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The impact of COVID-19 shocks on the volatility of stock markets in technologically advanced countries

Ning Zhang[a], Aiqun Wang[a], Naveed-Ul- Haq[b] and Safia Nosheen[b]

[a]School of Management, Jilin University, Changchun, China; [b]Department of Finance, University of Management and Technology, Lahore, Pakistan

ABSTRACT

This study examines the volatility of China and the most advanced countries of the world stock markets due to the pandemic of COVID-19 using the TGARCH model. This research study presents empirical support for the TGARCH specification for explaining the daily time dependence in the rate of information arrival to the market for stocks traded on China stock market. Using the sample containing closing stock market returns from 05 January 2015 to 04 April 2020 of sample countries, we found that through the COVID-19, there is no significant impact of returns volatility coming from advanced countries towards the China stock market. Further, results state that China has a significant impact on explaining the volatility of the most advanced countries of the world (Switzerland, Sweden, Netherlands, and the UK) except the U.S.A. during COVID-19. We found no significant impact of China stock market returns on the U.S.A.'s volatility, but there is a presence of leverage effect during COVID −19.

1. Introduction

The economic impact of the COVID-19 announcement as a pandemic may be short-term. However, this shock wave could badly affect the stock market over the long term. We are facing one of the biggest pandemics in history that transferred across the world. Due to the pandemic's impact, investors and markets face a high degree of uncertainty regarding both the physical and financial. The latest COVID-19 outbreak results in extraordinary volatility around all the leading financial markets. This situation guided the World Health Organisation (WHO) to announce the COVID-19 pandemic. Starting from February 2020, several shock waves were noticed in stock markets due to the current outbreak. This causes a continued increase in financial volatility in the perspective of COVID-19 uncertainty. Albulescu (2021) documented that the real economy is severely affected by this pre-pandemic period of COVID-19,

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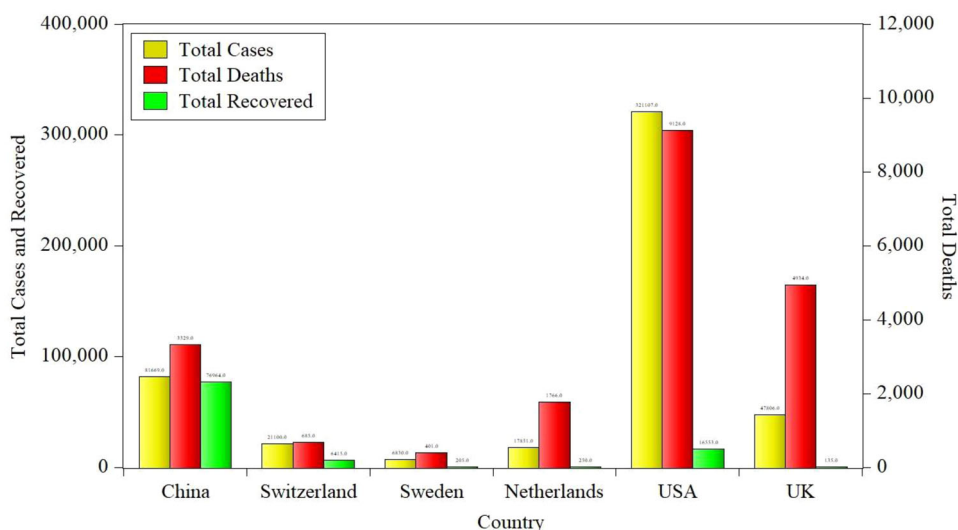
Figure 1. Country-wise COVID-19 cases, deaths, and recovered patients.
Source: Author Estimation.

which causes the fall of trade, tourism, and the transport industry and even generated local food shortages. In addition, the presence of stock market price bubbles, the impact of Covid-19 on the financial system could not be ignored.

Economic conditions, institutional issues, and market uncertainty can cause financial volatility (Hartwell, 2018). Announcements relating to macroeconomic issues also cause financial volatility. Onan et al. (2014) provide evidence that good and bad both types of announcements asymmetrically cause financial volatility. Karnizova and Li (2014) predict the U.S. recession using the interaction between EPU and stock market volatility, whereas Zhu et al. (2019) explore the influence of the fear index on the U.S. stock market volatility. Many Economies around the world have been affected by deadly viruses and causes a huge human loss. These include Zika in 2016, Ebola and Measles in 2014, MERS in 2013, Cholera in 2010, Swine Flu in 2009, Dengue Fever and Avian Flu in 2006, SARS in 2003, and 2019 is the emergence of a new coronavirus (COVID −19). This deadliest virus belongs to the Coronaviruses' family, which is common in animals, which became a major danger to human life and the world's financial markets. Almost all 199 countries of the works are the victim of this deadly virus, and two international conveyances, i.e., Diamond Princes Cruise ship harboured in Japan and Holland America's MS Zaandam Cruise ship, are also most affected.

The present research aims to capture the dynamic response of shocks from one to another stock market. The analysis seeks to capture the effect of COVID-19 Shocks on China and then compare it with the most advanced Countries of the World, i.e., Switzerland, Sweden, Netherland, UK, and the U.S. Global Innovation Index 2019 (WIPO, 2019). Figure 1 presents the country-wise cases, deaths, and recovered patients of COVID-19 from 5 January 2020 to 4 April 2020. We can see that the total number of cases and deaths is falling most in the U.S.A., which affected more. After the U.S.A., the second most country affected by COVID-19 is the UK, in which the death rate exceeds the cases registered as COVID-19. Similarly, Sweden, Netherlands,

and Switzerland fall in less-affected countries. The situation in China is positive, as it has a greater number of patients recovered from COVID-19.

The main purpose of the research is to examine the co-integration relation and the transmission of shocks from China to the most advanced countries from Jan. 2020–Apr. 2020 in the period of the current pandemic. The indices used in the study are China Stock Market Index is (SSE Composite Index), Switzerland stock Market Index used is (Swiss Market Index), Sweden, Stock Market Index used is (OMX Stockholm 30), U.S.A., Stock Market Index used is (S&P500), Netherland, Stock Market Index used is (AEX index), UK, Stock Market Index used is (FTSE 100).

2. Literature review

We can find that many epidemic diseases caused a big human and financial loss around the world in history. The financial analyst has always been concerned about the economic and financial impact of these pandemics. The two important streams of finance literature that are important for this research study are discussed as under,

2.1. Pandemic and economic cost

Before the COVID-19 outbreak, Severe Acute Respiratory (SAR), Ebola, and Middle East Respiratory Syndrome were also worldwide pandemics. The 2014 outbreak of the Ebola virus in West Africa was more damaging than all preceding pandemics. However, the social cost of the virus outbreak was not captured by its economic burden estimates. Huber et al. (2018) conduct a study to find the 2014 Ebola virus outbreak's economic and social burden in West Africa. Siu and Wong (2004) estimated the first deadly disease of the 21st century, SARS' economic impacts on Hong Kong's economy. Rizvi et al. (2020) findings show a significant loss in valuations across all sectors due to a possible decline in sales and increase in the cost of equity. In extreme cases, average firms in some sectors may lose up to 60% of their intrinsic value in one year. Mirza et al. (2020) examine the possible policy interventions to sustain solvency at a pre-Covid-19 level. Their findings suggest that for a moderate deterioration in economic conditions, a tax deferral is sufficient. However, in exacerbating business shocks, there should be hybrid support through debt and equity to avoid a meltdown. Yarovaya et al. (2020) findings Based on the macro and micro-level model specifications and using six distressed economic scenarios, indicate a significant deterioration in asset quality across exposure types, institutional size, and countries' profile. They document a substantial increase in the probability of default and a considerable reduction in capital adequacy across our sample.

A human capital loss is another major concern of an epidemic. In the long run, human destruction becomes a major hurdle for the economic progress of any economy. Barro and Sala-i-Martin (1995) recognise that human capital is very important for the long-term growth of any economy. Bloom, et al. (2001) state that the decrease in human capital affects economic growth negatively. Pandemics additionally

aggressively influence labour efficiency by restricting the activities of the labourers and imposing restrictions on their movements due to lock down situation.

