

RESEARCH ARTICLE

The effect of COVID-19 pandemic on global stock markets: Return, volatility, and bad state probability dynamics

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Abstract

This study investigates the impact of COVID-19 pandemic on stock returns, conditional volatility, conditional skewness and bad state probability. This study utilizes an asymmetric exponential generalized autoregressive conditional heteroscedasticity model to capture the asymmetric effect of positive and negative shocks (news) on conditional volatility. Using a sample consisting of international stock market indices in Brazil, China, Italy, India, Germany, Russia, Spain, United Kingdom, and United States, over the period from January 1, 2013 to December 31, 2020, we find unprecedented increases in conditional volatilities and bad state probabilities across all the markets. However, this impact is not symmetric across markets. Furthermore, we find that the negative affect of deaths is more pronounced, compared to the positive impact of recovered cases.

KEYWORDS

bad state probability, COVID-19, pandemic, stock market, volatility

1 | INTRODUCTION

In late 2019, a new virus called “COVID 19” had started to spread, causing “severe pneumonia.” Thus, this virus led to an extraordinary rate of death between the elderly and the most vulnerable in society, leading to an international social distancing and home isolation of more than 2 billion people worldwide, with tremendous social, political and economic consequences (Goodell, 2020; Sharif et al., 2020). Moreover, one of the commercial effects of this virus was an unexpected disruptions in the flow of goods and services, commodity prices and financial conditions, creating an economic disasters across many countries because of its impact on the production and supply chains in China, the United States, Europe, and Japan, as well as the most important economies in the world (IMF, 2020).

Significant changes in the financial structures of countries was caused by the “domino effect” created by retrenched investors in many countries (Kenourgios et al., 2011). This contagion effect in the global market led to unprecedented disturbing effects in different economies that were only comparable to the depression of 1920 (Corbet et al., 2020). Moreover, all the countries face a great health crisis, severe external demand shock, dramatic shrinking in global financial conditions, and a plunge in the commodity prices that will

have a severe effect on economic activity in commodity exporters (IMF, 2020). In addition, the outbreak of COVID-19 has been declared as a global pandemic on June, 2020 by the World Health Organization (WHO), which shaken the global financial markets. As of June 16, 2020, there are 9,653,048 confirmed cases and 491,128 deaths across the world for 216 Countries, areas or territories with cases, including emerging and developed countries (WHO, 2020).

The objective of this research is to analyze the influence of COVID-19 on the stock price behavior of equity market indices of selected nine countries. We selected the countries that had the largest confirmed cases of COVID-19 at the end of March and June 2020. Accordingly, the final sample included United States, Italy, Spain, United Kingdom, Germany, China, Brazil, Russia, and India. We also compare how the stock price behavior differs across the periods pre- and during the COVID-19 (to examine the initial effect of the shock of COVID-19 on the markets) and then between the first and second quarters during the COVID-19 period (to explore whether the markets are rebounded after the shock is being assessed and absorbed). Our analysis of stock market behavior is based on examining stock returns, conditional volatility, conditional skewness, and bad state probability, measured using a widely applied econometric model, an asymmetric exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model.

The advantage of this model is to allow for capturing the well-documented asymmetric effect of positive and negative shocks on conditional volatility as positive shocks may have less impact on volatility than the negative shocks (Alberg et al., 2008; Hentschel, 1995; Nelson, 1991). It is commonly known fact that volatility clustering produces heavier tails, as documented by Engle's (1982) seminal paper on autoregressive conditional heteroscedasticity (ARCH) model and its generalization by Bollerslev's (1986) paper on generalized autoregressive conditional heteroscedasticity (GARCH) model, and others (e.g., Tsay, 2010). However, since normal GARCH model links directly the kurtosis to the variance, it is unable to well capture the excess kurtosis that exists in financial returns and produces low probability of extreme realizations (extreme returns) than observed in the data. In addition, inclusion of conditional skewness in the model captures the asymmetry, and also impacts the persistence in conditional variance as highlighted by Harvey and Siddique (1999). To overcome these drawbacks when using the normal GARCH model, our EGARCH model adds two extra parameters in the distribution of returns, namely the skewness and kurtosis. Moreover, this model is augmented to capture the impact of the number of death and recovered cases to distinguish between the effects of negative information (deaths) versus positive information (recovered cases). Moreover, as any other major crisis, the COVID-19 pandemic was associated with an adverse impact on the financial markets, caused by panic, uncertainty, negative sentiment and investor pessimism during the pandemic. Hence, it was crucial for us to estimate bad state probabilities (i.e., the probability that stock market returns might fall below the expected returns) to quantify the likelihood of bad events, and assess the probability of markets downturns in bad times of high uncertainty.

Therefore, this paper contributes to the literature in several ways. First, this study extends the evolving literature on the impact of COVID-19 on stock market behavior. Although several studies have investigated how financial markets have been affected during COVID-19 period (Baker et al., 2020; Corbet et al., 2020), to the best of our knowledge, none have examined the impact of COVID-19 on global stock markets, using an asymmetric exponential EGARCH model with an emphasis on conditional volatility, conditional skewness and bad state probability. This allows for not only capturing the dynamic behavior of conditional variance but also taking into account the asymmetric impact of negative versus positive return innovations. Second, this study aims to estimate the impact of COVID-19 recovered cases and deaths on the conditional mean, conditional volatility and conditional skewness of the returns of equity market indices. By doing that, we distinguish between the impact of positive and negative information on stock market behavior to examine the asymmetric characteristics of stock market behavior. Third, we demonstrate how the COVID-19 pandemic can amplify bad state probability, which is important in a period when financial markets experience extreme uncertainty and investors' behavior is driven by their fear and panic. Therefore, this study adds not only to the literature on COVID-19's effect on stock markets but also to the overall literature on financial market crashes and crises. Fourth, our long analysis period (January 1, 2013 to December 31, 2020) enables us to compare the stock price behavior across not only the periods pre- and during the COVID-19 pandemic but

also the first and second quarters during the COVID-19 period. This allows for better understanding of how stock markets have initially reacted to the shock of COVID-19, compared to how they are rebounded after the shock is being absorbed. Moreover, our findings provide important implications for investors, practitioners and policy makers. For traders and investors seeking to invest in international stock markets, the results indicate which markets are most correlated and risky, which have strong consequences for portfolio optimization and implementation of profitable trading strategies. For practitioners, the findings allow to get insights into the dynamic behavior of stock markets in the countries that are heavily affected by the pandemic in order to examine the best investment options. For policy makers, the findings confirm the critical role that the political leadership and governments can play, via mitigating the spread of pessimistic views and negative feelings amid citizens, in conveying positive signals to the investors and thereby decreasing market uncertainty.

2 | LITERATURE REVIEW

Following such a huge worldwide crisis, the literature on the economic effects of COVID-19 has emerged quickly in recent months. For example, Ramelli and Wagner (2020) and Zaremba et al. (2020), among other, have investigated the adverse impact of COVID 19 on stock returns and volatility. Other studies have examined how the outbreak of COVID-19 affected the financial contagion in financial markets. For example, Akhtaruzzaman et al. (2020) examine how the COVID-19 period has affected the financial contagion between China and G7 countries and show that stocks listed across China and G7 countries have been associated with a significant increase in conditional correlations between their stock returns. Consistently, Just and Echaust (2020) show close dependence between S&P 500 index returns and both implied volatility and implied correlation during the COVID-19 period.

Other studies focus on exploring how COVID-19 has affected commodity markets. Gharib et al. (2021) examine the economic impact of COVID-19 on the causal relationship between crude oil and gold prices and find a bilateral contagion effect of bubbles in oil and gold markets during the recent COVID-19 outbreak. Sharif et al. (2020) analyze the connectedness between COVID-19, oil price volatility shock, the stock market, geopolitical risk and economic policy uncertainty in the United States. Their finding show that the effect of the COVID-19 on the geopolitical risk substantially higher than on the US economic uncertainty. In related context, Conlon and McGee (2020) examine the price behavior of Bitcoin during the COVID-19 bear market and provide empirical evidence casting doubt on the ability of Bitcoin to act as a safe-haven asset. While other studies focus on assessing the role of governmental policies in mitigating the negative impact of the pandemic on financial markets. For instance, Narayan et al. (2020) examine the effect of government responses of G7 countries to the coronavirus pandemic (COVID-19) on stock market returns, showing that lockdowns, travel bans, and economic stimulus packages have exerted a positive effect on the G7 stock markets. Ma et al. (2020) reveal that countries with more aggressive government fiscal policy exhibit a superior ability to decrease the adverse impact of the pandemic on GDP growth, while emerging market are most likely to

