stock exchange.

The remainder of the paper is organised as follows. "Literature review" presents a review of relevant literature. "Data and methodology" outlines the methodology employed and "Results and discussion" discusses the empirical results. Finally, "Conclusion" concludes the paper.

Literature review

There is a sizeable literature that investigates the impact of various pandemics on the world's economic and financial systems (Chen et al. 2007, 2009; Baker et al. 2012; Wang et al. 2013; Goodell 2020). This literature can be grouped into two strands: those studies that examine the economic impact of a pandemic (Aktar et al. 2021; Li et al. 2021) and those that analyse the effect of a pandemic on financial markets (Basuony et al. 2021; Chaudhary et al. 2020). The current paper focusses on the impact of COVID 19 on the stock markets of China, India, Pakistan, the UK and the US.

Economic impact of COVID 19

According to the WHO, the COVID virus has killed 6.13 million people worldwide with a total of 4811 million confirmed cases at the time of writing (WHO 2022). As mentioned previously, many countries implemented a series of lockdowns to limit the transmission of the virus. These policies, in turn, negatively affected production, disrupted supply chains and panicked financial markets (Bachman 2020; Sarkis et al. 2020). Vagliasindi (2021) attempted to quantify the impact of lockdowns and other responses to the virus on economic activity and found that these measures impacted negatively on different countries' output. The increased death rates associated with COVID 19 also resulted in lower economic activity.[8] More recently, Vuong et al. (2022) contended that, owing to concerns for human lives, the restrictions implemented by governments led to a deceleration of economic activities. This, in turn, had an adverse impact on financial markets. Given the close association between economic and financial activities, the crisis effect was notably pronounced in the financial system due to the slowdown in economic activities.

To highlight the impact of the pandemic on economic activity, Table 1 reports World Bank (WB) and IMF data for the 3-year period of 2020, 2021 and 2022. According to WB and IMF estimates, global output recorded a decline of 3.2 and

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[8] Economic activity was proxies for by electricity consumption.

Table 1 GDP growth projections (real GDP, annual percentage change)

Markets	2020		2021		2022	
	WB	IMF	WB	IMF	WB	IMF
US	− 3.2	− 3.4	5.9	5.9	1.9	2.0
UK	N/A	− 9.8	N/A	7.6	N/A	4.1
China	2.2	2.3	8.1	8.4	2.7	3.0
India	− 6.6	− 7.3	8.7	8.7	6.9	6.8
Pakistan	− 0.9	N/A	5.7	N/A	6.0	N/A

The table reports the annualised GDP growth of various regions for the years 2020, 2021 and 2022. Data for 2022 are estimated values up to October 2022. World Bank is indicated by (WB) and International Monetary Fund is indicated by (IMF). Sources: World Bank (2021, 2023), IMF (2021, 2023)

N/A not available

3.1%, respectively, in 2020. As per the January 2023 reports of the IMF and WB, global output increased to 6.2 and 5.9%, respectively, in the year 2021. After relaxing restrictions on the movement of goods and people, the US economy grew by more than 5.0% in 2022. Growth in China also maintained its momentum; these two international organisations reported a rise in GDP for China of 2.7–3.0% in 2022. According to the IMF, the UK growth rate was − 9.8% in 2020, although this rate increased to 7.6 and 4.1% in 2021 and 2022, respectively, assuming no further lockdowns. The Indian economy was devastated in 2020 with growth in GDP as per the WB and IMF of − 7.3%. The country recovered in 2021 and 2022 and recorded a positive growth rate of 8.7 and 6.9%, respectively. The volume of global trade declined by a negative rate of 8.2% in 2020, although it increased to 10.6 and 4.0% in 2021 and 2022, respectively.

COVID 19 and financial market volatility

A number of academics have examined the impact of the COVID 19 pandemic on stock market performance. Some have looked at several different markets. For example, focusing on the 18 Eurozone countries, Duttilo et al. (2020) investigated the impact of COVID 19 on the return and volatility of equities.[9] Daily data were used from 4th January 2016 to 31st December 2020. A Threshold GARCH (1, 1)-in-mean model was used for the analysis. Their results indicated that the response of the Euro area markets was different to the COVID 19 pandemic. In particular, the first wave of the COVID 19 pandemic was associated with a significant positive impact on the conditional volatility of equities traded in the Austrian, Belgian, Finnish, French,

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[9] The sample market indexes included the Austrian ATX, the Belgian BEL 20, the Cypriot CYMAIN, the Finnish OMXH 25, the French CAC 40, the German DAX, the Greek ATF, the Irish ISEQ 20, the Italian FTSE MIB, the Maltese MSE, the Dutch AEX, the Portuguese PSI 20, the Spanish IBEX 35, the Slovakian SAX, the Slovenian SBITOP and the OMXBBPI index for the Baltic states of Estonia, Latvia and Lithuania.

German, Irish, Italian, Dutch and Spanish markets. However, the second wave of COVID 19 had a significant impact on the stock market volatility of Belgium only.

Other academics have concentrated on one country. For example, Gherghina et al. (2021) examined the volatility of the Romanian stock market over the period January 2020 to April 2021 using daily returns data for the Bucharest Exchange Trading (BET) index. Employing a GARCH (1, 1) model, they found that the conditional volatility of returns increased in the first quarter of 2020 whereas, in the second and third quarters, volatility decreased. Based on their VAR estimation, they argued that there was no causal relationship between the COVID 19 pandemic and the performance of the BET index.

Using a broader family of GARCH models and disaggregated data for the Tunisian stock market, Fakhfekh et al. (2021) examined return volatility for the pre-COVID and COVID 19 periods; the authors studied daily closing price data for 12 sectors over the period 4th January 2016 to 30th April 2020 and the COVID crisis period. They employed four GARCH model specifications, including EGARCH, FIEGARCH, FIGARCH and TGARCH. Their results indicated that volatility was more persistent in all series during the COVID pandemic. The EGARCH model provided the most appropriate model of returns volatility for the building and construction materials, the construction and the food and beverage sectors. The FIGARCH model best characterised the data for the volatility of the services, financials and distribution sectors. According to the results of this study, the volatility of the consumer service, financials and distribution, industrials, basic materials and banking sectors was relatively higher and had a significant asymmetric effect during the COVID 19 period as compared with its pre-COVID 19 counterpart. By contrast, there was no significant asymmetric impact of good and bad news on the volatility of the building construction materials, construction and food and beverage sectors.