2.2. Pandemic and financial markets

Pandemic such as Severe Acute Repository Syndrome (SARS) outbreaks and Ebola virus outbreak has affected the stock markets around the world (Chen et al., 2007; Chen et al., 2018; Del Giudice & Paltrinieri, 2017; Goodell, 2020; Ichev & Marinč, 2018; Wang et al., 2013). Even So, the research on the scope to which pandemics affect stock returns is still scant.

We can start with the researchers' centred on the impact of the current spread on the financial market. Evidence from literature shows that the COVID-19 effect on financial markets is devastating compared to other crises that spread in the past (Baker et al., 2020; Umar, Rizvi, et al., 2021; Zhang et al., 2020). This research studies that look at the impact of a pandemic on the stock market include (Pavlyshenko, 2020; Topcu & Gulal, 2020; Umar, Mirza, et al., 2021), studies that examine volatility (Albulescu, 2021; Cheng & Yao, 2021; Su, Huang, et al., 2021; Su, Sun, et al., 2021), researchers analysing liquidity includes (Haroon & Rizvi, 2020; Su, Qin, Tao, Shao, et al., 2020; Su, Qin, Tao, & Umar, 2020; Zaremba et al., 2020) studies exploring herding include (Kizys et al., 2021), papers looking at the fund flows Pástor and Vorsatz (2020) or financial projections are examined by Bretscher et al. (2020), Gormsen and Koijen (2020) and Umar, Su, et al. (2021).

For the operation of financial markets, volatility acts as a barometer of financial risk and financial uncertainty. Volatility is crucial to assess uncertainty surrounding investments in financial assets and, therefore, it is of huge interest to financial industry regulators, mutual fund manager and individual investors, and policymakers. Researchers had attempted to establish an association between the pandemic COVID-19 and the volatility of the financial market. Baker et al. (2020) attempted to identify the impact of a current pandemic on stock market volatility. According to the study, the government limitations on commercial activity and restrictions on consumers are the major reasons for increased volatility. Zaremba et al. (2020) conclude that if government response to COVID-19, it mitigates the international stock market volatility. They provide evidence of the countries where governments take severe measures to curtail the dispersion of COVID-19, which causes an increase in stock market volatility. Measures may include the information campaigns and the termination of large-scale public functions. In addition, Onali (2020) reports that the U.S. stock market's volatility increases in response to the increase in positive cases and deaths.

Another associated category of research that assesses government action's influence on the stock market includes (Ashraf, 2020; Baig et al., 2021; Gao et al., 2021; Heyden & Heyden, 2020; Narayan et al., 2021). Ashraf (2020) describes that the government announcements of social distancing have a negative effect on stock market returns due to their adverse effect on economic activity, while an indirect positive effect through the reduction in COVID-19 confirmed cases using data across 77 countries. Heyden and Heyden (2020) study the short-term market reactions of U.S. and European stocks at the beginning of the COVID-19 pandemic. Authors conclude

that stock returns respond negatively to the declarations of the country-specific fiscal policy measures, whereas market calm in response to the monetary policy measures. Phan and Narayan (2020) look at the effect of government responses of G7 countries to the coronavirus pandemic on stock market returns. The study shows that lockdowns travel bans, and economic stimulus packages all had a positive effect on the stock markets. However, lockdowns were most effective in cushioning the effects of COVID-19.

Ramelli and Wagner's (2020) early results recommend that the stock market quickly responds to concerns about the possible economic consequences of the novel coronavirus. In particular, the cross-section of stocks shows that the amplification of the COVID-19 shock through financial channels started to disturb the investors. The relationship between U.S. stock performance and real-time changes in COVID-19 infection projections is negative (Alfaro et al., 2020). Schoenfeld (2020) research findings support that the pandemic prompted unprecedented changes in U.S. employment levels and the values of currencies, commodities, and bonds. Based on such findings, we can conclude that pandemics are systemically hurting financial markets.

Another stream of research focusing on the impact of the Pandemic worldwide is how the impact spread from one country to another. Ruiz Estrada (2020) pinpointed the waves in which the pandemic can instantaneously affect major markets such as Taiwan, Hong Kong, South Korea, and Japan and show the declining growth of GDP of all these economies. Using data from the 12 most-affected countries Zhang et al. (2020) map how the correlation between countries̀ stock markets before and after the Covid-19 crisis. The study results show that global financial market risks have increased substantially in response to the pandemic. The great uncertainty of the pandemic and its associated economic losses has caused markets to become highly volatile and unpredictable.

2.3. Theoretical framework

2.3.1. Black Swan theory

The Black Swan theory can be linked to sudden and unexpected events that can affect the stock market and commercial activities (A. A. Talib, 2001; B. A. Talib et al., 2007), discovering the then-novel black swan. Black Swan theory can be related to the emergence of Coronavirus that swamped the whole globe because of its unique nature. It has caused huge health and mortality rate as well spiralled into the world's stock markets. Black Swan Theory is used as a reference to relate those events that are highly unpredictable, and their effects on stock markets, money markets, and on the general economy are serious. As the Black Swan events are highly unpredictable, economic experts promote diversification of portfolios to mitigate the adverse effect of such incidents. The sudden outbreak of current COVID-19 bewildered and overwhelmed the world health experts, and even after many months of its emergence, no medicine has been found for a new virus that increased the rate of infection and deaths that caused the WHO to declare it a global pandemic. According to financial times, 2020, the associated effect of the pandemic has spiralled into different swings in the world's stock and money markets, causing depression among investors.

Another reason for the stock market unpredictable volatility spikes is the closure and restrictions of the national border in the labour movement that has affected global supply chains.

2.3.2. Prospect theory

Kahneman and Tversky (1979) established the Prospect theory, which emphasises that investors set and decide the portfolio under risk. Researchers advocate that investors avoid risk if they prefer investments with certain risk prospects in certain expected value. Prospect theory is centred around risk-averse investor's behaviour and anomalies, which explains the negative correlation between risk and return. Barberis et al. (2016) and Beale et al. (2019) also confirmed this phenomenon. Accordingly, prospect theory can be the explanation for the phenomenon for stock returns and pandemic negative relationship.

Based on the above-mentioned literature and theoretical background, the motivation for our study is to evaluate the behaviour of the financial market during the pandemic and compare the evidence with that of before the pandemic. The objective is to scrutinise the volatility of China stock market and the most advanced countries during the period of Covid − 19 in relevance with the period before the Pandemic. Investors and policymakers are eager to know how the stock market behaves in this different type of situation. For instance, policymakers are threatened with the choice between containing the virus and sustaining the economy. The study results can be source of information about the extent of the behaviour during the pandemic that will help determine how much sacrifice the relevant markets will have to endure to contain the virus. The findings are important for the smooth functioning of the stock market as it is believed that findings will unfold events during the pandemic and offer an area for future research.

3. Data and analysis

This study uses China and the most advanced countries of the world's stock market indices closing price data. These data were collected from Yahoo Finance website. The top 5 most advanced countries were selected according to the ranking of Global Innovation Index (GII), 2019 by the World Intellectual Property Organisation. The stock indices used are China Stock Market Index, SSE Composite Index, Swiss Market Index for Switzerland stock Market, MX Stockholm 30 for Sweden Stock Market Index, U.S.A., Stock Market Index used is S&P500, Netherland, Stock Market Index used is AEX index, UK, Stock Market Index used is FTSE 100.

The time frame of this study is 5 January 2012 − 3 April 2020, to capture the COVID-19 impact pandemic on stock returns of the full sample (05 January 2015 to 04 April 2020), before COVID-19 (05 January 2015 to 29 November 2019), and during COVID-19 (02 December 2019 to 03 April 2020).