TABLE 1 Summary of related literature

Study	Sample	Methodology	Main results
1. Albulescu (2020)	US stock market from March 11, 2020 to May 15, 2020.	OLS regression, stepwise procedure	The new confirmed cases are associated with higher financial volatility.
2. Baek et al. (2020)	US stock market from January 2, 2020 to April 30, 2020.	Two-regime Markov switching model	The volatility is more sensitive to the news of COVID-19 more than the economic indicators. Moreover, the negative COVID-19 news (number of deaths) is twice as impactful as positive COVID-19 news (recovered cases) suggesting a negativity bias.
3. Baig et al. (2021)	US stock market from January 13, 2020 to April 17, 2020	GARCH (1,1) model	The confirmed cases and deaths during COVID-19 are associated with a significant upturn in volatility and market illiquidity.
4. Bissoondoyal-Bheenick et al. (2020)	G20 countries stock market from January 22, 2020 to May 20, 2020	Bivariate fractionally integrated vector autoregressive model	The connectedness between stock return and volatility has increased during the COVID-19 pandemic.
5. Chaudhary et al. (2020)	United States, China, Japan, Germany, India, United Kingdom, France, Italy, Brazil, and Canada from January 1, 2019 to June 30, 2020	Unit root test; the ARCH effect test; and GARCH (1,1) model	The COVID-19 period is associated with negative mean returns for all market indices and higher volatility.
6. Choi (2020)	US stock market from January 2008 to May 2020.	Wavelet coherence analysis	The economic policy uncertainty during COVID-19 affects the sector volatility more than the global financial crisis for all sectors.
7. Liu et al. (2020)	Abu Dhabi, France, Germany, United States, United Kingdom, Malaysia, Indonesia, Korea, Russia, Japan, Australia, Canada, Singapore, Taiwan, Asia ex Japan, Thailand, Hong Kong, Shanghai, Shenzhen, Italy, and India from February, 21, 2019 to March, 18, 2020.	Market model; and OLS regression	The new confirmed cases during COVID-19 have a negative effect on stock abnormal returns. Countries in Asia, compared to other countries, experience more negative abnormal returns.
8. He, Sun, et al. (2020)	China stock market from June 3, 2019, to March 13, 2020.	Average adjusted return rate model; the market index adjusted return rate model; and the market model	COVID-19 has a negative effect on some industries; mining, electricity and heating, transportation, and environment. In contrast, other industries, for example, information technology, manufacturing, education, and health-care are more resilient to the pandemic.
9. He, Liu, et al. (2020)	Republic of China, Italy, South Korea, France, Spain, Germany, Japan, and the US stock market.	Conventional <i>t</i> tests; and nonparametric Mann-Whitney tests.	COVID-19 has a negative—but short term—effect on stock markets of affected countries.
10. Jelilov et al. (2020)	Nigeria stock market from February 27, 2020 to April 30, 2020.	Standard GARCH and the GJR-GARCH model	COVID-19 is associated with higher volatility and negative market returns.
11. Kotishwar (2020)	United States, Spain, France, Italy, China, and India from March 11, 2020 to April, 2020	VECM and CAAR model	All the selected indices have positively responded more in the post period after declaring the COVID-19 as pandemic on March 11, 2020, compared with the pre-period.
12. Lyocsa and Molnár (2020)	US stock market from November 2019 and ends in May 2020,	Nonlinear smooth transition regime switching model	Market volatility tends to motivate the returns autocorrelation of during times of great volatility.
13. Just and Echaust (2020)	US stock market from June 3, 2019 to June 12, 2020.	Two-regime Markov switching model	There is a close dependence between returns and both implied correlation and implied volatility but not with liquidity.
14. Mazur et al. (2020)	US stock market for the month of March 2020.	OLS regression	There are high positive stock returns in some sectors; healthcare natural gas, software stocks, and food. However, it falls dramatically in other sectors; petroleum, real estate, entertainment, and hospitality. Furthermore, lose-making stocks reveal a great volatility that is negatively correlated with stock returns.

(Continues)

TABLE 1 (Continued)

Study	Sample	Methodology	Main results
15. Narayan et al. (2020)	G7 countries stock market, from July 1, 2019 to April 16, 2020.	Time-series regression model	All the government polices during COVID 19 had a positive effect on the stock markets of the G7 countries.
16. Sharif et al. (2020)	US stock market from January 21, 2020 to March 30, 2020	Continuous wavelet transform, the wavelet coherence and the wavelet-based granger causality tests.	COVID-19 outbreak exhibits a greater effect on the US geopolitical risk and economic uncertainty more than on the US stock market.
17. Waheed et al. (2020)	Pakistani stock market from February 26, 2020 to April 17, 2020.	Auto regressive integrated moving average; and exponential smoothing (ES) approach	COVID-19 has a positive effect on KSE-100 index that has a positive increment in stock returns.
18. Yousef (2020)	G7 stock market indices for the period 2000–2020.	GARCH; and GJR-GARCH models	COVID-19 is associated with higher volatility in the G7 markets.
19. Zaremba et al. (2020)	Argentina, Australia, Austria, Bahrain, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia Croatia, Cyprus, Czechia, Denmark, Egypt, and Estonia from January 1, 2020 to April 3, 2020.	Capital asset pricing model (CAPM); three-factor model (FF); and four-factor model (CAR).	COVID-19 is associated with higher volatility
20. Zhang et al. (2020)	United States, Italy, China Mainland, Spain, Germany, France, United Kingdom, Switzerland, Korea, South, Netherlands, Japan, and Singapore from February 7, 2020 to March 27, 2020.	Pairwise correlations	COVID-19 is associated with higher volatility and systematic risk.

experience superior negative influences from COVID-19. Table 1 outlines a summary of related literature to provide more insights into the research approaches adopted by the studies depicted in Table 1. In-depth analysis has been conducted to categorize these studies in Table 1.

The first category considers mainly samples from developed countries. These studies adopt different methodology and statistical models using time-series regression model (e.g., Narayan et al., 2020); Two-regime Markov switching model (e.g., Baek et al., 2020; Just & Echaust, 2020); ordinary least square (OLS) (e.g., Albulescu, 2020; Mazur et al., 2020); GARCH (1,1) model (e.g., Baig et al., 2021; Yousef, 2020); Wavelet coherence analysis (e.g., Choi, 2020); nonlinear smooth transition regime switching model (e.g., Lyocsa & Molnár, 2020) and the wavelet coherence and the wavelet-based Granger causality tests (e.g., Sharif et al., 2020). On the other hand, the second category focus on samples from developing countries. The approaches used in these studies include: the average adjusted return rate model (e.g., He, Sun, et al., 2020); the market index adjusted return rate model and the market model (e.g., Jelilov et al., 2020); GARCH model (e.g., Waheed et al., 2020) and auto regressive integrated moving average and exponential smoothing.

While, in the third category, other studies provides empirical evidence based on both developed and developing markets. Those studies adopted various models, such as bivariate fractionally integrated vector autoregressive model (e.g., Bissoondoyal-Bheenick

et al., 2020); unit root test, the ARCH effect test, and the GARCH (1,1) model (e.g., Chaudhary et al., 2020); conventional *t* tests and nonparametric Mann–Whitney tests (e.g., He, Liu, et al., 2020); market model, and the OLS (e.g., Liu et al., 2020); pairwise correlations (e.g., Zhang et al., 2020); CAAR model (Kotishwar, 2020); and capital asset pricing model (CAPM), three-factor model (FF), and four-factor model (e.g., Zaremba et al., 2020).

3 | METHODOLOGY

3.1 | Data collection

In order to conduct this study, the selection of our sample covers both pre-COVID-19 period (January 1, 2013 to December 31, 2019) and during COVID-19 period (January 1, 2020 to December 31, 2020). We take the starting date of COVID-19 period as January 1, 2020, the next day when the first case of COVID-19 was reported to the WHO. On the other hand, we choose the first date of pre-COVID-19 period as January 1, 2013, to avoid and exclude the effect of the two crisis which are the worldwide financial crisis between 2007 and 2009 and European sovereign debt crisis between 2010 and 2012. So, it can be said that the data started from January 1, 2013 to the

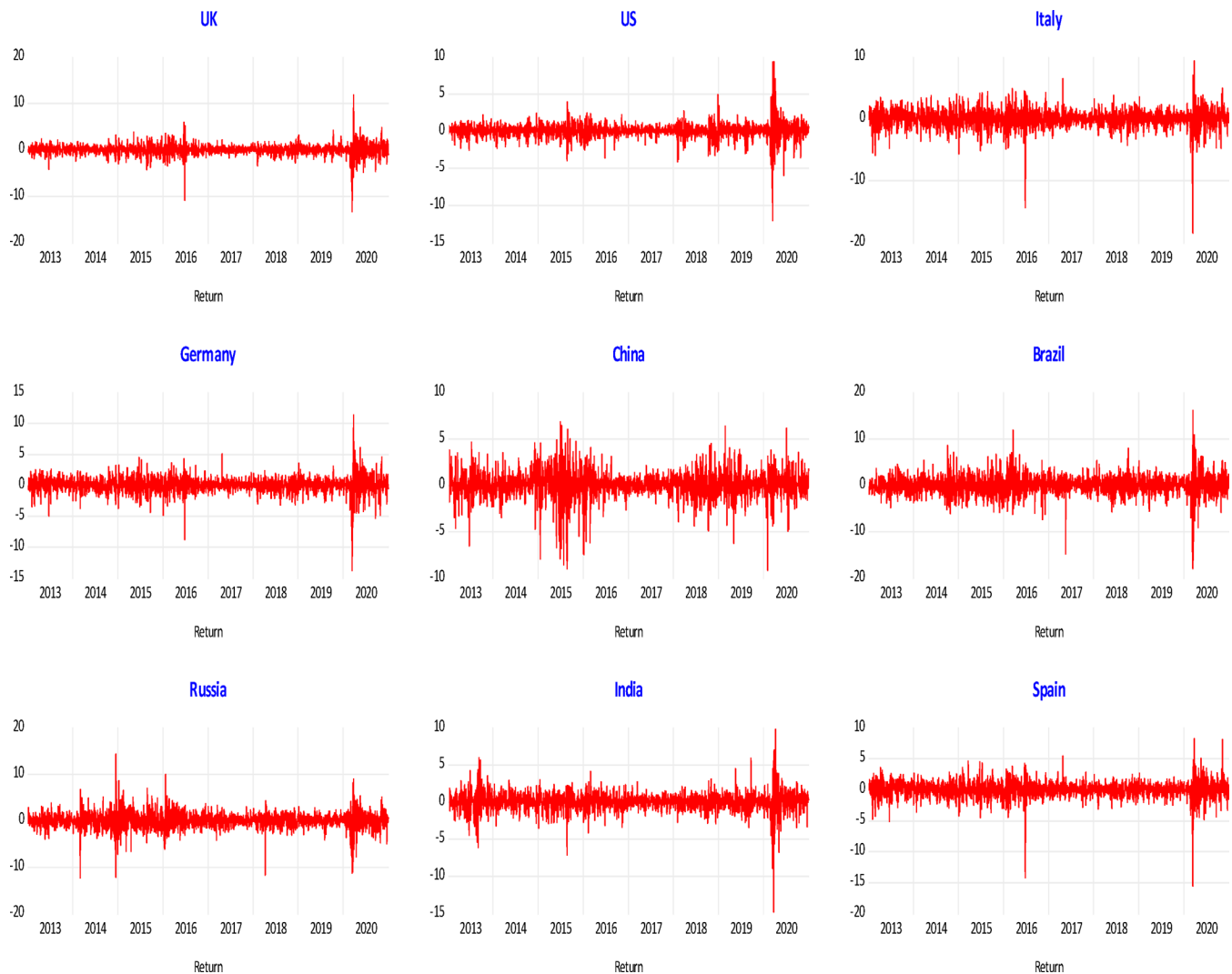


FIGURE 1 Time series plot of stock return from January 1, 2013, to December 31, 2020

December 31, 2020 which has been divided into pre COVID-19 and during COVID-19. Then, to explore how the markets initially reacted and got rebounded after the shock is being absorbed, we divide the first 6-month period during COVID-19 into two quarters to compare and examine the effect of COVID-19 over time where quarter 1 covers the period (January 1, 2020 to March 31, 2020) and quarter 2 covers the period (April 1, 2020 to June 30, 2020).