Yousfi et al. (2021) used daily data from 5th January 2011 to 21st September 2020, which covered the periods before and during the COVID 19 pandemic, for the Chinese and US stock markets. They examined the asymmetric effects of shocks on the correlations of the two markets and found evidence of contagion during the COVID 19 period. From the DCC-GARCH and ADCC-GARCH model results, they concluded that there were volatility transmissions between the Chinese and US equity markets. More specifically, they found that volatility spillovers were higher during the COVID 19 period than before the pandemic. They further confirmed that an increase in COVID 19 cases and deaths during the first and second waves of the pandemic increased the risk and uncertainty of the US stock market as well as that of the overall world economy. These findings align with those of Vuong et al. (2022), who identified heightened volatility transmissions from the Chinese market to the US market amid the COVID 19 pandemic.[10]

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[10] The research examined the transmission of volatility from the Chinese equity markets to the US equity markets, covering the timespan from January 2001 to October 2020. The analysis focused on three key US stock market indexes: the SandP 500, the Nasdaq Composite Index, and the DJIA. In representing China's stock market, the study considered the Shanghai Composite Index and the Shenzhen Composite Index. Daily data spanning the period from January 2001 to October 2020 were utilized for this investigation.

A larger number of markets was considered in an investigation by Basuony et al. (2021); these authors investigated returns for the markets of Brazil, China, Germany, India, Italy, Russia, Spain, the UK and the US over the period from 1st January 2013 to 31st December 2020. They divided the data into a pre-COVID 19 period from 1st January 2013 to 31st December 2019 and a COVID 19 period from 1st January 2020 to 31st December 2020. Using an EGARCH model, their results indicated that COVID 19 had an adverse impact on a majority of the equity markets studied, resulting in a rise in conditional volatilities. They further documented that the impact was not symmetric across all markets. For example, returns in China and Germany showed less pronounced changes in conditional volatility in comparison to price changes in Italy, the US and the UK. Furthermore, they found that the increase in the conditional volatility uncovered was not persistent during the COVID 19 period for all markets. They argued that news of deaths had a greater impact on the stock markets as compared to good news about an impending recovery, which further strengthened the evidence of an asymmetric impact of this crisis on financial markets.

To examine the dynamic volatility across Asia–Pacific nations, Vo et al. (2022) segmented the pandemic period into two distinct sub-periods. The first period encompassed the entire year 2020, whilst the second period spanned the time from January 2021 to January 2022.[11] Their results indicated an upsurge in volatility during the initial period, particularly in March 2020. Furthermore, they observed a subsequent decrease in volatility during the second period. They attributed this decline to governmental interventions aimed at pandemic control and the introduction of vaccines.

Khan et al. (2023) conducted an investigation into the market volatility and asymmetric behavior of Bitcoin, exchange rates, the U.S. stock market, gold, and oil and sugar prices during the COVID-19 pandemic. They employed the GJR-GARCH (1, 1) and EGARCH (1, 1) models on daily returns series spanning from 27 November 2018 to 15 June 2021. The results indicated a notable level of volatility persistence in all markets except gold and sugar during the pandemic period. The study affirmed the safe-haven characteristic of gold amid the crisis. These findings suggest that commodity derivatives can serve as a hedge against risk during turbulent periods.

Data and methodology

The current study analyses daily closing price data, which were obtained from Datastream. In particular, daily data are analysed for China (Shanghai Composite Index), India (BSE Sensex), Pakistan (KSE 100), the UK (FTSE 100) and the US (SandP 500).[12] The time period for the study is selected to incorporate both (1)

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[11] The study investigated the markets of Australia, China, India, Indonesia, Japan, Malaysia, New Zealand, the Philippines, Singapore, South Korea, Thailand and Vietnam.

[12] The time difference between the markets was not explicitly considered in this study. However, daily returns data were utilised by taking the logarithmic first difference of the price series, which partially addresses the issue of temporal misalignment. Moreover, given that this study examines markets from

the pre-COVID 19 period of 1st January 2016 to 31st December 2019; and (2) the COVID period of 1st January 2020 to 31st December 2021.[13] The returns of all the market indices were calculated using the formula:

$$R_{it} = Ln\left(\frac{P_{it}}{P_{it-1}}\right) \tag{1}$$

where R_{it} is the return on index i at the end of day t, P_{it} is the price level of the index at the end of day t, P_{it-1} represents the price level of the index for the previous day, and Ln represents the natural logarithm.

Financial time series data are used in this paper to examine changes in returns for different countries during the pandemic. Previously, the focus of many investigations has been on the mean equation assuming that the conditional variance of the disturbance term was constant over time (Asteriou and Hall 2007). However, in most financial time series, the variance is time varying and the volatility of the series changes from one period to another. Three common characteristics of financial time series data, including the leptokurtic nature of the distribution, volatility clustering and a leverage effect require models that can incorporate these features of the data. The volatility of equity returns is the main focus of this paper; it is an important consideration for financial market participants. More specifically, this paper models any conditional heteroscedasticity that may be present in returns; it explains any conditional variations in both the mean and variance of equity price changes. In addition, the analysis in this paper recognises that stock market volatility may be time varying and subject to clustering where periods of high (low) volatility are followed by periods of high (low) volatility. According to Rossetti et al. (2017), such volatility behavior can best be modelled by time varying volatility models.

Before applying GARCH modeling to assess volatility, it is imperative to conduct tests to ascertain stationarity and the existence of ARCH effects (Natarajan et al. 2014). In this study, the Augmented Dickey-Fuller (ADF) and Phillip and Perron (P-P) tests were employed. These tests operate under the null hypothesis of a unit root (indicating non-stationarity) against the alternative hypothesis of no unit root (indicating stationarity) in the time series. Subsequently, the examination proceeds to assess the presence of ARCH effects. The ARCH-LM test is utilized, assuming a null hypothesis of no ARCH effect, in contrast to the alternative hypothesis positing the existence of ARCH effects in the returns series. The outcome of these tests is detailed in Table 2.

An ARCH model was proposed by Engle (1982) to capture the time varying nature of volatility. The more generalised form of this ARCH model (GARCH) was

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Footnote 12 (continued)

diverse geographical locations, there are instances of overlapping trading hours, with the Chinese market having overlapping trading hours with India and Pakistan; India and Pakistan also share overlapping trading hours with the UK, and the UK market shares overlapping trading hours with the US. Additionally, all these markets operate from Monday to Friday. Consequently, news spillovers among these markets may occur through these channels.