Figure 2 presents the market capitalisation of China and the most advanced countries' stock indices. We can see that the U.S.A. stock market has the largest market share of 22923 US$Billion, among other sample countries. After the U.S.A., China's market share is 4026 US$Billion. Similarly, Switzerland, Sweden, Netherlands, and UK
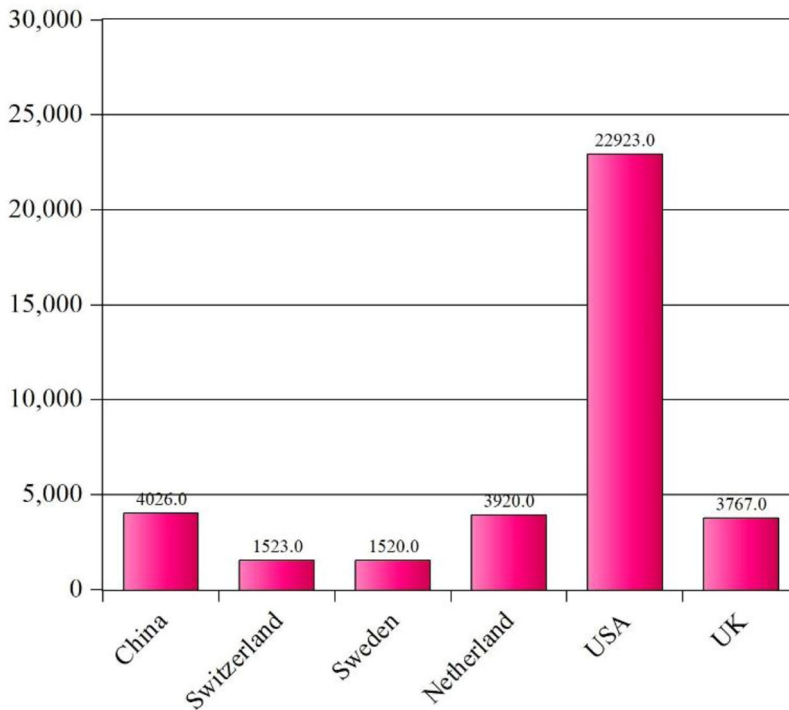
Figure 2. Market capitalization of China and the most advanced countries stock markets US$Billion.
Source: Author Estimation.

stock market capitalisation are 1523 US$Billion, 1520 US$Billion, 3920 US$Billion, and 3767 US$Billion, respectively.Using the following formula, we first calculate the stock returns,

$$Return_t = \ ln \ (R_t/R_{t-1}) \qquad\qquad .(1)$$

Were,
Return $_t$ = Daily stock returns of all the selected countries indices
ln = Natural log of daily stock prices
R_t = index Closing value at the day end
R_{t-1} = index Closing value on the previous day

Figures 3 and 4 explain the pattern of daily stock returns of all sample countries chosen for this study. At the end of 2019, the China and advanced countries stock markets were affected by a novel COVID-19 pandemic shock.

Similarly, Figure 4 demonstrated the volatility of the China and advanced countries' stock markets indices throughout 2015 to 2020. We can see that China, the U.S.A., Netherlands, and Switzerland have larger volatility in their stock indices since 2015, whereas Sweden and the UK have low volatility in their stock market indices.
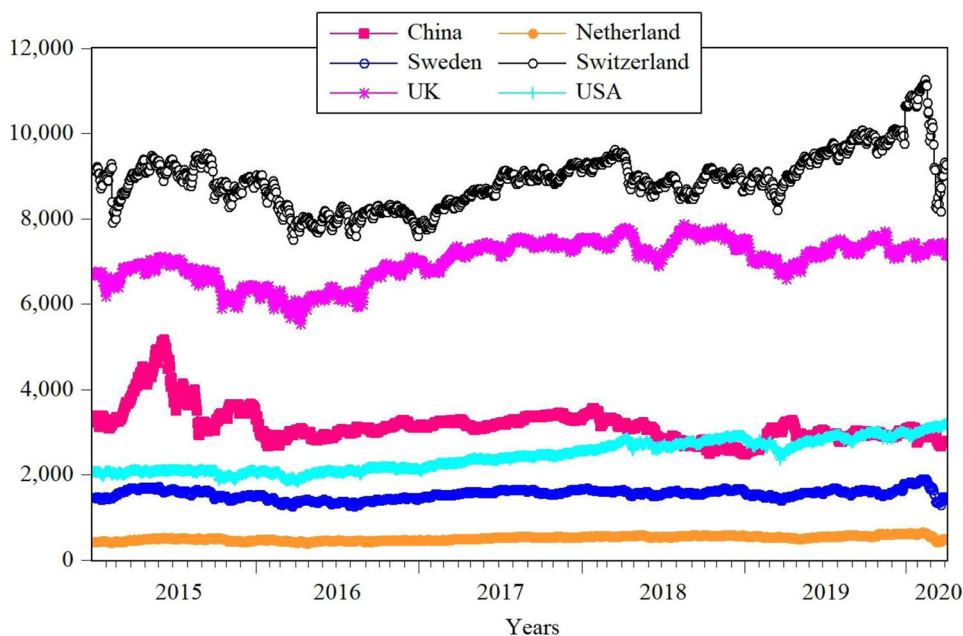
Figure 3. Stock returns of China and the most advanced countries stock markets indices (2015–2020).
Source: Author Estimation.
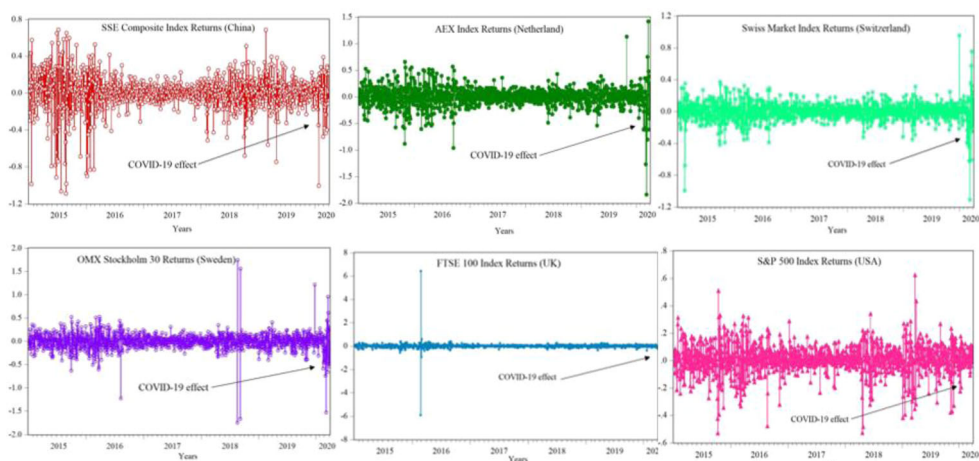
Figure 4. Stock returns of China and the sample countries stock markets indices COVID-19 effect.
Source: Author Estimation.

3.1. Data analysis techniques

This study incorporates different types of data analysis techniques such as descriptive statistics, correlation matrix, Autoregressive Conditional Heteroscedasticity (ARCH) test, and Generalised Autoregressive Conditional Heteroscedasticity (GARCH), Threshold ARCH (TARCH) models. Descriptive statistics analysis helps us to overlook the data initially. The correlation matrix shows the correlation among different stock indices over the period. Finally, to achieve the purpose of the study, we perform

the ARCH test, which is the first assumption to run the ARCH family models. If this assumption satisfies, then we can apply ARCH family models for our dataset.