To investigate the effect of COVID-19 on the stock returns of the selected countries as a sample of this study. We have chosen the countries in our sample according to the following steps. First, we nominated the top 10 countries that have confirmed cases of COVID-19 at the end of March 2020 (quarter 1) and at the end of June 2020 (quarter 2) as shown in Figure 1. Second, we selected the intersection (repeated) countries between the two groups (quarters) which are United States, Italy, Spain, United Kingdom, and Iran. We excluded Iran from our sample where we did not find any data of return index in the DataStream for this country. Third, we selected the unrepeated countries from the top highest five countries that have confirmed cases at the end of March and June 2020 (WHO, 2020). We found that Germany and China are the

countries selected from group of March 2020 and Brazil, Russia and India are the countries selected from the group of June 2020. Finally, the total countries that should be included in our sample after excluding Iran are nine countries which are United States, Italy, Spain, United Kingdom, Germany, China, Brazil, Russia, and India.

We collected the data in a daily basis for the return indices, confirmed cases, death cases and recovered cases for the nine countries and the world. The data obtained from the DataStream and the WHO. Daily returns were computed from the return index: using log-returns $r_{i,t} = \ln(P_{i,t}/P_{i,t-1})$, where $r_{i,t}$ is return and $P_{i,t}$ are the return and the price index obtained from DataStream. More details on the list of stock indexes, and the number of confirmed cases, deaths and recovered cases per country is provided in Table B1.

3.2 | Model specification

To model the marginal distribution of returns, we use the skewed t distribution of Hansen (1994). The density probability function of

TABLE 2 Descriptive statistics of returns for pre and during COVID-19

Panel A: Descriptive statistics of returns (Pre COVID-19)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	0.0059	0.0468	0.0192	0.0268	0.0314	0.0141	0.0315	-0.0108	0.0057
Median	0.0355	0.0348	0.0347	0.0338	0.0000	0.0000	0.0069	0.0056	0.0284
Maximum	5.9245	4.9594	6.4805	5.0559	6.8463	14.2929	5.9577	12.3657	5.4454
Minimum	-10.8713	-4.0979	-14.2922	-8.7517	-8.9720	-12.3383	-7.0767	-6.6138	-14.1669
SD	0.9691	0.7929	1.3780	1.0796	1.4745	1.6564	1.0859	1.0076	1.1884
Skewness	-0.7968	-0.4670	-0.7167	-0.4296	-0.6992	-0.1340	-0.1838	0.7654	-0.9843
Kurtosis	14.8623	6.7980	10.5345	6.8779	8.7818	13.0588	6.9780	18.8094	14.9519
Panel B: Descriptive statistics of returns (During COVID-19)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	-0.0277	0.0787	0.0381	0.0704	0.1197	-0.0385	-0.0121	0.0663	-0.0079
Median	0.0715	0.1791	0.1527	0.0999	0.0599	0.0482	0.0877	0.1758	0.0000
Maximum	11.8153	9.3828	9.3046	11.3622	6.1692	16.1127	9.0132	9.7535	8.1936
Minimum	-13.2503	-11.9841	-18.3670	-13.7633	-9.1178	-17.8490	-11.2529	-14.7715	-15.5523
SD	2.0921	2.1352	2.2645	2.1562	1.5162	3.4942	2.3786	2.1748	2.1801
Skewness	-0.5975	-0.5526	-2.2623	-0.7685	-0.9316	-0.8835	-0.7567	-1.4416	-1.2572
Kurtosis	12.7612	11.1900	21.3181	12.2151	9.2821	10.2674	7.6175	14.2676	13.7444

Note: This table reports descriptive statistics for daily stock returns. Panel A reports the results during the period per-the COVID-19 period (January 1, 2013 to December 31, 2019). Panel B reports the results during the COVID-19 period (January 1, 2020 to December 31, 2020).

the rescaled skewed t distribution of Hansen has the following form:

$$f(r_{t+1}) = \begin{cases} \frac{b_t c}{\sigma_t} \left(1 + \frac{1}{\nu-2} \left(\frac{b_t(r_{t+1}-\mu_t) + a_t \sigma_t}{(1-\eta_t)\sigma_t} \right)^2 \right)^{-\frac{\nu+1}{2}} & \text{if } r_{t+1} < \mu_t - \frac{a_t}{b_t} \sigma_t \\ \frac{b_t c}{\sigma_t} \left(1 + \frac{1}{\nu-2} \left(\frac{b_t(r_{t+1}-\mu_t) + a_t \sigma_t}{(1+\eta_t)\sigma_t} \right)^2 \right)^{-\frac{\nu+1}{2}} & \text{Otherwise} \end{cases} \quad (1)$$

here r_t is the country return, μ_t is the conditional mode of the return,¹ σ_t^2 is its conditional variance, ν is the shape parameter ($2 < \nu < \infty$), the parameter η_t is the conditional skewness parameter that governs the asymmetry of the distribution ($-1 < \eta_t < 1$) and

$$a_t = 4\eta_t c \frac{\nu-2}{\nu-1},$$

$$b_t^2 = 1 + 3\eta_t^2 + a_t^2$$

$$c = \frac{\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi(\nu-2)\left(\frac{\nu}{2}\right)}}.$$

The function $\Gamma(\cdot)$ is the Gamma function given by

$$\Gamma(z) = \int_0^{+\infty} t^{z-1} \exp[-t] dt,$$

The skewed t distribution reduces to the t distribution when the skewness parameter $\eta_t = 0$. This distribution is used in financial econometrics by Patten (2018). The distribution is asymmetric to the left if $-1 < \eta_t < 0$, and it is asymmetric to the right if $0 < \eta_t < 1$.

We allow for time-varying conditional means and variances of returns. The return equation is given by $r_t = \mu_t + \varepsilon_t$,

Where

$$\mu_t = \mu + \phi r_{o,t-1} + \theta_1 D_{t-1} + \theta_2 R_{c,t-1}, \quad (2)$$

$r_{o,t-1}$ is world return, D_{t-1} the total number of death due to COVID-19 and $R_{c,t-1}$ is the total number of recovered individuals and, μ , θ_1 , θ_2 , and ϕ are constant parameters.

To capture the dynamic behavior of conditional variance and take into account the asymmetric impacts of negative versus positive return innovations, the conditional variance σ_t^2 is modeled as an asymmetric EGARCH(1,1) of Nelson (1991) augmented by additional regressors and given by

$$\ln(\sigma_t^2) = \sigma + \alpha \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \delta \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \beta \ln(\sigma_{i,t-1}^2) + \phi_1 D_{t-1} + \phi_2 R_{c,t-1} \quad (3)$$

The parameters α , β , and δ capture respectively the news effect, the volatility persistence and the leverage effect. While ϕ_1 and ϕ_2 capture the effect of the number of death and recovered cases on the volatility. If

¹Notice that, because the distribution is asymmetric, μ_t is the conditional mode rather than conditional mean.

TABLE 3 Descriptive statistics of returns for COVID-19 (Quarter 1 and 2)

Panel A: Descriptive statistics of returns (COVID-19–Quarter 1)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	−0.4920	−0.2817	−0.4676	−0.4332	−0.1689	−0.5880	−0.5501	−0.5634	−0.5116
Median	−0.1075	0.0000	0.0000	0.0000	0.0000	−0.1963	−0.1827	−0.1686	−0.1201
Maximum	11.8153	9.3828	9.3046	11.3622	3.7682	9.0132	6.9799	4.7954	8.1936
Minimum	−13.2503	−11.9841	−18.3670	−13.7633	−9.1178	−11.2529	−14.7715	−11.6703	−15.5523
SD	3.0563	3.5030	3.3811	2.9335	2.0539	3.4945	3.2786	2.4860	3.0374
Skewness	−0.3791	−0.2062	−2.2717	−0.8181	−1.3578	−0.4817	−1.4128	−1.5467	−1.7786
Kurtosis	10.1960	5.6172	15.3190	11.9562	7.2691	5.0898	8.1837	8.2286	11.8126
Panel B: Descriptive statistics of returns (COVID-19–Quarter 2)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	0.1461	0.2995	0.2559	0.3942	0.1963	0.3061	0.2908	0.2092	0.1570
Median	0.0683	0.4250	0.1741	0.4017	0.0599	0.3524	0.1786	0.3361	0.0000
Maximum	4.8707	7.0331	3.8729	6.0529	2.8512	5.3739	9.7535	4.0199	5.0776
Minimum	−4.8315	−5.8944	−5.3393	−4.4606	−2.8501	−7.7157	−6.7127	−4.5935	−4.7903
SD	2.1118	1.9766	2.1604	2.3807	0.9559	2.3143	2.3296	1.7088	2.1649
Skewness	−0.2542	−0.1233	−0.5369	−0.0708	0.1400	−0.3938	0.5056	−0.0853	−0.1120
Kurtosis	2.7575	5.0620	2.9465	2.9249	4.4629	4.0272	6.7496	3.9342	2.6639

Note: This table reports descriptive statistics for daily stock returns. Panel A reports the results during the first quarter in the COVID-19 period (Jan. 1, 2020 to March 31, 2020). Panel B reports the results during the second quarter in the COVID-19 period (April 1, 2020 to June 30, 2020).