[13] The choice of sub-samples is supported by previous studies, such as Cheng et al. (2022).

Table 2 Unit root and ARCH-LM tests

Markets	ADF test		P-P test		Arch LM test
	Level	1st Diff	Level	1st Diff	
US	− 2.24	− 42.09*	− 2.21	− 42.09*	2.02
UK	0.29	− 16.42*	− 0.29	− 39.47*	45.11*
China	− 2.12	− 34.85*	− 2.21	− 35.12*	21.05*
India	− 2.47	− 39.56*	− 2.47	− 39.57*	37.58*
Pakistan	0.42	− 12.02*	0.68	− 47.42*	180.27*

The table shows the unit root test results for the whole sample period from January 1, 2016 to December 31, 2021

then proposed by Bollerslev (1986) to overcome some of the limitations associated with the simple ARCH model.[14]

The general form of the GARCH model can be written as;

$$y_t = \mu + bx_t + e_t \tag{2}$$

$$h_t = c + \sum_{i=1}^{p} \alpha_i \mu^2_{t-i} + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{3}$$

The simplest form of the GARCH model is the GARCH (1, 1) where the conditional variance equation is given by:

$$h_t = c + \alpha_1 \mu^2_{t-1} + \beta_1 h_{t-1} \tag{4}$$

where h_t is the conditional variance, α is the ARCH term and β is the GARCH term. The time varying volatility depends on the constant μ, the lagged value of the conditional variance h_{t-1} and the lagged value of the squared errors μ^2_{t-1}. The α ARCH term estimates the response of stock markets to shocks in returns and the β GARCH term estimates the length of time that it takes for the shock to die away. Hence, the higher the values of the α and β coefficients, the greater the persistence in volatility.

The standard GARCH model assumes that the market responds symmetrically to 'good' and 'bad' news. It takes into account the absolute values of the innovations and not their signs. Hence, a large positive shock will have the same magnitude as a large negative shock in the volatility series. However, in the literature, there is evidence that 'bad' news may have a greater impact on the volatility of returns as compared to 'good' news. For example, Basuony et al. (2021) found that the news of deaths (bad news) had more of an impact on stock market volatility as compared to the news of a recovery (good news), which further strengthens the evidence of an asymmetric impact of a crisis on financial markets.

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[14] Limitations of ARCH models include overfitting and violation of the non-negativity constraints in the data series (Yousef, 2020).

To examine the impact of COVID 19 on returns and volatility, a dummy variable for COVID 19 was added, which assumes the value of 0 for the pre-COVID period and 1 for the COVID period. The GARCH model is modified by including a COVID 19 dummy variable in both the conditional mean and the conditional variance equations:

$$y_t = \mu + \rho Covid_t + e_t \tag{5}$$

$$h_t = c + \alpha_1 \mu^2{}_{t-1} + \beta_1 h_{t-1} + \xi_1 Covid_t \tag{6}$$

To capture any asymmetric impact of 'good' and 'bad' news, Glosten et al. (1993) and Zakoian (1994) proposed a Threshold GARCH (TGARCH) model. The specification for the conditional variance equation in a TGARCH (1, 1) model is given as:

$$h_t = c + \alpha_1 \mu^2{}_{t-1} + \beta_1 h_{t-1} + \gamma_1 \mu^2{}_{t-1} \lambda_{t-1} \tag{7}$$

To capture the impact of COVID 19, equation [7] is modified as follows:

$$h_t = c + \alpha_1 \mu^2{}_{t-1} + \beta_1 h_{t-1} + \gamma_1 \mu^2{}_{t-1} \lambda_{t-1} + \xi_1 Covid_t \tag{8}$$

where λ_t takes the value of 1 for $\mu_t < 0$ (bad news) and 0 when $\mu_t > 0$ (good news). This model recognises that 'good' and 'bad' news may have different impacts. Good news has an impact of α_1 and bad news has an impact of $(\alpha_1 + \gamma_1)$. γ_1 is the asymmetry or leverage term and any value greater than 0 for this coefficient means that there is an asymmetry in how returns respond to news; a value equal to 0 would suggest that the return volatility is characterised by symmetry. As the current paper estimates the impact of COVID 19 on stock market volatility; the TGARCH model is employed for the analysis.

Finally, to check on the impact of volatility shocks for each market's returns, a separate model is estimated for each individual market taken as the dependent variable and the rest of the markets as the regressors in the variance equation.

Results and discussion

Preliminary data analysis

Table 3 reports summary statistics for the daily logarithmic returns of the sample indices. Panel A of the table reports descriptive statistics for the entire sample period from 1st January 2016 to 31st December 2021, while Panels B and C document summary statistics for the pre-COVID 19 period (1st January 2016–31st December 2019) and the COVID period (1st January 2020–31st December 2021), respectively. The mean daily return varied from 0.0001% for China and the UK to 0.0005% for India and the US, indicating that the sample markets reacted differently to the pandemic. The minimum return values of all indices were negative, with the exception of China, and these minima were all observed in the month of March 2020. For the Chinese market, the largest single daily reduction of returns was 8.0%

Table 3 Descriptive statistics for the whole sample period, the Pre-COVID period and the COVID period

	China	India	Pakistan	UK	US
Panel A: whole sample period					
Mean	0.0001	0.0005	0.0002	0.0001	0.0005
Median	0.0000	0.0003	0.0000	0.0003	0.0005
Maximum	0.0555	0.0859	0.0468	0.0867	0.0897
Minimum	− 0.0804	− 0.1411	− 0.0710	− 0.1151	− 0.1276
Std. dev	0.0110	0.0111	0.0110	0.0104	0.0114
Skewness	− 1.1019	− 1.6319	− 0.6134	− 1.0769	− 1.1361
Kurtosis	11.2895	29.5774	7.7268	19.6146	26.2075
JB Statistic	4797.52*	46,755.1	1555.1	18,302.8	35,457.2
Prob	0.0000	0.0000	0.0000	0.0000	0.0000
LM Statistic	36.98*	45.11*	21.05*	37.58*	180.28
N	1565	1565	1565	1565	1565
Panel B: Pre-COVID period					
Mean	− 0.0001	0.0004	0.0002	0.0002	0.0004
Median	0.0000	0.0001	0.0000	0.0002	0.0004
Maximum	0.0545	0.0519	0.0404	0.0352	0.0484
Minimum	− 0.0731	− 0.0346	− 0.0476	− 0.0352	− 0.0418
Std. dev	0.0112	0.0080	0.0102	0.0080	0.0080
Skewness	− 1.1955	0.2396	− 0.1545	− 0.5139	− 0.6382
Kurtosis	11.3958	6.1096	4.7935	5.4328	7.8664
JB Statistic	3380.66	429.07	143.80	261.07	1098.91
Prob	0.0000	0.0000	0.0000	0.0000	0.0000
N	1042	1042	1042	1042	10,422
Panel C: COVID period					
Mean	0.0003	0.0007	0.0001	− 0.0004	0.0007
Median	0.0000	0.0009	0.0000	0.0005	0.0014
Maximum	0.0555	0.0468	0.0867	0.0867	0.0897
Minimum	− 0.0804	− 0.1410	− 0.0710	− 0.1151	− 0.1277
Std. Dev	0.0108	0.0157	0.0125	0.0141	0.0162
Skewness	− 0.8894	− 1.7947	− 1.0990	− 1.2216	− 1.0618
Kurtosis	10.9605	21.2531	9.8399	16.3054	18.3478
JB Statistic	1447.11	7526.76	1122.66	3980.34	5221.39
Prob	0.0000	0.0000	0.0000	0.0000	0.0000
N	522	522	522	522	522