The focus of the study is to look at the financial application of this novel COIVD-19 pandemic shock on the stock market's volatility of China and advanced countries of the world. The econometric test determines how the data is utilised to figure the mean and fluctuation of the return, restrictive on the past data. While numerous determinations have been considered for the mean return and have been utilised in the activities to gauge the future returns, essentially no techniques are accessible before presenting ARCH models. The essential clear instrument is the rolling standard deviation. The standard deviation was determined utilising a fixed number of the latest perceptions. For instance, each day, this could be determined utilising the latest month (22 days) of information. It is helpful to consider this the principal ARCH model; it accepts that the fluctuation of the upcoming return is a similarly weighted normal of the squared residuals from the most recent 22 days. The supposition of equivalent loads appears to be ugly as one would feel that the later occasions would be more pertinent and, in this way, ought to have higher loads. Besides, the presumption of zero loads for perceptions over one-month-old is likewise unpleasant. The ARCH model proposed by Engle (1982) lets these loads be boundaries to be assessed. In this way, the model permitted the information to decide the best loads to estimate the change (Engle, 1982). They are presented by (Bollerslev's, 1986) GARCH model that simplifies this model. The GARCH model is an extension of the ARCH model. A GARCH model may have lesser boundaries contrasted with an ARCH model. The GARCH group of models have been consistently appeared to give more exact results, and, along these lines, the utilisation of the GARCH model has become the standard technique for displaying instability in monetary time arrangement information.

In the past, many pieces of research focused on investigating the co-integration among the stock indices of developed economies. Therefore, in this study, we applied ARCH family models to the daily stock returns of China and the most advanced country's stock markets to catch the volatility due to the COVID-19 pandemic shock. In this regard, we utilise GARCH models for observing the news elements in the sample time series data. The GARCH models also understand the different types of dynamic behaviours of stock markets due to the good or bad news (Khan et al., 2014).

To apply the GRACH family models (GARCH, EGARCH, TARCH), we first analyse our data and check the assumptions of applying GRACH family models. GARCH model measures the effect of any shock on the change that keeps on sending itself during the contiguous time span, as a bigger one trails a huge shock, and a more modest one trails a little shock. However, the process of the transmission of shocks is examined by the nonlinear specification (Clements 2005; Islam 1984). EGARCH model helps investigate the shock, which may emphatically impact the difference because a negative shock in the system causes more prominent misfortune in returns than the additions from a positive shock. At last, the TARCH model estimates the importance and relative commitment of negative shock in the system that destabilises fluctuation (Khan et al., 2014).

We run six estimation models under three parameters, i.e., full sample, sample before COVID-19, and sample during COVID-19, in the following manner:

- Model 1 = China C and variance regressors most advanced countries (Switzerland, Sweden, UK, U.S.A., and the Netherlands)
- Model 2 = Switzerland C and china
- Model 3 = Sweden C and China
- Model 4 = Netherland C and China
- Model 5 = U.S.A. C and China
- Model 6 = UK C and China

The various reasons for instability in the stock returns have been clarified from the overall system of the internal theories of the business cycle, and out of which, the multiplier acceleration theory proposed by Samuelson (1939) has acquired prominence. It has been seen that the expected value of stochastic term μ_t is the time-varying in the volatile stock market. Subsequently, demonstrating return arrangement in such a market requires a logical structure that can adapt to deviations in stock returns. For this reason, in the wake of fulfilling the presumption for choosing the suitable model, we adopt TARCH model estimations proposed by Glosten et al. (1993) and Zakoian (1994).

The TARCH model is more powerful than the ARCH and GARCH models. Both specifications are symmetric as both positive and negative shocks of a similar size are blessed to receive have a similar impact by the square of the residuals. The TGARCH model, then again, is equipped for checking for any genuinely critical distinction between when the stock is positive and when it is negative. TARCH model works by including dummy variables in the variance equation of the model (Asteriou & Hall, 2015). We estimate the TGARCH (1) model in the following form:

$$r_t = \mu_0 + \mu_1 r_{t-1} + \mu_t \qquad (2)$$

$$h_t = \gamma + \alpha\mu^2_{t-1} + \beta \ \mu^2_{t-1}\zeta_{t-1} + \delta h_{t-1} \qquad (3)$$

where Equations (1) and (2) above show the original form of the TARCH. There are two equations of the TARCH model (Mean and Variance equations).

Equation (1), shows the mean equation of the TARCH model in which the ordinary least square (OLS) model is incorporated in the autoregressive form for stock returns. Equation (2) demonstrates the variance equation of the TARCH model that incorporates the time-varying behaviour of μ_t. In this equation, γ, α, β, and δ are the parameters of the model that has to be estimated. The parameter r, β, must be significant and positive for testing the irregularities in the news. Either the case may be, the bad news has a larger effect on the volatility of the series than good news. The dummy variable used in this variance equation is ζ_t, which shows 1 for $u_t < 0$, 0 when $u_t > 0$ so that 'good news' and 'bad news' have a changing impact.

4. Results and discussion

The sample period of this study is further divided into three sub-periods: full sample (05 January 2015 to 04 April 2020), before COVID-19 (05 January 2015 to 29

November 2019), and during COVID-19 (02 December 2019 to 03 April 2020). Overall, the full sample period (05 January 2015 to 04 April 2020) was chosen to capture the impact and dynamic relationship among China's stock market and the world's most advanced countries, and the COVID-19 pandemic. The rationale behind choosing the large sample is to obtain reliable results in estimating our TARCH model. If we incorporate more time periods before the event in the model, and the greater the difference, the more significant possible influence on the spill over effects.

4.1. Results of descriptive statistics and correlation matrix

Tables 1–3 describe the summary statistics of the sample data. The whole dataset contains 1269 observations, and the average value of China stock returns for five years period is 3157.799, and similarly, the Netherlands has 501.7646, Sweden has 1543.907, Switzerland has 8904.371, the UK has 7000.836, and finally, the U.S.A. stock market index has 2440.508 mean index value. The results also show that the standard

Table 1. Descriptive statistics of the full sample (05 January 2015 to 04 April 2020).

	China	Netherland	Sweden	Switzerland	UK	U.S.A.
Mean	3157.799	501.7646	1543.907	8904.371	7000.836	2440.508
Maximum	5166.350	629.2300	1900.280	11263.01	7859.200	3205.370
Minimum	2464.363	382.6100	1246.100	7496.620	5537.000	1829.080
Std. Dev.	413.8427	53.08794	110.1540	646.8450	490.5976	354.3013
Skewness	1.895044	0.062776	−0.084816	0.571971	−0.669893	0.199227
Kurtosis	8.344422	2.140144	3.214108	3.967717	2.547722	1.665431
Observations	1269	1269	1269	1269	1269	1269

Source: Author Estimation.

Table 2. Descriptive statistics of the sample before COVID-19 (05 January 2015 to 29 November 2019).

	China	Netherland	Sweden	Switzerland	UK	U.S.A.
Mean	3172.928	497.2813	1535.090	8821.743	6982.499	2399.614
Median	3116.351	501.8900	1555.870	8892.170	7053.700	2368.060
Maximum	5166.350	599.0300	1719.930	10066.53	7859.200	3025.860
Minimum	2464.363	382.6100	1246.100	7496.620	5537.000	1829.080
Std. Dev.	422.6104	48.87791	98.68695	541.4796	501.4985	328.2793
Skewness	1.813887	−0.122404	−0.600662	−0.161086	−0.57477	0.210895
Kurtosis	7.920465	1.880459	2.534350	2.473391	2.393186	1.597337
Observations	1187	1187	1187	1187	1187	1187

Source: Author Estimation.

Table 3. Descriptive statistics of the sample during COVID-19 (02 December 2019 to 03 April 2020).

	China	Netherland	Sweden	Switzerland	UK	U.S.A.
Mean	2938.800	566.6623	1671.533	10100.47	7266.277	3032.475
Median	2969.724	603.7700	1688.875	10090.75	7284.100	3007.090
Maximum	3115.570	629.2300	1900.280	11263.01	7429.800	3205.370
Minimum	2660.170	404.1000	1292.270	8160.790	7067.000	2847.110
Std. Dev.	118.7112	67.67838	172.3936	841.7335	95.14352	88.84678
Skewness	−0.49966	−1.105189	−0.594282	−0.684228	−0.28065	0.030958
Kurtosis	2.200937	2.682591	2.169163	2.502143	2.040093	2.059185
Observations	82	82	82	82	82	82

Source: Author Estimation.

Table 4. Correlation matrix of the full sample (05 January 2015 to 04 April 2020).