TABLE 4 Correlation matrix

	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
United Kingdom	1.00								
	-								
United States	0.68	1.00							
	(0:00)	-							
Italy	0.87	0.66	1.00						
	(0:00)	(0:00)	-						
Germany	0.91	0.66	0.92	1.00					
	(0:00)	(0:00)	(0:00)	-					
China	0.38	0.28	0.28	0.35	1.00				
	(0:00)	(0:00)	(0:00)	(0:00)	-				
Brazil	0.66	0.75	0.67	0.66	0.31	1.00			
	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	-			
Russia	0.78	0.51	0.74	0.77	0.28	0.59	1.00		
	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	-		
India	0.61	0.39	0.56	0.56	0.45	0.51	0.49	1.00	
	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	-	
Spain	0.89	0.65	0.92	0.90	0.31	0.70	0.73	0.58	1.00
	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	(0:00)	-

Note: *p* values are in parenthesis.

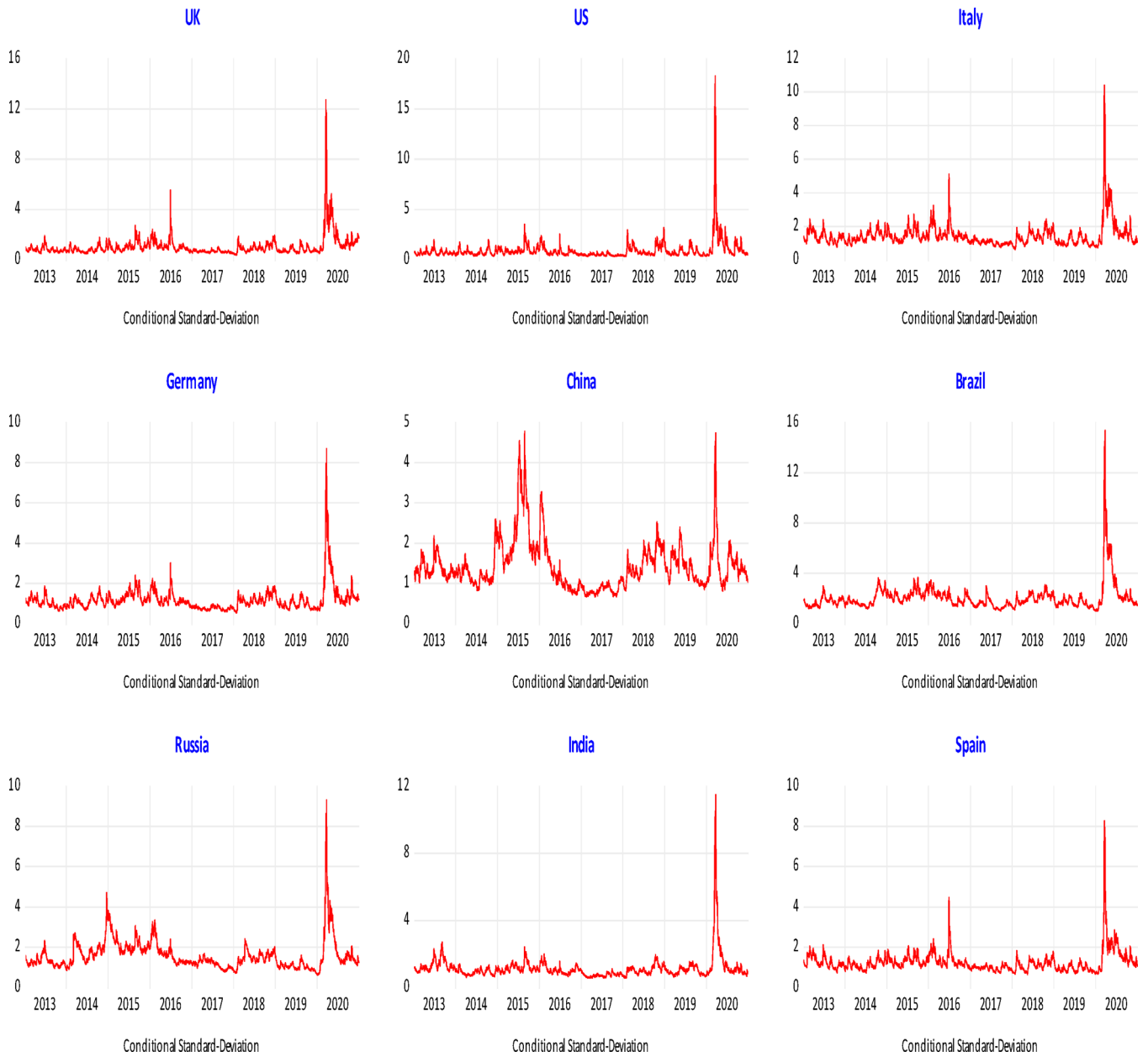


FIGURE 2 Time series plot of conditional volatility from January 1, 2013, to December 31, 2020

$\alpha - \delta < 0$ and $|\alpha - \delta| > \alpha + \delta$ then bad news have higher effect on volatility than good news. This can be seen clearly by rewriting the variance equation as

$$\ln(\sigma_t^2) = \begin{cases} \sigma + (\alpha - \delta) \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln(\sigma_{it-1}^2) + \phi_1 D_{t-1} + \phi_2 R_{c,t-1} & \text{if } \varepsilon_{t-1} < 0 \\ \sigma + (\alpha + \delta) \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln(\sigma_{it-1}^2) + \phi_1 D_{t-1} + \phi_2 R_{c,t-1} & \text{Otherwise} \end{cases} \quad (4)$$

Since $\alpha - \beta < 0$ and $|\alpha - \delta| > \alpha + \delta$, bad news ($\varepsilon_{t-1} < 0$) have higher effect on the volatility than good news ($\varepsilon_{t-1} > 0$). We use also a constant and time varying covariates to model skewness which results in time varying skewness. To constrain the conditional skewness between -1 and 1 , we use the shifted logistic function and model the conditional skewness η_t as

$$\eta_t = \frac{2}{1 + \exp[-(\kappa_0 + \kappa_1 r_{w,t-1} + \kappa_2 D_{t-1} + \kappa_3 R_{c,t-1})]} - 1,$$

where $\kappa_0, \kappa_1, \kappa_2$, and κ_3 are constant parameters capturing the skewness dynamics.

Proposition 1. The probability for the market to be in bad state ($r_{t+1} < \mu_t - \frac{a_t}{b_t} \sigma_t$) is given by²:

$$\text{Prob}\left(r_{t+1} < \mu_t - \frac{a_t}{b_t} \sigma_t\right) = \frac{1 - \eta_t}{2}$$

²Appendix A: Proof of Proposition 1.

TABLE 5 Bad state probability during periods per- and during the COVID-19

Panel A: Bad state probability (Before COVID-19)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	0.5362	0.5677	0.5525	0.5322	0.4850	0.4985	0.5299	0.5174	0.5487
Median	0.5350	0.5671	0.5529	0.5314	0.4842	0.4981	0.5295	0.5170	0.5486
Maximum	0.6035	0.6019	0.5643	0.5758	0.5268	0.5211	0.5541	0.5418	0.5576
Minimum	0.4890	0.5441	0.5346	0.5024	0.4572	0.4834	0.5136	0.5011	0.5428
SD	0.0141	0.0070	0.0036	0.0089	0.0084	0.0045	0.0049	0.0049	0.0018
Skewness	0.7147	0.7318	-0.7860	0.7431	0.7746	0.7714	0.7596	0.7641	0.7663
Kurtosis	4.6610	4.7326	4.8657	4.7506	4.8248	4.8296	4.8014	4.8118	4.8220
Panel B: Bad state probability (During COVID-19)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	0.5798	0.5472	0.5180	0.5805	0.5050	0.4863	0.4958	0.5416	0.4919
Median	0.5619	0.5625	0.5345	0.5693	0.5235	0.4814	0.5090	0.5049	0.4833
Maximum	0.7908	0.6298	0.6023	0.7390	0.6000	0.5595	0.7093	0.7798	0.5709
Minimum	0.4903	0.3683	0.2404	0.4403	0.3712	0.4361	0.0586	0.4676	0.4265
SD	0.0604	0.0495	0.0558	0.0514	0.0494	0.0208	0.1110	0.0759	0.0468
Skewness	1.8032	-1.7234	-3.1002	0.6441	-1.2085	1.0957	-2.3606	1.8215	0.2462
Kurtosis	5.6327	5.6377	12.8640	3.2700	3.8491	4.8427	9.7593	5.0637	1.5943

Note: This table reports descriptive statistics for bad state probability. Panel A reports the results during the period per-the COVID-19 period (January 1, 2013 to December 31, 2019). Panel B reports the results during the COVID-19 period (January 1, 2020 to December 31, 2020). Bad state probability is estimated using an asymmetric EGARCH (1, 1) of Nelson (1991). See model specification in Section 3.

Abbreviation: EGARCH, exponential generalized autoregressive conditional heteroscedasticity.

4 | EMPIRICAL RESULTS

Table 2 the daily stock returns for the nine countries during the period of pre-COVID-19 that starts from January 1, 2013 to December 31, 2019 and the COVID-19 period that starts from January 1, 2020 to December 31, 2020. The descriptive statistics show that the mean of stock returns for the period of pre-COVID-19 are positive for all countries in the sample except India that has a negative return as shown in Panel (A). The mean of United States refers to the highest positive stock return while Spain and United Kingdom returns experienced the lowest positive mean. On the other hand, during the period of COVID-19, Panel (B) demonstrates that the United Kingdom, Brazil, Russia and Spain have, on average, negative returns, while the United States, Italy, Germany, China, and India have positive returns. As it can be also shown in Figure 1, the markets initially exhibit a sharp decline in 2020 before being rebounded for the remainder of the year.