Panel A of the table reports descriptive statistics for the whole sample period (January 2016 to December 2021) while Panel B shows the summary statistics for the pre-COVID period (January 2016 to December 2019) and Panel C documents the descriptive statistics for the COVID period (January 2020 to December 2021). In particular, each panel of the table reports values for the Mean, Median, Maximum, Minimum, Standard Deviation, Skewness, Kurtosis, Jarque–Bera (JB) and number of observations (N)

on 3rd February 2020. The highest single-day plunge in the Indian market of -14.1% was on 23rd March 2020. The minimum return for the US SandP 500 of − 12.8% was on 16th March 2020.[15] In the UK, the FTSE 100 recorded its lowest return of − 11.5% on 12th March 2020, while the minimum return of − 7.1% in the Pakistani

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[15] This was the worst day in Wall Street's history when the market reached a 20 year low with this single day decrease.
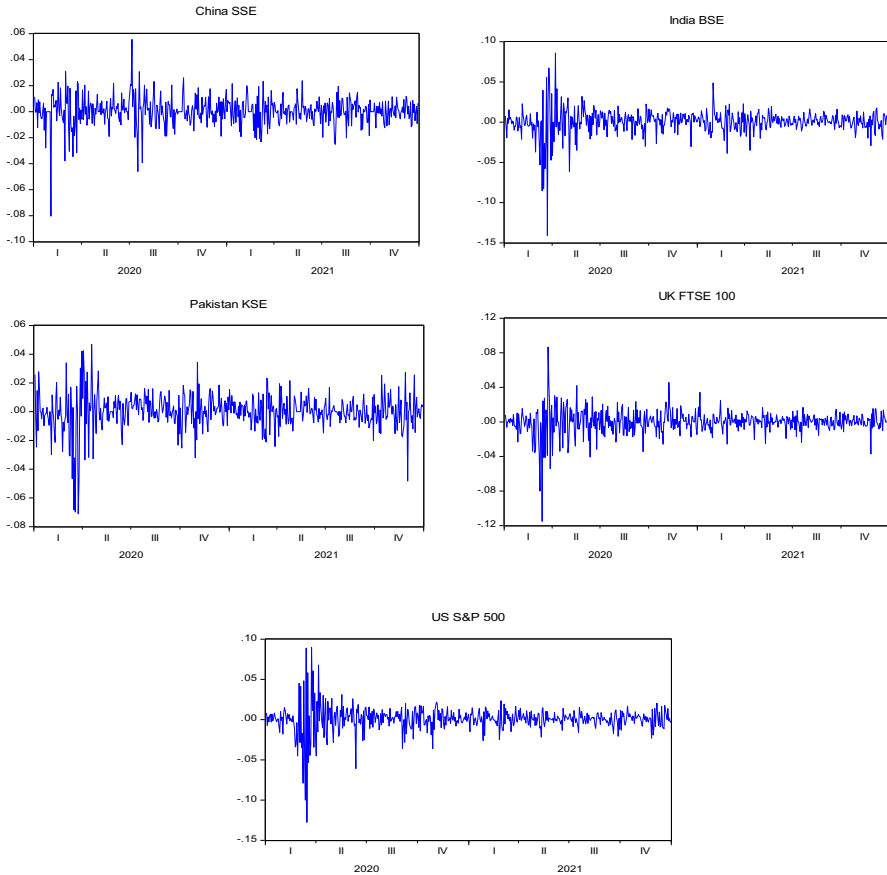
Fig. 1 Time series plots of the return series during the COVID pandemic. The figure shows a time plot of all of the return series over the period from 1st January 2020 to 31st December 2021

market was recorded on 24th March 2020. The standard deviation values indicate that the risk level increased in all markets in the COVID period as compared to the pre-COVID period. The skewness values are, in general, negative for all markets in the entire sample period as well as during the pandemic. The kurtosis values for all markets are higher than that expected in a normal distribution, indicating a leptokurtic distribution for the whole sample period as well as for the two sub-periods. In general, the kurtosis values for the COVID period are higher than for the pre-COVID period, indicating fatter tails during the pandemic. The Jarque–Bera test values further confirm that the daily returns series are not normally distributed; all p-values are 0.000.