	China	Netherland	Sweden	Switzerland	UK	U.S.A.
China	1	–	–	–	–	–
Netherland	−0.235126673	1	–	–	–	–
Sweden	0.219032151	0.698755911	1	–	–	–
Switzerland	0.052756422	0.737448664	0.791453524	1	–	–
UK	−0.127280277	0.764543654	0.662215478	0.51099353	1	–
U.S.A.	−0.466530931	0.8336028	0.517693353	0.642917139	0.767780351	1

Source: Author Estimation.

Table 5. Correlation matrix of the sample before COVID-19 (05 January 2015 to 29 November 2019).

	China	Netherland	Sweden	Switzerland	UK	U.S.A.
China	1	–	–	–	–	–
Netherland	−0.234127357	1	–	–	–	–
Sweden	0.282878742	0.63045408	1	–	–	–
Switzerland	0.131858104	0.671371145	0.737062906	1	–	–
UK	−0.110777465	0.822441999	0.726130562	0.556426612	1	–
USA	−0.455470337	0.886835	0.511395474	0.608213686	0.795097096	1

Source: Author Estimation.

**Table 6.** Correlation matrix of the sample during COVID-19 (02 December 2019 to 03 April 2020).

	China	Netherland	Sweden	Switzerland	UK	U.S.A.
China	1	–	–	–	–	–
Netherland	0.663083172	1	–	–	–	–
Sweden	0.674979064	0.897862551	1	–	–	–
Switzerland	0.628189767	0.91711367	0.970908269	1	–	–
UK	0.189802625	−0.32752942	−0.160661176	−0.218571694	1	–
U.S.A.	−0.503626977	−0.74527114	−0.526439536	−0.57179993	0.293545224	1

Source: Author Estimation.

deviation is larger in Switzerland, the UK, the U.S.A., and China compared to Sweden and Netherlands in the full sample.

Table 2 displays a summary of statistics of China and the most advanced countries of the world before the COVID-19 pandemic. It contains a sample of 1187 observations, and the average values of stock returns of China, Netherlands, Sweden, Switzerland, the UK, and the U.S.A. are 3172.928, 497.281, 1535.090, 8821.743, 6982.499, 2399.614, respectively. Before COVID-19, the standard deviation of stock markets is the same as in the full sample, i.e., larger in Switzerland, UK, U.S.A., and China and smaller in Netherlands and Switzerland. Table 3 presents the descriptive statists of sample data during COVID-19, and it includes 82 observations. The results show that variations and stock markets during COVID-19 are greater in Switzerland with 841.7335, China 118.7112, Sweden 172.3936 and less in UK 95.1435 and U.S.A. with a standard deviation of 88.8467.

The results of the correlation matrix of the sample countries' stock marks are given in Tables 4–6. The results show that the stock market of the Netherland has a slight correlation with Sweden, Switzerland UK, and the U.S.A. in the whole sample and sample before COVID-19, whereas, during the COVID-19 pandemic, China's stock return is correlated with Netherlands, Switzerland, and Sweden. Similarly, Netherlands' stock market is correlated with Sweden and Switzerland, and finally, the Sweden stock market shows a positive correlation with the Switzerland stock market during COVID-19.
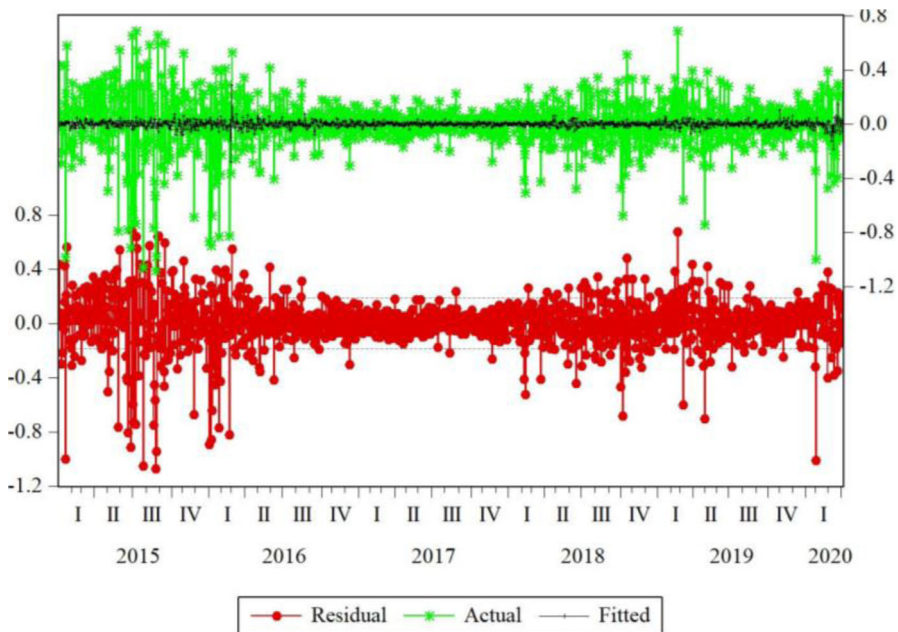
Figure 5. Residuals plot for testing the volatility clustering.
Source: Author Estimation.

4.2. Results of model selection (ARCH, GARCH, EGARCH, and TARCH)

To apply the ARCH family models, first, we test the assumptions of the dataset. There are two ways to test the assumptions of applying ARCH family models. The first one is testing the clustered volatility of stock returns by using the plotting of the residuals. Second, to check the existence of the ARCH effect (Gouriéroux 2012). The ARCH impact can be tried in pre-assessment and just as post-assessment examination. Post-assessment checks the remaining ARCH impact, for example, regardless of whether restrictive heteroscedasticity has been taken out. For that purpose, it is applied to stand-ardised residuals of the fitted model called the LM-test for the ARCH impact in the residuals (Engle 1982). The normality tests are used to check the behaviour of the ARCH effect if normality can be described by conditional error distribution.

Figure 5 demonstrates the graph of residuals of the ARCH model to test the clustered volatility in the dataset. It shows the residuals and the fluctuation of the residuals over the period. We can see that the period of low volatility trends in stock markets to be trailed by the time of lower unpredictability for a delayed period and, the time of high instability followed by the times of high unpredictability for a drawn-out period, both situations happen at the same time, so we can say that assumption of running GARCH models is satisfied Miles, (2011).

For robustness, we use the ARCH effect test. The null hypothesis of the ARCH effect test is 'There is no ARCH effect'. Table 7 shows the outcome of the ARCH effect test, and we can see that the Prob. value of observed R squared is < 0.05, which rejects the null hypotheses and accepts the alternate hypotheses, and that is 'There is ARCH effect' Bera and Higgins (1993).

Table 7. ARCH test for the testing ARCH effect.

F-statistic	59.67823	Probability. F (1,1275)		0.000
Observed R-Seq.	57.09923	Probability. Chi-Square (1)		0.000
Comprised observations after adjustments: 1277				
Variables	Coeff.	S. E	T-Stat	Prob.
Constant	0.027299	0.002949	9.256441	0.000
RESID ∘ 2 (-1)	0.211283	0.02735	7.725169	0.000

Source: Author Estimation.

Table 8. Results of the GARCH model.

Dependent variable: CHINA_RETURN Included observations: 1278 Convergence achieved after 53 iterations				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003182	0.003213	0.990324	0.322
Variance equation				
C	9.23E-05	4.27E-05	2.162777	0.031
RESID(-1)∘2	0.088943	0.0069	12.89041	0.000
GARCH(-1)	0.914079	0.005493	166.4224	0.000
NETHERLAND_RETURN	−0.0005	0.000884	−0.56553	0.572
SWEDEN_RETURN	−0.003396	0.001834	−1.85141	0.064
SWITZERLAND_RETURN	0.001557	0.002573	0.60513	0.545
UK_RETURN	−0.003722	0.001839	−2.0236	0.043
U.S.A._RETURN	0.011411	0.001938	5.889411	0.000
Akaike info criterion		−0.971532		
Schwarz criterion		−0.935243		
Hannan-Quinn criteria.		−0.957905		
GARCH = C(2) + C(3)*RESID(−1)∘2 + C(4)*GARCH(−1) + C(5) *NETHERLAND_RETURN + C(6)*SWEDEN_RETURN + C(7) *SWITZERLAND_RETURN + C(8)*UK_RETURN + C(9) *USA_RETURN				

Source: Author Estimation.