Next, we seek examine how the markets initially reacted and got rebounded after the shock is being absorbed. Therefore, we focus our analysis on the first 6 months that have been divided into two quarters to compare and examine the effect of COVID-19 over time where quarter 1 covers the period (January 1, 2020 to March 31, 2020) and quarter 2 covers the period (April 1, 2020 to June 30, 2020). Table 3 depicts the returns during the period of COVID-19 for the first two quarters of the year 2020. The mean of stock returns for all nine countries are negative for the quarter 1 (starts from

January 1, 2020 to March 31, 2020) which indicates that all countries had shock in their stock markets resulted from the pandemic COVID-19. Brazil, India, Russia and Spain are the highest countries that have been affected dramatically by the decrease in their stock returns. Finally, Panel (B) shows that all countries have been shifted their means of returns to be positive in the second quarter of the pandemic which indicates that these countries have taken actions and adopted some strategies to deal with the COVID-19.

Table 4 reveals that all countries are positively correlated and pairwise correlations are strongly significant. Therefore, there is no possible risk diversification for investors via buying all countries' indices. However, the investors can invest in US market and Chinese market as the market give positive average returns even during COVID-19 period as demonstrated in Table 2. This fact is supported by the results in Table 3 since the average returns during the first quarter of COVID-19 are -0.2817 for United States and -0.1689 for China exhibiting lower losses after the shock.

As demonstrated in Tables 2 and 3, all indices' returns exhibit skewed distribution with fat tails. That is, the returns have negative skewness, meaning that the probability of losing an amount of money buying a country index is higher than the probability of gaining the same amount. Also, fatter tails of the distribution of returns reveal that there is high probability to get extreme returns than the normal, that is, either extreme gains or extreme losses. In the other side, Figure 1 shows that there is a volatility clustering and volatility persistence, as there are periods of high volatility followed by periods of

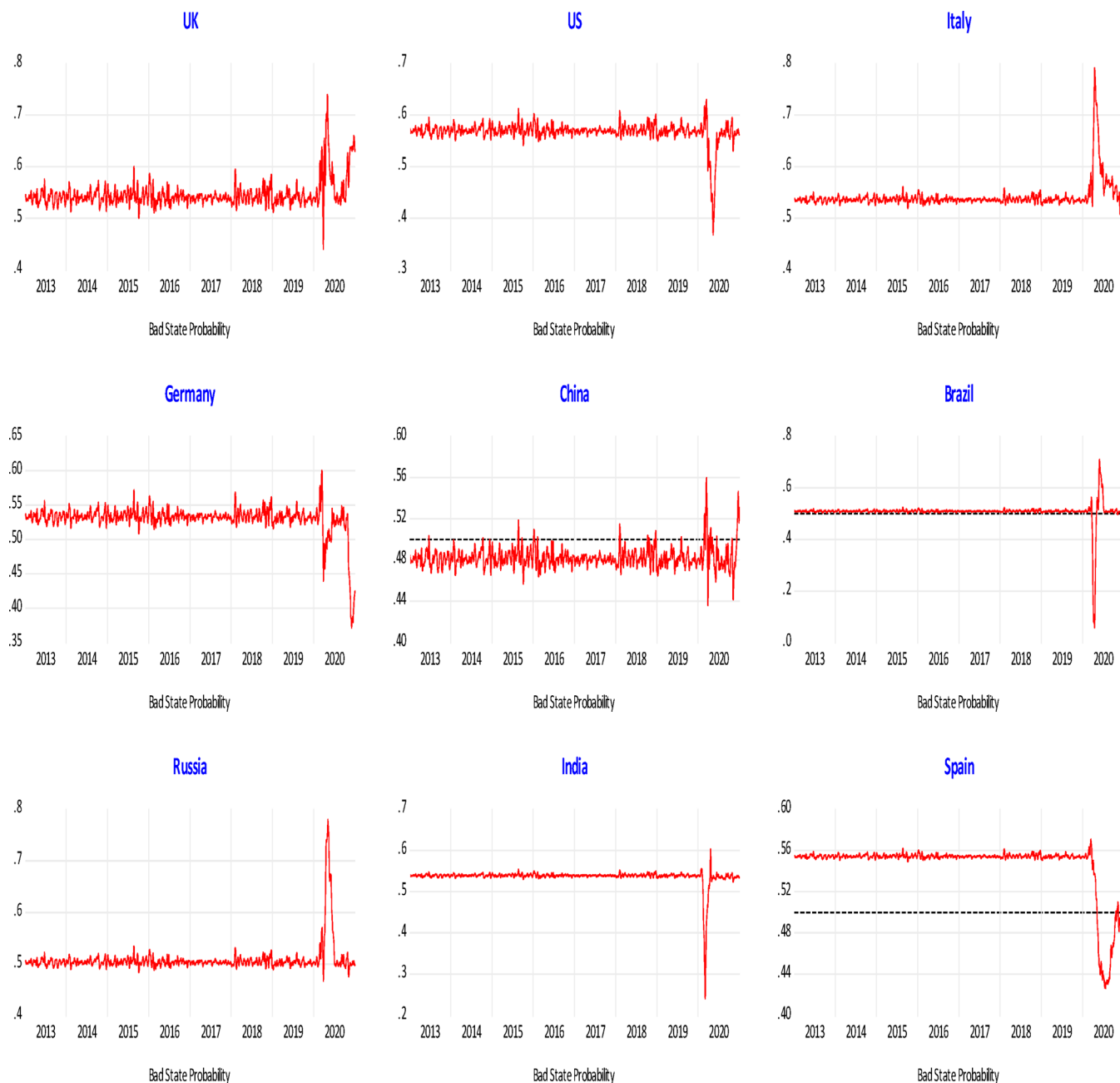


FIGURE 3 Time series plot of bad state probability from January 1, 2013, to December 31, 2020

high volatility and periods of low volatility followed by periods of low volatility. Accordingly, the conditional volatility is computed using an asymmetric EGARCH (1, 1) of Nelson (1991) to capture these stylized facts of returns. That is, the model (skewed t -distribution of Hansen) comprises two key parameters capturing the dynamics of the asymmetry and fat tailedness of the distribution. In one side, the parameter ηt controls the shape of the distribution and hence capture the degree asymmetry and hence governs the probability of bad state of the market. In the other side, the parameter ν captures the likelihood of extreme returns. Model specification is presented in Section 3.

Figure 2 displays the dynamics of the estimated conditional volatility across the selected countries. As mentioned, we compute

the conditional volatility, using an asymmetric EGARCH (1, 1) of Nelson (1991). Stock price crashes unfolded extreme volatility during the COVID-19 pandemic, which led to unprecedented rise in conditional volatilities across all the markets, as it can be apparent in the graph. Unsurprisingly, the highest levels of volatility are observed in the United States and the United Kingdom while countries, like China and Germany, exhibit less conditional volatility. The surge in new cases and deaths despite the government's efforts to mitigate the spread of COVID-19 in the United States and the United Kingdom were associated with the spread of pessimistic views and negative feelings amid both the political leadership and citizens, which has adversely affected market uncertainty. In

TABLE 6 Bad state probability during the COVID-19 period

Panel A: Bad state probability (COVID-19—First quarter)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	0.5490	0.5748	0.5642	0.5415	0.5104	0.5052	0.5361	0.5242	0.5573
Median	0.5376	0.5683	0.5528	0.5330	0.5020	0.5001	0.5304	0.5190	0.5501
Maximum	0.6418	0.6338	0.6750	0.6142	0.6144	0.5473	0.5808	0.5692	0.6388
Minimum	0.4294	0.5091	0.5324	0.4693	0.4024	0.4696	0.4931	0.4843	0.4598
SD	0.0435	0.0264	0.0377	0.0320	0.0567	0.0166	0.0185	0.0181	0.0269
Skewness	-0.0151	0.0989	2.1395	0.2484	0.1151	0.7884	0.4838	0.6865	0.6808
Kurtosis	3.5721	3.5546	6.2434	3.3359	2.2083	3.5398	3.5053	3.4929	7.4751
Panel B: Bad state probability (COVID-19—Second quarter)									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	0.6655	0.6275	0.7638	0.5082	0.4854	0.5681	0.5400	0.6327	0.4042
Median	0.6473	0.6347	0.7613	0.5140	0.4805	0.5533	0.5247	0.6428	0.3868
Maximum	0.8028	0.8487	0.8495	0.5584	0.6056	0.7598	0.7984	0.7950	0.7070
Minimum	0.5796	0.4578	0.6554	0.3997	0.4374	0.3488	0.4934	0.5079	0.1649
SD	0.0679	0.0964	0.0630	0.0407	0.0324	0.1047	0.0594	0.0754	0.1776
Skewness	0.5293	-0.1579	-0.2771	-1.2338	1.9720	0.1336	2.7601	-0.0306	0.0394
Kurtosis	1.9312	2.2201	1.6978	3.9283	7.3752	2.4528	10.5667	1.9907	1.4047

Note: This table reports descriptive statistics for bad state probability. Panel A reports the results during the first quarter in the COVID-19 period (January 1, 2020 to March 31, 2020). Panel B reports the results during the second quarter in the COVID-19 period (April 1, 2020 to June 30, 2020). Bad state probability is estimated using an asymmetric EGARCH (1, 1) of Nelson (1991). See model specification in Section 3.

Abbreviation: EGARCH, exponential generalized autoregressive conditional heteroscedasticity.

contrast, the stock markets in China and Germany appear to have suffered less and the prompt intervention of their governments to control the spread of the virus appeared to convey positive signals to the investors and mitigate the prevailing market uncertainty. As it can be also shown, the excessive increase in conditional volatility appears not to be persistent during the COVID-19 period as for all the markets the figure exhibits a significant fall in the conditional volatility once the shock has been absorbed.