Figures 1 and 2 show the daily return series of all five indices during the COVID period from January 2020 to December 2021 and the pre-COVID 19 period of January 2016–December 2019, respectively. The graphs in Fig. 1 highlight high levels of volatility during the pandemic in all five markets. In addition, all the indices show
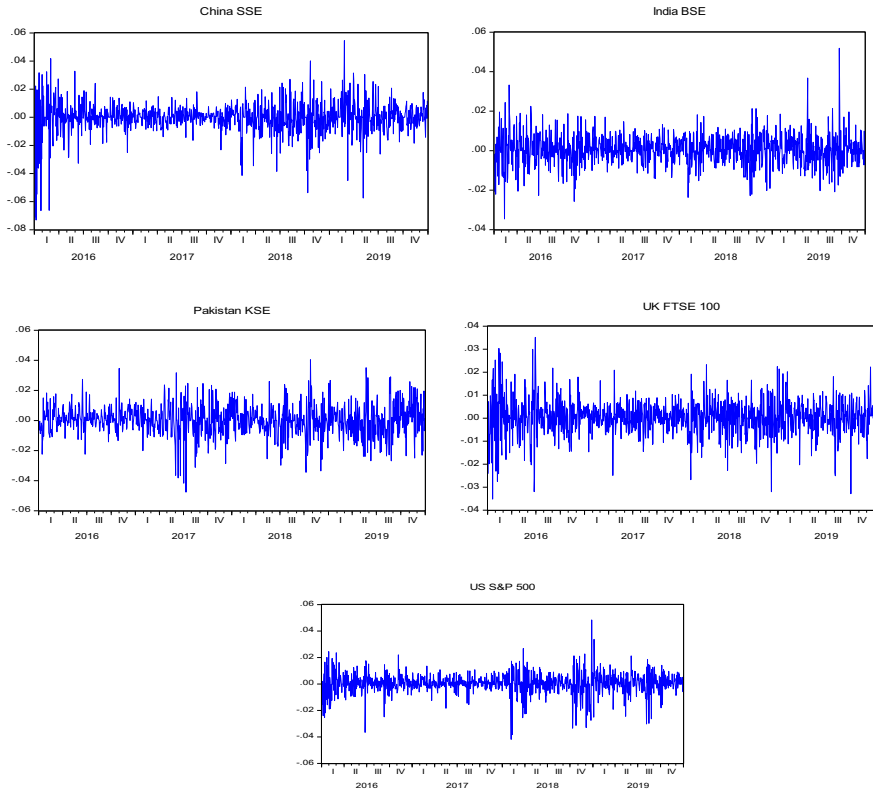
Fig. 2 Time series plot of the return series during the pre-COVID 19 period. The figure shows a time plot of all of the return series over the period from 1st January 2016 to 31st December 2019

volatility clustering; hence, the volatility in one period appeared to affect future volatility. Figure 2 highlights that, in the pre-COVID period, volatility was comparatively low; however, volatility clustering was evident during the pre-COVID period as well.

Table 4 reports the correlation results for the index return series over the entire sample period from 1st January 2016 to 31st December 2021 in Panel A. The correlation results for the two sub-periods of pre-COVID 19 (1st January 2016 to 31st December 2019) and COVID 19 (1st January 2020 to 31st December 2021) are reported in Panels B and C, respectively. A visual inspection of Table 4 indicates that the correlation among all markets in all three periods remained positive. However, the correlation coefficients in the COVID period were higher as compared to their counterparts in the entire sample period as well as in the pre-COVID 19 period. The highest correlation value of 0.648 between the UK and US market was reported for the COVID period, as compared to 0.478 and 0.586 in the pre-COVID and whole sample periods, respectively. As the returns for these two markets declined at the same time in response to news about the spread of COVID, it is not surprising

Table 4 Return correlations for the sample markets for the whole sample period, the pre-COVID period, and the COVID period—1st January 2016–31st December 2021

	China	India	Pakistan	UK	US
Panel A: whole sample period					
China	1.000	1.000	1.000	1.000	1.000
India	0.267	0.168	0.091	0.586	
Pakistan	0.130	0.454	0.064		
UK	0.222	0.325			
US	0.171				
Panel B: Pre-COVID Period: 1st Jan 2016–31st Dec 2019					
China	1.000	1.000	1.000	1.000	1.000
India	0.227	0.045	0.075	0.478	
Pakistan	0.093	0.328	0.006		
UK	0.214	0.208			
US	0.154				
Panel C: COVID period: 1st Jan 2020–31st Dec 2021					
China	1.000	1.000	1.000	1.000	1.000
India	0.344	0.278	0.110	0.648	
Pakistan	0.194	0.526	0.115		
UK	0.254	0.382			
US	0.212				

The table shows the return correlations between each of the sample markets for the whole sample period, the pre-COVID 19 period and the COVID period

that the correlation increased. The correlation among all markets increased in the COVID period, which indicates a strong association amongst the markets during the period of the pandemic. According to Roll (1989), stock markets across the globe become more closely linked during a crisis period. More recently, Khan et al. (2022) found that integration among the markets increased after the GFC. These increased linkages amongst the markets have important implications for international investors who are considering cross-country portfolio investment.

In order to check the stationarity of the data, the current paper uses Augmented Dicky Fuller (ADF) and Phillip and Perron (P-P) tests. The results presented in Table 2 show that the time series are non-stationary in levels, but are stationary in first differenced form, having lower coefficient values than the critical values at the 1.0% level of significance. In addition, Table 2 reveals that the ARCH-LM test statistics are highly significant, showing the presence of ARCH effects in the residuals of the return series at the 1.0% level. These results confirm estimation using the GARCH family models and, hence, the use of the standard GARCH model and Threshold GARCH models employed in this study are justified.

GARCH models results

Table 5 reports the results for a simple GARCH (1,1) model for all the stock market indices of the sample countries. The conditional mean equation coefficient for the Indian, Pakistani and US equity markets are positive and statistically significant. In the variance equation, the coefficient for the constant variance term (c), the ARCH

Table 5 Standard GARCH (1,1) model results

	China	India	Pakistan	UK	US
μ	0.0002 (0.885)	0.0009 (4.556)*	0.0007 (2.997)*	0.0003 (1.300)	0.0009 (5.715)*
c	1.58×10^{-6} (5.947)*	1.75×10^{-6} (3.999)*	3.81×10^{-6} (4.581)*	4.16×10^{-6} (6.431)*	4.47×10^{-6} (9.917)*
α	0.0662 (11.808)*	0.0905 (10.525)*	0.1168 (9.333)*	0.1231 (8.950)*	0.2363 (12.466)*
β	0.9205 (174.785)*	0.8919 (78.315)*	0.8532 (59.041)*	0.8278 (43.287)*	0.7278 (37.529)*
(α + β)	0.9867	0.9824	0.9700	0.9509	0.9641
AIC	− 6.4203	− 6.6542	− 6.3971	− 6.6932	− 6.8374
SC	− 6.4066	− 6.6405	− 6.3835	− 6.6796	− 6.8237

Figures in parentheses indicate the Z-statistic values. (*) indicates significance at the one per cent level, (**) indicates significance at the five per cent level and (***) indicates significance at the ten per cent level

term (α) and the GARCH term (β) are positive and statistically significant for all the market indices. The coefficients (α) and (β) in the variance equation represent the response of equity returns to news. More specifically (α) represents recent news whereas (β) represents more distant news. The significant values for both of these coefficients indicate that both 'immediate' and 'more distant' news had a significant impact on stock market volatility. Furthermore, the high values of (β) indicate that this volatility was persistent and that shocks to the conditional variance took a long time to die away.