4.2.1. Estimations of GARCH model

To estimate the suitable GARCH model, we follow the technique for the model selection. The data rules depend on the assessment of the Kullback–Leibler data measure (Sin & White, 1996) and are common speculations of the standard rules, yet considering the heteroscedastic idea of the information that more boundaries are assessed for AR-GARCH models than for AR models. The most mainstream measures for choosing the proper GARCH model are the Akaike data rule (AIC) and Schwarz Information Criterion (SIC), and HQIC (Hannan-Quinn data basis). The point is to track down the model with the least worthy of the chose data standard (Lin & Dayton, 1997).

Tables 8–10 describe different GARCH models with different parameters (GARCH, EGARCH, and TARCH) to find the best appropriate model for data analysis. The results show that the model estimated in Table 10 (TARCH) has the lowest AIC value, i.e., −0.97002, so the TARCH model is more appropriate for achieving the instability of stock markets due to the novel COVID-19 pandemic. The TARCH model measures the significance and proportional contribution of a negative shock that destabilises the variance Khan et al. (2014). Our study finds the negative shock from China towards the most advanced countries globally, so the TARCH model is most suitable for our analysis.

Table 9. Results of the EGARCH model.

	Dependent variable: CHINA_RETURN Included observations: 1278 Convergence achieved after 41 iterations			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002761	0.003322	0.831197	0.406
Variance equation				
C	−0.140565	0.011687	−12.0279	0.000
C(3)	0.159279	0.014296	11.14123	0.000
C(4)	−0.007902	0.01108	−0.71317	0.476
C(5)	0.993955	0.002017	492.6846	0.000
C(6)	−0.181255	0.060396	−3.00112	0.003
C(7)	−0.218976	0.133558	−1.63956	0.101
C(8)	0.519042	0.178522	2.907439	0.004
C(9)	−0.324093	0.137077	−2.36431	0.018
C(10)	0.588779	0.151715	3.880812	0.000
Akaike info criterion		−0.977236		
Schwarz criterion		−0.936914		
Hannan-Quinn criteria.		−0.962094		

LOG(GARCH) = C(2) + C(3)*ABS(RESID(−1)/@SQRT(GARCH(−1))) + C(4) *RESID(−1)/@SQRT(GARCH(−1)) + C(5)*LOG(GARCH(−1)) + C(6) *NETHERLAND_RETURN + C(7)*SWEDEN_RETURN + C(8) *SWITZERLAND_RETURN + C(9)*UK_RETURN + C(10) *USA_RETURN

Source: Author Estimation.

Table 10. Results of the TARCH model.

	Dependent variable: CHINA_RETURN Included observations: 1278 Convergence achieved after 65 iterations			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003341	0.003397	0.983447	0.3254
Variance equation				
C	9.04E-05	4.24E-05	2.131426	0.0331
RESID(−1)∘2	0.091464	0.011876	7.701372	0.000
RESID(−1)∘2*(RESID(−1)<0)	−0.005068	0.012896	−0.392947	0.6944
GARCH(−1)	0.914392	0.005795	157.7886	0.000
NETHERLAND_RETURN	−0.000519	0.000886	−0.585249	0.5584
SWEDEN_RETURN	−0.003417	0.001848	−1.848672	0.0645
SWITZERLAND_RETURN	0.001451	0.002645	0.548553	0.5833
UK_RETURN	−0.00378	0.001854	−2.039552	0.0414
U.S.A._RETURN	0.011595	0.002318	5.00245	0.000
Akaike info criterion		−0.97002		
Schwarz criterion		−0.929699		
Hannan-Quinn criteria.		−0.954879		

GARCH = C(2) + C(3)*RESID(−1)∘2 + C(4)*RESID(−1)∘2*(RESID(−1)<0) + C(5)*GARCH(−1) + C(6)*NETHERLAND_RETURN + C(7) *SWEDEN_RETURN + C(8)*SWITZERLAND_RETURN + C(9) *UK_RETURN + C(10)*USA_RETURN

Source: Author Estimation.

4.3. Results of TARCH models

The SEARCH model is estimated in six parameters to determine the volatility of the most advanced countries' stock markets indices due to the COVID-19 pandemic shock transmitted from China stock market. We estimate model 1 by putting dependent variables China stock market and variance regressors as advanced countries. In model 2, Switzerland is the dependent variable, and the variance regressor is China stock market. In model 3, Sweden's stock market returns are the dependent variable,

Table 11. TARCH results of model 1 full sample (05 January 2015 to 04 April 2020).

	Dependent variable: CHINA_RETURN Included observations: 1278			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003341	0.003397	0.983447	0.3254
Variance equation				
C	9.04E-05	4.24E-05	2.131426	0.0331
RESID(−1)∘2	0.091464	0.011876	7.701372	0.000
RESID(−1)∘2*(RESID(−1)<0)	−0.005068	0.012896	−0.392947	0.6944
GARCH(−1)	0.914392	0.005795	157.7886	0.000
NETHERLAND_RETURN	−0.000519	0.000886	−0.585249	0.5584
SWEDEN_RETURN	−0.003417	0.001848	−1.848672	0.0645
SWITZERLAND_RETURN	0.001451	0.002645	0.548553	0.5833
UK_RETURN	−0.00378	0.001854	−2.039552	0.0414
USA_RETURN	0.011595	0.002318	5.00245	0.000

Source: Author Estimation.

Table 12. TARCH results of model 1 before COVID-19 (05 January 2015 to 29 November 2019).

	Dependent variable: CHINA_RETURN Included observations: 1195			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002305	0.003476	0.663185	0.5072
Variance equation				
C	3.04E-05	3.20E-05	0.949438	0.3424
RESID(−1)∘2	0.076149	0.011362	6.702175	0.000
RESID(−1)∘2*(RESID(−1)<0)	−0.013506	0.012562	−1.075151	0.2823
GARCH(−1)	0.931084	0.006025	154.5463	0.000
NETHERLAND_RETURN	0.000668	0.00089	0.750684	0.4528
SWEDEN_RETURN	−0.002859	0.001958	−1.459962	0.1443
SWITZERLAND_RETURN	0.003099	0.002641	1.173406	0.2406
UK_RETURN	−0.000963	0.001931	−0.498823	0.6179
USA_RETURN	0.007178	0.002656	2.702205	0.0069

Source: Author Estimation.

and the variance regressor is China's stock market. Similarly, in models 4, 5, 6, the dependent variable is Netherland, U.S.A., UK, and the China stock market variance regressor. Each model has three parameters (full sample, before COVID-19 and sample during COVID-19). The estimations of six estimated TARCH presented from Tables 11–29.

4.3.1. Results of TARCH model 1

Tables 11–13 shows the result of model 1 that is estimated for capturing the volatility of China stock market due to the shock in the financial system during the COVID-19 pandemic. Table 11 the analysis is conducted for full sample and model estimations show that ARCH and GARCH term in the model is significant to explain the volatility of stock markets. The variance equation results show that only the UK and U.S.A. significantly explain China's volatility in the full sample. Table 12 shows the results before COVID-19, which shows that ARCH and GARCH terms are significant, and only the U.S.A. stock market is significant in explaining the volatility of the China stock market before the COVID-19 shock. Table 13 shows the model 1 results during

Table 13. TARCH results of model 1 during COVID-19 (02 December 2019 to 03 April 2020).