As any other major crisis, the initial market reaction to the COVID-19 pandemic is associated with panic, uncertainty, negative sentiment and investor pessimism, which exerted an adverse impact on the financial markets. To get more insights into this impact, we estimate the bad state probabilities to compare how the likelihood of bad events differs across the periods pre- and during the COVID-19 (to examine the initial effect of the shock of COVID-19 on the markets) and between the first and second quarters during the COVID-19 period (to examine whether the markets get rebounded after the shock is being assessed and absorbed). As demonstrated in Table 5 and Figure 3, the impact of the COVID-19 was visible worldwide on the major equity markets, which generally experienced noticeable increase in bad state probabilities, indicating that market participants perceived the event as a global shock and so it has reflected on their adverse expectation with respect to the market behavior. In comparison with the time period before COVID-19, we observe—on average—an increase in bad state probabilities across the United Kingdom, Germany, Brazil and India. In contrast, the United States, Russia, China, Italy, and Spain exhibit a decrease in bad state probabilities.

Again, these findings should not be surprising due to the pessimistic views and negative feelings which were prevailing amid both the political leadership and citizens in markets, such as the United Kingdom and Germany, after the COVID-19 pandemic; in contrast other markets (e.g., Russia and China) were associated with relatively lower market uncertainty not only due to their economic/political strength but also to their prompt response to markets' fears and investors' worries. It is also worth mentioning that bad state probability exhibited larger SD and maximum values in all the markets, which indicates that the probability of stock market declines becomes more volatile and is expected to move up to larger highest values compared the period pre-COVID-19 pandemic.

A closer examination of the behavior of bad state probability during the first two quarters in the COVID-19 period, as displayed in Table 6, reveals that bad state probability differs during the second quarter in the COVID-19 period (April 1, 2020 to June 30, 2020) as compared to that of the first quarter period (January 1, 2020 to March 31, 2020). This difference between the two quarters varies across countries. For example, except for Germany, China and Spain, bad state probability becomes—on average—higher during the second quarter. As expected, Italy exhibits the highest increase in bad state probability (by ~35% from 0.5642 to 0.7638) during the second quarter in the COVID-19 period caused by soaring levels of uncertainty and investors' pessimism due to the surge in new cases and deaths despite the government's efforts (e.g., lockdowns, stimulus packages and travel bans) to mitigate the spread of COVID-19. Again, among the markets that experienced higher bad state probability during the

TABLE 7 The influence of COVID-19 deaths and recovered cases on stock returns, conditional volatility, and conditional skewness

	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Panel A: Mean return									
W.Return	0.21452***	-0.05065**	0.1165***	0.19813***	0.22967***	0.03282	0.26894***	0.35395***	0.21442***
Death	0.000085	-0.00055	-0.00014*	0.00045	0.00110	-0.00094	0.00400	-0.00191	0.00019
Recovery	0.00764***	-0.00029	0.000044**	-0.0000	-0.0000	0.00104***	-0.00025	0.00014	-0.0000
Panel B: Conditional volatility									
W.Return	-0.13901***	-0.14547***	-0.09288***	-0.07532***	-0.05982***	-0.0856***	-0.07210***	-0.07293***	-0.08029***
Death	0.00018***	0.00719*	0.0000***	0.0000*	-0.00013	-0.0000	0.00077	0.00015	0.0000*
Recovery	0.00068	-0.0000	-0.000016***	-0.0000	0.0000	0.0000	-0.0000	0.0000*	-0.0000
Panel C: Conditional skewness									
W.Return	0.17341***	0.12271**	0.06966	0.10813**	0.10326***	0.03841	0.08670*	0.03899	0.02154
Death	-0.00069***	0.00916	-0.00036**	0.00014	-0.0005	0.00738***	-0.00611	-0.00151	0.00030
Recovery	0.01420**	0.00083	0.0000*	0.0000*	0.0000	-0.00225*	0.00011	0.00036	0.0000

Note: This table provides the results from the regression estimation of COVID-19 deaths and recovered cases on stock returns, conditional volatility and conditional skewness. Dependent variable is mean return that represents the daily percentage changes in the selected markets' stock indices in Panel A, while it is conditional volatility modeled using an asymmetric EGARCH(1,1) of Nelson (1991) in Panel B, and it is conditional skewness estimated using an asymmetric EGARCH(1,1) of Nelson (1991) in Panel C. See model specification in Section 3. W.Return is average daily percentage returns of MSCI World Index; Death is the total number of daily deaths; Recovery is the total number of daily recovered cases.

Abbreviation: EGARCH, exponential generalized autoregressive conditional heteroscedasticity.

*Significant at 10%.

**Significant at 5%.

***Significant at 1%.

TABLE 8 Diagnostic tests

	JB	CM	W	AD
United Kingdom	3:11 (0:21)	0:06 (0:81)	0:05 (0:68)	0:40 (0:84)
United States	5:04 (0:08)	0:11 (0:54)	0:11 (0:24)	0:76 (0:51)
Italy	2:47 (0:29)	0:10 (0:56)	0:09 (0:33)	0:82 (0:47)
Germany	2:00 (0:37)	0:04 (0:95)	0:03 (0:88)	0:26 (0:96)
China	9:08 (0:02)	0:16 (0:37)	0:13 (0:14)	1:19 (0:27)
Brazil	7:39 (0:02)	0:31 (0:13)	0:28 (0:01)	2:12 (0:08)
Russia	6:12 (0:05)	0:19 (0:29)	0:19 (0:05)	1:40 (0:20)
India	4:24 (0:12)	0:05 (0:88)	0:05 (0:76)	0:37 (0:88)
Spain	0:06 (0:97)	0:05 (0:88)	0:05 (0:68)	0:38 (0:87)

Abbreviations: AD, Anderson–Darling test; CM, Cramer–von Mises test; JB, Jarque–Bera test; W, Watson test.

second quarter, Russia has the lowest increase (by 0.73% from 0.5361 to 0.5400), which can be attributed to Russia's policies that helped subdue panic and so mitigated the adverse effects of the pandemic on the stock markets, in addition to the impact of the positive news associated with Russia's experimental COVID-19 vaccines. On the other hand, China, Germany and Spain experienced lower bad state probability during the second quarter in the COVID-19 period, which might reflect that investors' confidence has been resorted, and so stock markets in these counties have recovered quicker than the other markets. The prompt intervention of the government in China and Germany to control the spread of the virus managed to maintain business and confidence and conveyed positive signals to the stock markets, whereas in Spain the noticeable decline in daily new cases and deaths starting from April might have positively influenced the financial markets and so reflected on the fall in bad state probability in the second quarter during the COVID-19 period. Taken together, these findings suggest that for risk-averse investors, Chinese market is more attractive since the average of bad state probability is the lowest among all countries and is less than 50% during the second quarter of COVID-19 period as shown in Tables 5 and 6.

After gaining insights into how the risk–return behavior of stock markets differed across the periods pre- and during the COVID-19 and between the first and second quarters during the COVID-19 period, we further investigate the impact of COVID-19 (proxied by the number of deaths and recovery cases) on stock returns, conditional volatility and conditional skewness. Table 7 reports the results. Our dependent variable is mean return that represents the daily percentage changes in the selected markets' stock indices in Panel A, while it is conditional volatility modeled using an asymmetric EGARCH (1,1) of Nelson (1991) in Panel B, and it is conditional skewness estimated using an asymmetric EGARCH

(1,1) of Nelson (1991) in Panel C. In general, our results are in line with the findings on the adverse impact of financial crises in general (e.g., Novotny, 2010; Sarkar & Patel, 1998) and the COVID-19 pandemic in specific (e.g., Baek et al., 2020; Chaudhary et al., 2020; Zhang et al., 2020). Particularly, for our independent variable “mean return,” we observe a consistently negative relationship between coronavirus death cases and stock return only in the Italy, whereas the coefficients are insignificant in the other markets. As for the impact of recovery, the coefficient is only consistently positive and statistically significant in the United Kingdom, Italy and Brazil while it remains insignificant in other markets. In economic terms, an increase in death cases by 1000—in Italy, for example,—is associated with about 0.014% decrease in average stock returns while an increase in recovered cases by 1000 is associated with about 0.0044% increase in average stock returns.

With respect to our dependent variable “conditional volatility,” the number of coronavirus death cases is found to be significantly positively associated with conditional volatility in the United Kingdom, the United States, Italy, Germany, and Spain. For example, an increase in the number of death cases in the United Kingdom by 1000 is associated with about a 0.018% increase in conditional volatility. In contrast, the findings across the other markets exhibit generally insignificantly positive coefficients (Russia, and India) or inconsistently negative coefficients (Brazil and China). The findings on the impact of recovered cases reveal a consistently negative and significant association only in Italy. For our dependent variable “conditional skewness,” we find a significant impact of the number of deaths on conditional skewness in the United Kingdom, Italy, and Brazil. We observe mixed results on the relationship with number of recovered cases and conditional skewness across the markets.

5 | ROBUSTNESS TESTS

To further explore the robustness of our analysis, diagnoses tests will be performed as follows:

The CDF skewed t distribution of Hansen is given by

$$F(r_{t+1}) = \begin{cases} \frac{1-\eta_t}{2} T\left(\frac{b_t(r_{t+1}-\mu_t)+a_t\sigma_t}{(1-\eta_t)\sigma_t}, \nu\right) & \text{if } r_{t+1} < \mu_t - \frac{a_t\sigma_t}{b_t} \\ \frac{1-\eta_t}{2} + \frac{1+\eta_t}{2} T\left(\frac{b_t(r_{t+1}-\mu_t)+a_t\sigma_t}{(1+\eta_t)\sigma_t}, \nu\right) & \text{Otherwise} \end{cases}$$

Let $\varepsilon_{t+1} = r_{t+1} - \mu_t$ be the error term, then the distribution of ε_{t+1} is

$$F(\varepsilon_{t+1}) = \begin{cases} \frac{1-\eta_t}{2} T\left(\frac{b_t\varepsilon_{t+1}+a_t\sigma_t}{(1-\eta_t)\sigma_t}, \nu\right) & \text{if } \varepsilon_{t+1} < -\frac{a_t\sigma_t}{b_t} \\ \frac{1-\eta_t}{2} + \frac{1+\eta_t}{2} T\left(\frac{b_t\varepsilon_{t+1}+a_t\sigma_t}{(1+\eta_t)\sigma_t}, \nu\right) & \text{Otherwise} \end{cases}$$

If the model is well specified, then $u_{t+1} = F(\varepsilon_{t+1})$ will follow the uniform distribution on (0, 1). In addition, the standardized residual $Z_{t+1} = \Phi^{-1}(u_{t+1})$ will follow the normal distribution with mean zero

³We note that lower value of ν means fatter tails and thus higher likelihood of extreme returns. We also note that when $\nu \geq 30$, the normal distribution approximate very well the Student distribution.