Table 5 also reveals that the sum of the ARCH and GARCH coefficients (α + β) is close to one for each market. Such a result implies that a shock at time t tends to remain for a relatively long time in the future. Hence, the results indicate that volatility persistence and shocks may lead to a permanent change in the conditional variance (h_t). Furthermore, as the values of (α + β) are less than one, it shows that a mean-reverting process characterises volatility in all markets.

Table 6 presents the results of the GARCH (1, 1) model with the COVID variable in the conditional mean and conditional variance equations. The results show that COVID 19 had a significant positive impact on the conditional variance of all the indices except the KSE 100 index.[16] These results are in agreement with the findings of Yousef (2020) and Chaudhary et al. (2020), indicating that COVID 19 was associated with a significant rise in stock market volatility.[17] Based on the results in Tables 2 and 5, the null hypothesis of no change in volatility can be rejected. Hence, the change in volatility appears to be significant.

Table 7 reveals the results of the TGARCH model including the COVID 19 variable. The coefficients (α) and (β), which represent the ARCH and GARCH terms

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[16] According to Sharma (2020), COVID 19 had a statistically significant effect on stock market volatility. The impact of the pandemic varied across countries, with markets in higher income countries overreacting in the beginning and bouncing back more rapidly than their lower-income counterparts.

[17] Yousef (2020) examined the G7 markets whereas Chaudhary et al. (2020) investigated the markets of the US, China, Japan, Germany, India, the UK, France, Italy, Brazil and Canada.

Table 6 GARCH (1,1) with COVID 19 results

	China	India	Pakistan	UK	US
μ	0.0001 (0.533)	0.0008 (3.759)*	0.0005 (2.046)**	0.0003 (1.661)***	0.0009 (5.177)**
ρ	0.0002 (0.411)	0.0004 (0.806)	0.0003 (0.609)	− 0.0002 (− 0.435)	0.0002 (0.408)
Variance equation					
c	1.38×10^{-6} (5.607)*	1.84×10^{-6} (4.058)*	4.08×10^{-6} (4.584)*	4.22×10^{-6} (5.841)*	3.94×10^{-6} (9.621)*
α	0.0627 (10.729)*	0.0874 (9.682)*	0.1173 (9.164)*	0.1296 (8.489)*	0.2248 (11.544)*
β	0.9208 (170.658)*	0.8866 (67.535)*	0.8517 (57.142)*	0.8046 (34.082)*	0.7262 (34.853)*
(α + β)	0.9835	0.9740	0.9690	0.9342	0.9510
ξ	$1.42\times10{-6}$ (5.585)*	$1.81\times10{-6}$ (2.956)*	$-5.40\times10{-7}$ (0.429)	$4.41\times10{-6}$ (4.509)*	$4.17\times10{-6}$ (4.492)*
AIC	− 6.4231	− 6.6567	− 6.3951	− 6.70302	− 6.8447
SC	− 6.4026	− 6.6361	− 6.3746	− 6.6825	− 6.8242

Figures in parentheses indicate the Z-statistic values. (*) Indicates significance at the one per cent level, (**) indicates significance at the five per cent level and (***) indicates significance at the ten per cent level

Table 7 TGARCH (1,1) with COVID 19 variable

	China	India	Pakistan	UK	US
μ	0.0001 (0.504)	0.0005 (2.372)**	0.0004 (1.261)	0.0001 (0.478)	0.0006 (3.113)**
ρ	0.0002 (0.391)	0.0003 (0.580)	0.0002 (0.436)	− 0.0002 (− 0.492)	9.01×10^{-5} (0.211)
Variance equation					
c	1.40×10^{-6} (5.655)*	2.24×10^{-6} (7.053)*	4.15×10^{-6} (5.093)*	3.11×10^{-6} (6.291)*	3.76×10^{-6} (9.582)*
α	0.0606 (9.746)*	− 0.0142 (− 2.367)**	0.0187 (1.706)***	0.0081 (0.689)	0.0927 (7.497)*
β	0.9203 (167.443)*	0.8989 (96.184)*	0.8624 (58.973)*	0.8621 (49.491)*	0.7313 (35.288)*
$(\alpha + \beta)$	0.9809	0.8847	0.8811	0.8702	0.9510
ξ	1.41×10^{-6} (4.945)*	1.55×10^{-6} (3.169)*	$- 3.97 \times 10^{-7}$ (− 0.546)	3.38×10^{-6} (4.905)*	4.70×10^{-6} (5.745)*
γ	0.0046 (0.622)	0.1603 (10.307)*	0.1681 (7.148)*	0.1582 (6.825)*	0.2542 (7.192)*
AIC	− 6.4219	− 6.7071	− 6.4324	− 6.7227	− 6.8678
SC	− 6.3979	− 6.6832	− 6.4085	− 6.6988	− 6.8439

Figures in parentheses indicate the Z-statistic values. (*) indicates significance at the one per cent level, (**) indicates significance at the five per cent level and (***) indicates significance at the ten per cent level

in the TGARCH model, are all statistically significant, indicating the presence of ARCH and GARCH effects. The magnitude of the ARCH term parameter ranges from 0.0606 for the Chinese market to 0.0927 for the US market. The GARCH term coefficients are much higher for all markets, ranging from 0.7313 for the US market to 0.9203 for the Chinese market. The sum of the coefficient $(\alpha + \beta)$ terms is close to one for each index, indicating a high degree of volatility persistence and long memory in the index series. The asymmetric term measured by (γ) is positive and significant for all markets except China indicating an asymmetric effect for news in these markets.[18] The findings suggest that negative shocks had a larger impact on the conditional variance as compared to good news. Hence, the negative shocks associated with the COVID 19 pandemic resulted in a higher conditional volatility in these markets.

The coefficient representing the COVID 19 pandemic (ξ) was highly significant for the sample markets, which further confirms the results of the GARCH (1,1) models that are reported in Table 7. However, the magnitude of the impact varies across the sample markets; the US had the highest coefficient value for the COVID 19 variable in the table. This variation in magnitude may be due to different stages of the outbreak of COVID 19 in different countries. It may also indicate that each markets' assessment of the impact of the pandemic was not the same in the different countries; some countries may have been judged to be more resilient to the damaging impact of the virus. In addition, the composition of the equity indices may have varied from country to country with the shares of certain sectors performing better than others in response to news of COVID.