	Dependent variable: CHINA_RETURN			
	Included observations: 83			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.036194	0.049094	0.737243	0.461
Variance equation				
C	0.031208	0.01344	2.321973	0.0202
RESID(−1)∘2	0.048302	0.771717	0.06259	0.9501
RESID(−1)∘2*(RESID(−1)<0)	−0.010269	0.763538	−0.013449	0.9893
GARCH(−1)	0.573059	0.235533	2.433029	0.015
NETHERLAND_RETURN	0.015736	0.054638	0.288	0.7733
SWEDEN_RETURN	−0.062891	0.034561	−1.819733	0.0688
SWITZERLAND_RETURN	−0.054217	0.063045	−0.859966	0.3898
UK_RETURN	0.157132	0.066353	2.368112	0.0179
USA_RETURN	−0.091745	0.118392	−0.774929	0.4384

Source: Author Estimation.

Table 14. TARCH results of model 2 full sample (05 January 2015 to 04 April 2020).

	Dependent variable: SWITZERLAND_RETURN			
	Included observations: 1278			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001998	0.002321	0.860792	0.3894
Variance equation				
C	0.001148	8.67E-05	13.24368	0.000
RESID(-1)∘2	−0.029526	0.004339	−6.804568	0.000
RESID(−1)∘2*(RESID(−1)<0)	0.586963	0.035499	16.53441	0.000
GARCH(−1)	0.67779	0.001717	394.6793	0.000
CHINA_RETURN	0.000481	0.000544	0.882501	0.3775

Source: Author Estimation.

Table 15. TARCH results of model 2 before COVID-19 (05 January 2015 to 29 November 2019).

	Dependent variable: SWITZERLAND_RETURN			
	Included observations: 1117			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000266	0.002366	0.112454	0.9105
Variance equation				
C	0.000396	6.47E-05	6.127405	0.000
RESID(−1)∘2	−0.052259	0.014127	−3.699139	0.0002
RESID(−1)∘2*(RESID(−1)<0)	0.282341	0.032336	8.731374	0.000
GARCH(−1)	0.867785	0.017891	48.50407	0.000
CHINA_RETURN	−0.000192	0.000446	−0.430516	0.6668

Source: Author Estimation.

Table 16. TARCH results of model 2 during COVID-19 (02 December 2019 to 03 April 2020).

	Dependent variable: SWITZERLAND_RETURN			
	Included observations: 83			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.037487	0.02325	1.61233	0.1069
Variance equation				
C	0.020912	0.007232	2.891703	0.0038
RESID(−1)∘2	0.207386	0.234589	0.884037	0.3767
RESID(−1)∘2*(RESID(−1)<0)	−0.070236	0.27258	−0.257672	0.7967
GARCH(−1)	0.544137	0.12962	4.197936	0.000
CHINA_RETURN	−0.148923	0.034583	−4.306242	0.000

Source: Author Estimation.

Table 17. TARCH results of model 3 full sample (05 January 2015 to 04 April 2020).

Dependent variable: SWEDEN_RETURN				
Included observations: 1278				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance equation				
C	0.001472	0.000126	11.71732	0.000
RESID(−1)∘2	−0.010906	0.002667	−4.088751	0.000
RESID(−1)∘2*(RESID(−1)<0)	0.391796	0.0341	11.48975	0.000
GARCH(−1)	0.806963	0.009818	82.19339	0.000
CHINA_RETURN	−0.007182	0.000936	−7.670164	0.000

Source: Author Estimation.

Table 18. TARCH results of model 3 before COVID-19 (05 January 2015 to 29 November 2019).

Dependent variable: SWEDEN_RETURN				
Included observations: 1195				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.002761	0.003864	0.714445	0.475
Variance equation				
C	0.001082	0.000147	7.376053	0.000
RESID(−1)∘2	−0.020649	0.014689	−1.405752	0.1598
RESID(−1)∘2*(RESID(−1)<0)	0.311618	0.052976	5.882212	0.000
GARCH(−1)	0.840099	0.018058	46.52188	0.000
CHINA_RETURN	−0.006375	0.001122	−5.679786	0.000

Source: Author Estimation.

Table 19. TARCH results of model 3 during COVID-19 (02 December 2019 to 03 April 2020).

Dependent variable: SWEDEN_RETURN				
Included observations: 83				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.018995	0.031818	0.596983	0.5505
Variance equation				
C	0.027519	0.007039	3.909455	0.0001
RESID(−1)∘2	0.093975	0.092311	1.018026	0.3087
RESID(−1)∘2*(RESID(−1)<0)	0.121957	0.173195	0.704157	0.4813
GARCH(−1)	0.579831	0.088808	6.529072	0.000
CHINA_RETURN	−0.211732	0.033491	−6.322039	0.000

Source: Author Estimation.

Table 20. TARCH results of model 4 full sample (05 January 2015 to 04 April 2020).

Dependent variable: NETHERLAND_RETURN				
Included observations: 1278				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance equation				
C	0.000528	9.16E-05	5.762091	0.000
RESID(−1)∘2	−0.011697	0.000764	−15.30283	0.000
RESID(−1)∘2*(RESID(−1)<0)	0.203523	0.01815	11.21344	0.000
GARCH(−1)	0.902475	0.00674	133.89	0.000
CHINA_RETURN	−0.003066	0.001306	−2.346993	0.0189

Source: Author Estimation.

Table 21. TARCH results of model 4 before COVID-19 (05 January 2015 to 29 November 2019).

	Dependent variable: NETHERLAND_RETURN Included observations: 1195		
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.003931	0.003744	1.049983	0.2937
Variance equation				
C	0.00044	8.65E-05	5.085817	0.000
RESID(−1)∘2	−0.011536	0.001038	−11.10833	0.000
RESID(−1)∘2*(RESID(−1)<0)	0.179955	0.018188	9.894396	0.000
GARCH(−1)	0.910084	0.007242	125.6634	0.000
CHINA_RETURN	−0.003059	0.001258	−2.43155	0.015

Source: Author Estimation.

Table 22. TARCH results of model 4 during COVID-19 (02 December 2019 to 03 April 2020).

	Dependent variable: NETHERLAND_RETURN Included observations: 83		
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	−0.001174	0.039379	−0.029817	0.9762
Variance equation				
C	0.031642	0.009494	3.332949	0.0009
RESID(−1)∘2	0.019265	0.035357	0.544853	0.5859
RESID(−1)∘2*(RESID(−1)<0)	0.207793	0.145143	1.431646	0.1522
GARCH(−1)	0.558434	0.092263	6.052645	0.000
CHINA_RETURN	−0.230687	0.066357	−3.476441	0.0005

Source: Author Estimation.

Table 23. TARCH results of model 5 full sample (05 January 2015 to 04 April 2020).

	Dependent variable: USA_RETURN Included observations: 1278		
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance equation				
C	0.000736	8.37E-05	8.795132	0.000
RESID(−1)∘2	0.000684	0.012542	0.054543	0.9565
RESID(−1)∘2*(RESID(−1)<0)	0.342591	0.038359	8.931062	0.000
GARCH(−1)	0.776251	0.023907	32.47009	0.000
CHINA_RETURN	0.002256	0.000554	4.07539	0.000

Source: Author Estimation.

Table 24. TARCH results of model 5 before COVID-19 (05 January 2015 to 29 November 2019).

	Dependent variable: USA_RETURN Included observations: 1195		
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.004087	0.002545	1.606015	0.1083
Variance equation				
C	0.000697	8.72E-05	7.987557	0.000
RESID(−1)∘2	0.000158	0.014099	0.011188	0.9911
RESID(−1)∘2*(RESID(−1)<0)	0.310431	0.035198	8.819654	0.000
GARCH(−1)	0.787086	0.024368	32.3003	0.000
CHINA_RETURN	0.002348	0.000578	4.0657	0.000

Source: Author Estimation.

the COVID-19 pandemic and states that ARCH and GARCH terms are not significant, and during COVID-19, only U.S.A. stock market is significant in explaining the volatility in China stock market.

Table 25. TARCH results of model 5 during COVID-19 (02 December 2019 to 03 April 2020).

| | Dependent variable: USA_RETURN | | | |
	Included observations: 83			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.011954	0.00541	2.209566	0.0271
Variance equation				
C	0.00067	0.000175	3.819377	0.0001
RESID(−1)∘2	−0.14665	0.07165	−2.046755	0.0407
RESID(−1)∘2*(RESID(−1)<0)	0.555969	0.197926	2.808972	0.005
GARCH(−1)	0.659273	0.122582	5.378205	0.000
CHINA_RETURN	−0.001722	0.002406	−0.715533	0.4743

Source: Author Estimation.