TABLE 9 ARCH-LM test for conditional heteroscedasticity

Panel A: Residuals autoregressive conditional heteroscedasticity LM test									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Statistic	278.9342	798.0081	132.7790	252.9038	209.8375	580.3271	299.4189	500.9419	164.2774
p value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: This table reports residuals autoregressive conditional heteroscedasticity LM test (ARCH test).

TABLE 10 Descriptive statistics of GARCH volatility and model's implied volatility estimates

Panel A: Descriptive statistics of GARCH volatility estimate									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	1.7663	1.7979	2.5892	1.8007	2.4452	5.3868	3.1208	1.8084	1.8911
Median	0.7329	0.4883	1.6719	1.1545	1.6705	3.3963	1.9388	1.0192	1.3203
Maximum	152.7427	315.4359	110.2596	81.2990	22.6002	212.1903	81.7621	130.1726	70.6085
Minimum	0.1561	0.1058	0.3961	0.2977	0.4427	0.9992	0.3907	0.3148	0.4380
SD	7.0897	12.1587	5.3752	4.1293	2.5897	11.5398	4.7278	6.2353	3.6070
Skewness	15.0822	18.0271	12.8925	11.9263	3.6957	11.4057	8.9267	13.8604	13.0494
Kurtosis	264.4052	367.1540	206.1879	175.2792	20.4280	163.1646	114.4171	223.4008	203.6618
Panel B: Descriptive statistics of conditional variance estimate									
	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Mean	2.8938	3.0164	3.2559	2.1051	2.5414	8.4952	3.6843	2.0532	2.0798
Median	0.7808	0.5571	1.7562	1.1948	1.6934	3.4044	1.9404	1.0668	1.4317
Maximum	613.6490	1065.3360	228.3696	173.5321	43.0289	633.4338	124.5595	174.0941	94.4947
Minimum	0.1575	0.1210	0.4045	0.3016	0.4482	1.0015	0.3919	0.3244	0.4753
SD	20.4377	33.2760	9.5061	7.1241	2.9790	35.5551	7.9912	7.7245	4.2972
Skewness	22.8204	25.6049	14.4875	16.0421	5.0390	11.0604	8.6459	13.5524	14.2181
Kurtosis	609.7289	727.8897	282.3976	312.5928	41.8738	147.6355	95.3432	224.7273	243.1128

Note: This table reports descriptive statistics for GARCH volatility and model's implied volatility estimates.

TABLE 11 Skewness (degree of asymmetry)

	United Kingdom	United States	Italy	Germany	China	Brazil	Russia	India	Spain
Skewness	-0.0928	-0.1362	-0.0838	-0.0587	0.0348	-0.0148	-0.0178	-0.0742	-0.0924
Kurtosis	6.5146	5.6191	6.3843	5.3717	3.5579	4.7521	4.5341	4.4694	7.1694

and SD one, where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution and $\Phi^{-1}(\cdot)$ is its quantile, that is, $\Phi^{-1}(\cdot)$ is the inverse of $\Phi(\cdot)$. To assess the quality of the model (robustness check) and test the specification of the models, we estimated residual $\hat{u}_{t+1} = F(\hat{\varepsilon}_{t+1})$ which under a correct specification should be independent and uniformly distributed. Following Vlaar and Palm (1993) and Berkowitz (2001), if the model is well specified, the estimated residual $\hat{Z}_{t+1} = \Phi^{-1}(\hat{u}_{t+1})$ follows the standard normal distribution with mean zero and SD one. Using the normalized run four classical tests: Cramervon Mises, Anderson-Darling, Watson empirical distribution, and Jarque-Bera tests. Table 8 summarized the results of the four tests. We notice from the table that the null hypothesis that the model is well specified is not rejected at least at 1% confidence level

for all the four test and hence the model does capture all the stylized facts highlighted in the literature concerning returns.

As mentioned before, since normal GARCH model link directly the kurtosis to the variance, it is unable to well capture the excess kurtosis that exists present in financial returns, resulting in having low probability of extreme realizations (extreme returns) than observed in the data. Therefore, we also conduct a Lagrange multiplier (LM) test for the presence of GARCH effect, as Table 9 illustrates, the null hypothesis is strongly rejected for all countries, testifying for the existence of the effect of GRACH on extreme returns.

In addition, Table 10 provides the descriptive statistics of the GARCH conditional volatility and conditional variance of the proposed model. While in the normal GARCH they are equal, in our model the

conditional variance is higher than the GARCH volatility. This testifies that the estimated risk implied by the proposed model is higher than in the normal case, with the case of Brazil exhibiting the highest level. Furthermore, in the normal GARCH model the distribution is symmetric (skewness = 0) meaning that there is equal probability of losing or gaining the same amount of money investing in the financial market, the results of our model produces in average negative skewness ($\eta < 0$) as Table 11 (second row) shows. These results signify that the distribution is left asymmetric which translate in higher probability of losing an amount of money than gaining the same amount except for the case of China where $\eta > 0$ and hence the likelihood of gain is higher than the likelihood of loss.

The model also captures also the likelihood of extreme events (extreme returns) since the kurtosis parameter ν is small than 30^3 (infinite for the normal distribution) as Table 11 (third row) shows. It is even smaller for the case of China, Brazil, Russia, and India compared with other countries, attesting that the likelihood of extreme returns is higher in the emerging countries than the developing ones. We mention that the case of China is the most extreme.

6 | CONCLUSION

This study attempts to explain how COVID-19 pandemic has affected the stock market behavior of international equity indices in nine markets. Unlike other studies we focus on several dimensions of a stock market, that is, stock returns, conditional volatility, conditional skewness, and bad state probability, measured using an asymmetric exponential GARCH model. Furthermore, we have examined the influence of COVID-19-related death cases and recovered cases on these indicators. Unsurprisingly, our findings show that COVID-19 has exerted adverse impact on major equity markets, which led to unprecedented rise in conditional volatilities and bad state probabilities across all the markets. However, this impact is not symmetric across all the markets. For example, China and Germany exhibit less conditional volatility; in contrast, Italy, the United States and the United Kingdom experience excessive volatility and bad state probability. Furthermore, we also find that the excessive increase in conditional volatility appears not to be persistent during the COVID-19 period as for all the markets the conditional volatility exhibits a significant fall once the shock has been absorbed. With respect to the impact of COVID-19-related deaths and recovered cases on stock price behavior, the overall findings reveal that the negative affect of deaths is more pronounced, compared to the positive impact of recovered cases. These findings confirm prior empirical findings on the adverse impact triggered by financial crises (Novotny, 2010; Sarkar & Patel, 1998) and the COVID-19 pandemic (Baek et al., 2020; Chaudhary et al., 2020; Zhang et al., 2020). Moreover, our findings provide important implications for investors, practitioners and policy makers. For traders and investors seeking to invest in international stock markets, the results indicate which markets are most correlated and risky, which have strong consequences for portfolio optimization and implementation of profitable trading strategies. For practitioners, the findings allow to get insights into the dynamic behavior of stock markets in the countries that are heavily affected by

the pandemic in order to examine the best investment options. For policy makers, the findings confirm the critical role that the political leadership and governments can play, via mitigating the spread of pessimistic views and negative feelings amid citizens, in conveying positive signals to the investors and thereby decreasing market uncertainty.

AUTHOR CONTRIBUTIONS

Mohamed A. K. Basuony developed the idea, collected all the required data, and drafted and revised the manuscript, in addition to supervising the work. Mohammed Bouaddi performed the model and empirical analysis (tables and figures), in addition to writing the methodology. He also revised the manuscript. Heba Ali wrote and interpreted the empirical results, introduction and conclusion, in addition to revising the final manuscript. Rehab EmadEldeen wrote the literature section and provided a summary table of all the papers, in addition to revising the final manuscript. All authors read and approved the final manuscript.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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REFERENCES

- Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2020). Financial contagion during COVID-19 crisis. *Finance Research Letters*, 38, 101604. <https://doi.org/10.1016/j.frl.2020.101604>
- Alberg, E., Shalit, H., & Yosef, R. (2008). Estimating stock market volatility using asymmetric GARCH models. *Applied Financial Economics*, 18, 1201–1208.
- Albulescu, C. (2020). COVID-19 and the United States financial markets' volatility. *Finance Research Letters*, 38, 101699. <https://doi.org/10.1016/j.frl.2020.101699>
- Baek, S., Mohanty, S., & Glambsky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters*, 37, 101748. <https://doi.org/10.1016/j.frl.2020.101748>
- Baig, A., Butt, H., Haroon, O., & Rizvi, S. (2021). Deaths, panic, lockdowns and US equity markets: The case of COVID-19 pandemic. *Finance Research Letters*, 38, 101701. <https://doi.org/10.1016/j.frl.2020.101701>
- Baker, S., Bloom, N., Davis, S., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market impact of COVID-19. *National Bureau of Economic Research*, 26945.
- Berkowitz, J. (2001). Testing density forecasts, with applications to risk management. *Journal of Business & Economic Statistics*, 19(4), 465–474.
- Bissoondoyal-Bheenick, E., Do, H., Hu, X., & Zhong, A. (2020). Learning from SARS: Return and volatility connectedness in COVID-19. *Finance Research Letters*, 41, 101796. <https://doi.org/10.1016/j.frl.2020.101796>
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31, 307–327.
- Chaudhary, R., Bakhshi, P., & Gupta, H. (2020). Volatility in international stock markets: An empirical study during COVID-19. *Journal of Risk and Financial Management*, 13(9), 208. <https://doi.org/10.3390/jrfm13090208>
- Choi, S. (2020). Industry volatility and economic uncertainty due to the COVID-19 pandemic: Evidence from wavelet coherence analysis. *Finance Research Letters*, 37, 101783. <https://doi.org/10.1016/j.frl.2020.101783>