Volatility spillover changes associated with COVID-19

According to Thangamuthu et al. (2022), volatility spillovers occur across markets due to interdependence. As market participants and policy-makers need to understand the underlying drivers of cross-country stock market correlations and volatility, this paper analyses the volatility transmissions across markets. Table 8 compares the results of the pre-COVID 19 and COVID 19 periods for the five stock market indices to capture the dynamic responses of returns in one market to shocks in its own as well as other markets. In particular, each index in the series is used as a dependent variable and the other four markets are employed as regressors in the conditional variance equation. A separate model is run with each market identified as the dependent variable (taken one at a time) in the two sub-periods. The results

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[18] The less pronounced effect of the COVID-19 pandemic on the Chinese market compared to the US market, as observed by Basouney et al. (2021) and Khan (2024), can be attributed to the significant growth of the Chinese market and the timely interventions by the Government in that country to curtail the spread of COVID 19. Furthermore, Cheng et al. (2022) conducted a study on 19 global stock markets and discovered that the Chinese market was largely disconnected from the global system in terms of volatility transmission. They provided strong empirical evidence suggesting that volatility spillovers in global stock markets did not originate from the Chinese market. These findings from prior research corroborate the results documented here, indicating that the insignificant nature of the asymmetric term in the Chinese market implies a lack of significant impact from 'bad' news.

Table 8 TGARCH model results for the pre-COVID and COVID 19 periods

	China	India	Pakistan	UK	US
Pre-COVID 19 variance equation					
China	–	– 0.0004*	7.82×10^{-6}	– 0.0006*	0.0003
India	$- 2.47 \times 10^{-6}$	–	6.25×10^{-6}	– 0.0004**	– 0.0004***
Pakistan	– 0.0001	0.0003	–	– 0.0009*	0.0007*
UK	– 0.0003***	– 0.0004*	8.40×10^{-5}	–	– 0.0004*
US	– 0.0001**	– 0.0003*	1.63×10^{-5}	– 0.0004*	–
COVID 19 variance equation					
China	–	8.58×10^{-6}	– 0.0009*	– 0.0012*	0.0004
India	– 0.0001	–	0.0002	– 0.0005**	– 0.0007***
Pakistan	– 0.0016*	– 0.0012***	–	0.0003	2.89×10^{-5}
UK	0.0009	– 0.0003	0.0006*	–	– 0.0003*
US	– 0.0004	– 0.0007**	0.0010*	– 0.0004***	–

The table reports the results of a TGARCH model for the pre-COVID 19 and COVID 19 periods. Each market is regressed as a dependent variable on the rest of markets as independent variables. (*) indicates significance at the one per cent level, (**) indicates significance at the five per cent level and (***) indicates significance at the ten per cent level

indicate that, in the pre-COVID 19 period, the Indian and the UK stock markets helped to explain conditional volatility in the Chinese market. Shocks in the UK and the US stock markets were statistically significant in explaining equity volatility in the Indian and Pakistani markets. Variations in the UK market were explained by volatility in the Chinese, Indian and US markets. By contrast, the Chinese, Indian and UK markets were significant in explaining volatility in the US market.

In the COVID period, the Pakistani and the UK markets were significant in explaining variations in the Chinese market. Changes in volatility in the UK and US markets impacted volatility in the Indian market. The Indian and Chinese markets were significant in explaining volatility in the Pakistani market in the COVID 19 period. The Chinese, Pakistani and US markets helped explain volatility in the UK market. Finally, the coefficients for the Indian, Pakistani and UK markets were significant in explaining volatility in the US market. Thus, spillovers for the Pakistani and Chinese markets differed for the COVID 19 period in terms of the countries which explained market volatility. These results are in line with Cheng et al. (2022) who found that the European, Australian and US markets were more closely linked during COVID 19 while China was disconnected from the global stock market volatility spillover network. Overall, the results in Table 8 show higher significant values in the COVID 19 period even where volatility sources were the same, indicating more pronounced linkages in terms of volatility spillovers among the markets. The volatility transmission shows significant spillovers among the markets as COVID 19 spread. These spillovers increased during the COVID crisis resulting from financial instability and economic uncertainties. The results support Li and Majerowska (2008)'s argument that, in order to analyse the linkages amongst markets, it is not only returns that are strongly associated but also volatility, and when markets are integrated, shocks in one market will influence not only the return but also volatility in other markets. The results in Table 8 confirm that, due to the pandemic,
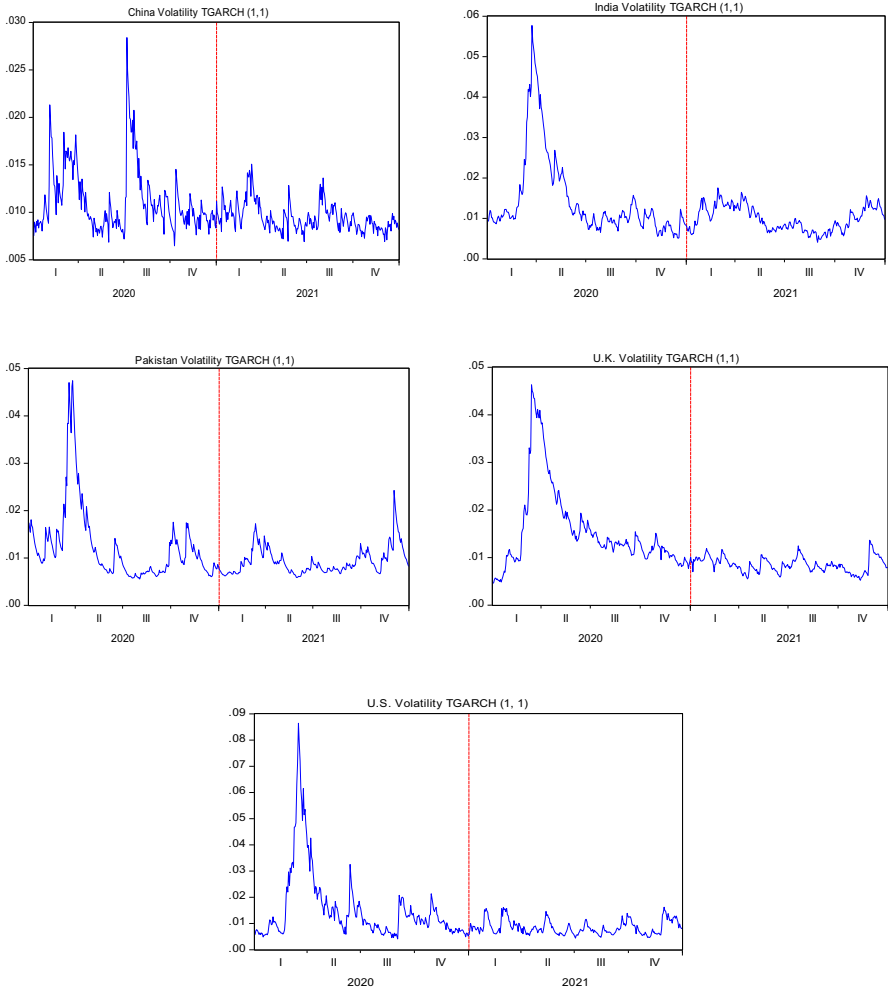
Fig. 3 Conditional volatility using TGARCH (1, 1). The figures show the time series plots of conditional volatility from 1 January 2020 to 31 December 2021