Table 27. TARCH results of model 6 full sample (05 January 2015 to 04 April 2020).

| | Dependent variable: UK_RETURN | | | |
	Included observations: 1278			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
Variance equation				
C	0.048456	0.00243	19.93828	0.000
RESID(−1)∘2	0.039319	0.066515	0.591124	0.5544
RESID(−1)∘2*(RESID(−1)<0)	0.023988	0.067142	0.357269	0.7209
GARCH(−1)	0.464739	0.003828	121.4189	0.000
CHINA_RETURN	−0.114397	0.004993	−22.91342	0.000

Source: Author Estimation.

Table 28. TARCH results of model 6 before COVID-19 (05 January 2015 to 29 November 2019).

| | Dependent variable: UK_RETURN | | | |
	Included observations: 1195			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	9.47E-05	0.022867	0.00414	0.9967
Variance equation				
C	0.051572	0.002449	21.06166	0.000
RESID(−1)∘2	0.033908	0.067325	0.503645	0.6145
RESID(−1)∘2*(RESID(−1)<0)	0.030609	0.068137	0.449226	0.6533
GARCH(−1)	0.463415	0.003514	131.8734	0.000
CHINA_RETURN	−0.121462	0.005045	−24.07774	0.000

Source: Author Estimation.

Table 29. TARCH results of model 6 during COVID-19 (02 December 2019 to 03 April 2020).

| | Dependent variable: UK_RETURN | | | |
	Included observations: 83			
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.01278	0.009667	1.321987	0.1862
Variance equation				
C	0.003414	0.000969	3.524468	0.0004
RESID(−1)∘2	−0.019173	0.104865	−0.182832	0.8549
RESID(−1)∘2*(RESID(−1)<0)	0.012006	0.092493	0.129799	0.8967
GARCH(−1)	0.554042	0.147779	3.749118	0.0002
CHINA_RETURN	−0.0223	0.003326	−6.705255	0.000

Source: Author Estimation.

4.3.2. Results of TARCH model 2

Tables 14–16 reported the results of model 2 in which the dependent variable is the Switzerland stock market and the variance regressor is the China stock market.

Results show that the ARCH and GARCH terms are significant in the full sample, while China stock returns are insignificant. Before COVID-19 sample same ARCH and GARCH terms are significant, while China stock returns are insignificant. While during the COVID-19 sample, the ARCH term is insignificant and GARCH terms significant, and China stock market returns significantly impact the volatility of Switzerland stock market returns.

4.3.3. Results of TARCH model 3

Model 3 results are reported in Tables 17–19 below, in which the dependent variable is Sweden stock returns, and the variance regressor is the China stock returns. The results show that ARCH and GARCH terms are significant in the full sample, and China's stock return has significantly impacted the volatility of Sweden's stock returns. Before COVID-19 and during samples, the results show that the ARCH term is insignificant and the GARCH term is significant in both scenarios, and China has a significant impact on the volatility of the Sweden stock returns.

4.3.4. Results of TARCH model 4

Model 4 results are reported in Tables 20–22, in which the dependent variable is Netherland stock returns, and variance regressor is China stock returns. The results show that in the full sample and before the COVID-19 sample, the ARCH and GARCH terms are significant, and China stock returns are also significant, while during the COVID-19 sample, the ARCH term is insignificant and the GARCH term is insignificant and the same in this case China stock returns significantly impact the volatility of Sweden stock returns.

4.3.5. Results of TARCH model 5

Model 5 results are reported in Tables 23–25, in which the dependent variable U.S.A. stock returns and variance regressor is China stock returns. The results show that ARCH and GARCH terms are significant in the full sample, and China stock returns are significant. Before the COVID-19 sample, the ARCH term is insignificant, while the GARCH term and China stock returns are significant. During the COVID-19 sample, The ARCH and GARCH both terms are significant, while China stock returns cause no volatility of U.S.A. stock returns.

4.3.6. Results of TARCH model 6

Finally, model 6 results can be seen from Tables 27–29, in which the dependent variable is UK stock returns and the variance regressor is the China stock returns. The results show that in all three scenarios, the ARCH term is insignificant. However, the GARCH term is significant, and China's market returns significantly impact the volatility of UK stock market returns in full, before and during the COVID-19 sample.

5. Conclusion and policy implications

This study examines the volatility of China and the most advanced countries of the world stock markets due to the pandemic of COVID-19 for the period of 2015 to

2020. The period for a sample is further divided into three parts, full, before, and during the COVID-19 sample. The study provides empirical support for the TGARCH specification for explaining the daily time dependence in the rate of information arrival to the market for stocks traded on China stock market. This study concludes that in model 1, in which we estimate the impact of the stock returns volatility of advanced countries on China stock market, findings of the full sample and COVID-19 sample, only U.S.A. significantly explain the volatility in China stock market returns. While during the COVID-19 period, there is no significant impact of stock returns volatility communing from advanced countries towards China stock market return. In model 2, we find that in full and before the COVID-19 sample, no significant impact of China stock returns on Switzerland stock returns is seen, but there is a persistence of positive leverage effect in both cases. The leverage effect means that a positive shock has less effect on the conditional variance (Switzerland stock returns) as compared to a negative shock or news. It means that the good news or shock or error generates less variance or volatility than the bad news (COVID-19 pandemic news). During the COVID-19 sample, the China stock returns significantly impact, explaining the volatility of Switzerland stock market returns. The existence of free trade between China and Switzerland well explains the reason for shock transfer. Model 3 results capture the Sweden and China impact of stock returns volatility, in which we find that China stock returns significantly explain the Sweden stock returns volatility in all three scenarios, but the leverage effect exists in the only full sample and before the COVID-19 sample. In the Netherlands model (model 4), we find the same results as in the case of Sweden, in which China stock returns have a significant impact on explaining the volatility of Netherlands stock market returns. In the U.S.A. (model 5), we find that China has a significant impact on explaining the stock market volatility of the U.S.A. stock market in full and before the COVID-19 sample with a positive leverage effect. While during the COVID-19 sample, we find that China stock returns do not significantly impact U.S.A. stock returns, but leverage effect can be seen in this case. Finally, in the UK model (model 6), we find no leverage effect in all three scenarios but the full sample, before COVID-19 and during COVID-19 sample, China stock returns have a significant impact on explaining the stock markets returns volatility of the UK stock market. The study results expose that the volatility in selected countries indices has increased due to the pandemic situation. Findings of Tripathy (2017), Mishra (2017), Ahmad et al. (2018), and Chaudhary et al. (2020) support the findings of this study.

5.1. Policy implication

This study supports prospect theory, a well-known theory of markets. According to the theory, people are more scared of failure than the benefit inspires them. We can state that if people are given two alternate choices, they will select a minimum chance of loss despite the alternate that has more chance of gains. Likewise, in pandemics, the investors will participate in stocks that show less volatility caused by the current pandemic. This study provides important implications for the policymakers of advanced and other countries where the current pandemic gives shock to the entire

financial markets. First, due to a disturbing situation in almost all the countries because of the outbreak of COVID-19, this study illustrates the functions of transmission of shocks among the major stock indices. Second, this study describes the usefulness of the TARCH model, which is one of the GRACH family models an advanced level of time series analysis. That model looks at how markets are interconnected and communicates shocks from one economy to another economy. Finally, this study is primarily for policymakers of the world's most advanced countries, for formulating their countries' economic and innovation policies. This can be done by analysing the co-movements of the correlated stock indices and market variations. This research recommends that health policies be executed during the pandemic to restrict the spread of deadly disease, and macroeconomic policies can also be the target to minimise the financial and economic losses. Portfolio managers can also take advantage of the research findings for creating a superior portfolio to receive better accomplishment.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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