- Conlonm, T., & McGee, R. (2020). Safe haven or risky hazard? bitcoin during the COVID-19 bear market bitcoin during the COVID-19 bear market. *Finance Research Letters*, 35, 101607.
- Corbet, S., Hou, Y., Hu, Y., Lucey, B., & Oxley, L. (2020). Aye Corona! The contagion effects of being named Corona during the COVID-19 pandemic. *Finance Research Letters*, 38, 101591. <https://doi.org/10.1016/j.frl.2020.101591>
- Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50, 987–1007.
- Gharib, C., Mefteh-Wali, S., & Jabeur, S. (2021). The bubble contagion effect of COVID-19 outbreak: Evidence from crude oil and gold markets. *Finance Research Letters*, 38, 101703.
- Goodell, J. (2020). COVID-19 and finance: Agendas for future research. *Finance Research Letters*, 35, 101512. <https://doi.org/10.1016/j.frl.2020.101512>
- Harvey, C., & Siddique, A. (1999). Conditional skewness in asset pricing tests. *The Journal of Financial and Quantitative Analysis*, 34, 465–487.
- Hansen, B. (1994). Autoregressive conditional density estimation. *International Economic Review*, 35(3), 705–730.
- He, P., Sun, Y., Zhang, Y., & Li, T. (2020). COVID-19's impact on stock prices across different sectors—An event study based on the Chinese stock market. *Emerging Markets Finance and Trade*, 56(10), 2198–2212. <https://doi.org/10.1080/1540496X.2020.1785865>
- He, Q., Liu, J., Wang, S., & Yu, J. (2020). The impact of COVID-19 on stock markets. *Economic and Political Studies*, 8(3), 275–288. <https://doi.org/10.1080/20954816.2020.1757570>
- Hentschel, L. (1995). All in the family: Nesting symmetric and asymmetric GARCH models. *Journal of Financial Economics*, 39, 71–104.
- IMF. (2020, April). *The great lockdown*. Retrieved from <https://www.imf.org/en/Publications/WEO/Issues/2020/04/14/weo-april-2020>.
- Jelilov, G., Iorember, P., Usman, O., & Yua, P. (2020). Testing the nexus between stock market returns and inflation in Nigeria: Does the effect of COVID-19 pandemic matter? *Journal of Public Affairs*, 20, 1–9. <https://doi.org/10.1002/pa.2289>
- Just, M., & Echaust, K. (2020). Stock market returns, volatility, correlation and liquidity during the COVID-19 crisis: Evidence from the Markov switching approach. *Finance Research Letters*. doi: <https://doi.org/10.1016/j.frl.2020.101775>, 37, 101775
- Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money*, 21(1), 92–106. <https://doi.org/10.1016/j.intfin.2010.08.005>
- Kotishwar, A. (2020). Impact of COVID-19 pandemic on stock market with reference to select countries—A study. *Academy of Accounting and Financial Studies Journal*, 24(4), 1–9.
- Liu, H., Manzoor, A., Wang, C., Zhang, L., & Manzoor, Z. (2020). The COVID-19 outbreak and affected countries stock markets response. *International Journal of Environmental Research and Public Health*, 17(8), 2800. <https://doi.org/10.3390/ijerph17082800>
- Lyocsa, S., & Molnár, P. (2020). Stock market oscillations during the corona crash: The role of fear and uncertainty. *Finance Research Letters*, 36, 101707.
- Ma, C., Rogers, J., & Zhou, S. (2020). *Global economic and financial effects of 21st century pandemics and epidemics*. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3565646.
- Mazur, M., Dang, M., & Vega, M. (2020). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance Research Letters*, 38, 101690. <https://doi.org/10.1016/j.frl.2020.101690>
- Narayan, P., Phan, D., & Liu, G. (2020). COVID-19 lockdowns, stimulus packages, travel bans, and stock returns. *Finance Research Letters*, 38, 101732. <https://doi.org/10.1016/j.frl.2020.101732>
- Nelson, D. (1991). Conditional heteroskedasticity in asset return: A new approach. *Journal of the Econometric Society*, 59(2), 347–370. doi: <https://doi.org/10.2307/2938260>
- Novotny, J. (2010). *Were stocks during the financial crisis more jumpy: A comparative study* (Vol. 416). Center for Economic Research and Graduate Education and Economics Institute (CERGEE) Working Paper Series.
- Patten, J. (2018). Time-varying systemic risk: Evidence from a dynamic copula model of CDS spreads. *Journal of Business & Economic Statistics*, 36(2), 181–195.
- Ramelli, S., & Wagner, A. (2020). Feverish stock price reactions to COVID-19. *Swiss Finance Institute Research*, 9, 622–655. <https://doi.org/10.1093/rcfs/cfaa012>
- Sarkar, A., & Patel, S. (1998). Stock market crises in developed and emerging markets (SSRN 76168). <https://doi.org/10.2139/ssrn.76168>
- Sharif, A., Aloui, C., & Yarovaya, L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. *International Review of Financial Analysis*, 70, 101496. <https://doi.org/10.1016/j.irfa.2020.101496>
- Tsay, R. (2010). *Analysis of financial time series*. John Wiley & Sons.
- Waheed, R., Sarwar, S., Sarwar, S., & Khan, M. (2020). The impact of COVID-19 on Karachi stock exchange: Quantile-on-quantile approach using secondary and predicted data. *Journal of Public Affairs*, 20(4), e2290. <https://doi.org/10.1002/pa.2290>
- WHO. (2020). *Coronavirus disease (COVID-19), situation report 152*. Retrieved from <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports/>.
- Yousef, I. (2020). Spillover of COVID-19: Impact on stock market volatility. *International Journal of Psychosocial Rehabilitation*, 24(6), 18069–18081.
- Vlaar, P. J., & Palm, F. C. (1993). The message in weekly exchange rates in the European monetary system: mean reversion, conditional heteroscedasticity, and jumps. *Journal of Business & Economic Statistics*, 11(3), 351–360.
- Zaremba, A., Kizys, R., Aharon, D., & Demir, E. (2020). Infected markets: Novel coronavirus, government interventions, and stock return volatility around the globe. *Finance Research Letters*, 35, 101597. <https://doi.org/10.1016/j.frl.2020.101597>
- Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 36, 101528. <https://doi.org/10.1016/j.frl.2020.101528>

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APPENDIX A

In the following proof, we derive the probability of bad state. The probability π_t at time t of the market to be in bad state at time $t + 1$ is given by

$$\pi_t = \text{Prob}\left(r_{t+1} < \mu_t - \frac{a_t}{b_t}\sigma_t\right) = \int_{-\infty}^{\mu_t - \frac{a_t}{b_t}\sigma_t} \frac{b_t c}{\sigma_t} \left(1 + \frac{1}{\nu-2} \left(\frac{b_t(r_{t+1} - \mu_t) + a_t\sigma_t}{(1-\eta_t)\sigma_t}\right)^2\right)^{-\frac{\nu+1}{2}} dr_{t+1}$$

Let $z_t = \frac{b_t(r_{t+1} - \mu_t) + a_t\sigma_t}{(1-\eta_t)\sigma_t}$, then

$$\pi_t = \int_{-\infty}^{\frac{a_t}{b_t}\sigma_t} \frac{b_t c}{\sigma_t} \left(1 + \frac{1}{\nu-2} \left(\frac{b_t(r_{t+1} - \mu_t) + a_t\sigma_t}{(1-\eta_t)\sigma_t}\right)^2\right)^{-\frac{\nu+1}{2}}$$

$$dr_{t+1}$$

$$= (1-\eta_t) \int_{-\infty}^0 c \left(1 + \frac{1}{\nu-2} z_{t+1}^2\right)^{-\frac{\nu+1}{2}} dz_{t+1} = (1-\eta_t)(0, \nu) = \frac{1-\eta_t}{2}$$

The last equality follows from the fact that $T(\chi, \nu)$ is the CDF of the standard Student t distribution of χ (with degree of freedom ν) evaluated at zero.

TABLE B1 Descriptive statistics

Panel A: List of stock indexes							
Country	Index						
United Kingdom	FTSE100						
United States	S&P 500 COMPOSITE						
Italy	FTSE MIB INDEX						
Germany	DAX 30 PERFORMANCE						
China	SHANGHAI SHENZHEN CSI 300						
Brazil	BRAZIL BOVESPA						
Russia	MOEX RUSSIA INDEX						
India	The BSE SENSEX						
Spain	IBEX 35						

Panel B: COVID-19 related cases							
Country	Confirmed cases		Death cases		Recovered cases		
	June, 30	March, 31	June, 30	March, 31	June, 30	March, 31	
United Kingdom	221,904	17,766	43,730	1789	344	135	
United States	1,912,534	134,071	127,393	3883	781,655	5507	
Italy	166,865	71,844	34,767	12,428	190,248	15,729	
Germany	143,512	47,094	8957	687	177,795	13,656	
China	64,450	63,056	4634	3311	78,479	76,238	
Brazil	1,044,929	4135	59,594	201	790,040	127	
Russia	457,063	1703	9320	17	412,650	121	
India	396,142	1070	16,893	35	334,821	123	
Spain	194,143	69,802	28,355	8464	150,376	19,259	

Note: This table reports the list of stock indexes (Panel A), and the number of confirmed cases, deaths and recovered cases per country.