the volatility transmissions among the sample countries increased as compared to the pre-COVID 19 period. These results further support the argument that linkages among the markets increased in the turbulent periods as compared to normal periods.

Figure 3 shows the dynamic patterns of estimated conditional volatility, measured in terms of conditional standard deviations, across the sample countries. The asymmetric TGARCH (1, 1) model was used to compute the conditional volatility. A red dotted line highlights the periods before and after the announcement of the

first COVID 19 vaccine on December 31, 2020.[19] As illustrated by the figure, the COVID 19 pandemic resulted in stock price crashes, leading to a massive surge in conditional volatilities across all of the sample markets. The figure shows that the US market experienced the highest peak in estimated volatility (0.315), followed by India (0.246), Pakistan (0.079), the UK (0.071), and China (0.0286) during the COVID 19 pandemic. Most notably, these peaks are prominent during March 2020. As expected, the US and Indian markets demonstrated the highest levels of volatility, while China exhibited comparatively lower conditional volatility. These findings corroborate those of Basuony et al. (2021) who noted that there was greater volatility in the US market and relatively lower volatility in the Chinese market.

Despite governmental efforts to curb the spread of COVID 19, the increase in new cases and deaths led to negative sentiment in the US, which had a significantly negative effect on stock market volatility. By contrast, the Chinese stock markets were less affected; a prompt government response to the escalation in new cases and deaths conveyed a positive signal to investors, which helped to minimise market uncertainty. The TGARCH (1, 1) model also indicates that the significant increase in conditional volatility diminished during the COVID-19 period for all sample markets. That is, the shocks were absorbed by these markets and conditional volatility decreased. Furthermore, the figure shows that there was a decrease in financial market volatility because of the introduction of a vaccine towards the end of 2020. This vaccine development resulted in expectations of recovery and the re-establishment of a new global normal. Overall, these findings are in line with those documented by To et al. (2023), who noted that there was a reduction in volatility in 32 stock markets following the initiation of a vaccine programme.

Conclusion

The current study examines the impact of COVID 19 on the stock market volatility of a selection of developed and emerging markets. Daily closing price data were examined for the period from 1st January 2016 to 31st December 2021. The descriptive statistics indicated that all of the sample markets recorded their lowest daily returns in the COVID period, with the Indian and the US market experiencing a decrease of 14.1 and 12.8%, respectively. The standard deviation values were high for all markets in the COVID 19 period. In addition, all markets exhibited negative skewness and high kurtosis during the pandemic. The return correlations between the markets increased in the COVID period as compared to the pre-COVID period for all markets, indicating more cohesiveness among the markets during the COVID pandemic.

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[19] The Comirnaty COVID 19 mRNA vaccine was granted emergency use listing by the WHO, making the Pfizer/BioNTech vaccine the inaugural recipient of the WHO's emergency validation since the onset of the pandemic. The Assistant-Director General for Access to Medicines and Health Products, Dr. Mariângela Simão, conveyed the successful vaccine launch announcement on 31st December 2020.

The results of the GARCH (1, 1) model indicated that the ARCH and GARCH term coefficients were positive and significant for all markets, suggesting that both more recent and old news have a significant impact on the conditional variances of these markets. In addition, the results showed persistent and long-term volatility in these markets, signifying that the shocks to the conditional variance take a long time to die away.

The results for the GARCH (1,1) with COVID 19 as an exogenous dummy variable in the mean and variance equation indicated that the coefficient estimating the pandemic was both positive and highly significant for most of the sample markets. These results are in agreement with Yousef (2020) and Chaudhary et al. (2020), and indicate that COVID 19 led to a significant increase in stock market volatility. However, the magnitude of the impact varied across the sample markets, perhaps because of the different stages of the outbreak of COVID 19 in different countries. This result may also indicate that the assessment of the impact of the pandemic was different across markets; investors may have judged some countries to be more or less resilient to the damaging impact of the virus. In addition, the shares of certain sectors may have performed better or worse than others in response to news of COVID.

The results from the TGARCH (1, 1) model with COVID 19 as a dummy variable further confirmed the results of the GARCH (1,1) model with COVID 19 as a variable. This model also revealed that the coefficient for COVID 19 in the variance equation had a significant positive impact on the conditional variance for the markets. This implies that COVID 19 resulted in an overall increase in stock market volatility. The asymmetry coefficient was found to be highly significant in all markets, suggesting that COVID 19 had a stronger impact on stock market volatility as compared to any good news that emerged in these countries during the period of analysis. In addition, these findings suggest evidence against market efficiency, particularly in the emerging markets. This perspective is supported by the "meteor shower" hypothesis, which posits that volatility in one market tends to propagate to another market, leading to a sequence of volatile days across markets. The implications of the "meteor shower" hypothesis may signify shortcomings in market efficiency, as suggested by Dang et al. (2023). Furthermore, according to Khan et al. (2022), the identification of volatility spillovers (and their changes) among markets potentially serves as evidence against market efficiency and underscores the susceptibility of markets to external shocks.

The results of the study have important implications for the portfolio allocation decisions of retail investors and portfolio managers in situations of crisis, like COVID 19, or other similar unexpected events; that is, changes in market volatility spillovers and return correlations may require investors to rebalance their portfolios. The results are also useful to investors as they highlight market behavior during a situation of extreme stress. That is, the response of markets to the pandemic may be useful in terms of the formulation of risk mitigation strategies. Finally, policy-makers may find the results of this study useful as they can plan policies for market stability given information about the net receivers and net transmitters of market shocks. In addition, in determining their response to any possible future pandemic, policy-makers can learn from these results and implement a cheaper and more timely response than happened during COVID 19.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

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