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Assessment of volatility in Asian stock markets during covid-19 pandemic period by using ARCH/ GARCH model

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ABSTRACT

The purpose of this study is to investigate the volatility and leverage effect of the eight Asian covid-19 cases recorded in county stock market indexes during the novel coronavirus outbreak (Covid-19). Daily time series data of observed stock market indices from 1st February to 30th April 2021 were evaluated using descriptive statistics, the GARCH model, the EGARCH model, and the TGARCH model. During the outbreak of Covid-19, the standard deviation number substantiates the increase in volatility in a specific stock market index. The GARCH result confirms the presence of higher volatility in all of the studied stock markets, except the Malaysia (KLCI Index) stock market, during the Covid-19 era. In all eight nations analyzed, the asymmetry coefficient is negative, indicating that variance increases more after negative residuals (stock returns) than after positive residuals (returns). During the outbreak of the coronavirus pandemic, the EGARCH finding demonstrates that the leverage effect exists in observed stock market indices. The outcome demonstrates the impact of unfavorable news on certain worldwide stock market activity during the Covid-19 pandemic's breakout.

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1. INTRODUCTION

COVID-19 was first brought to the world's attention in January of 2020. The rapid spread of the virus, as well as an increasing number of confirmed cases, spurred the Chinese government to take swift action. The entire city of Wuhan was put on lockdown on January 23, 2020, startling the entire world and proving to be a highly effective policy intervention by the Chinese government. A week later, the WHO declared the epidemic in China a global public health emergency (PHEIC). At the time, there were 7,711 confirmed cases, with only 83 cases outside of China in 18 countries. South Korea was the second country to see a big COVID-19 outbreak, which was quickly followed by Iran. The second country to see a large COVID-19 outbreak was South Korea, which was swiftly followed by Iran. In one week, South Korea went from 31 to over 1,000 occurrences, whereas Iran grew from zero to over 1,000 in 12 days. Using data from the John Hopkins Coronavirus Resource Center, the confirmed cases for the six most severely affected countries are plotted over time. While China and South Korea were still under control in March, attention switched to Europe and the United States. Although the United States has the highest number of verified cases, Italy has the highest death rate. As a result of the WHO's formal declaration of a global pandemic, financial markets around the world have begun to plummet. For example, the S& P 500 reached a high of 3386.15 on February 19, 2020, before dropping to 2237.40 on March 23, 2020, and almost a 30% decrease in just one month. The standard deviation of daily returns was 0.0069 in February and 0.0268 in March. In 2003, SARS, or severe acute respiratory syndrome, was estimated to cost the world between $30 and $100 billion. While SARS was primarily a Chinese issue, the COVID-19 outbreak has already become a global tragedy, behaving as if it were "the once-in-a-decade sickness." The worldwide economic impact is expected to be substantially bigger. COVID-19 was first brought to the world's attention in January of 2020. The rapid spread of the virus, as well as an increasing number of confirmed cases, spurred the Chinese government to take swift action. The first objective of this study is to reveal the link between stock market risks and COVID-19 outbreaks. Along with India and China countries in the eight confirmed cases were chosen (based on data as of 28th May 2021). These countries have a total of 17.8 percent cumulative cases and 10.22 percent (table 1) of cumulative deaths and all of them have mixed developed stock markets. The standard deviations of daily returns are used to calculate market risk.

2. REVIEW OF LITERATURE

Neo kosmidis (1991) in their study collected data for four US stock indexes (Dow Jones, Nasdaq, NYSE, S&P500 ARCH, GARCH (1,1), EGARCH (1,1) Multivariate volatility models from March 2003 to March 2009. Based on the AIC minimum criterion, the study shows that the EGARCH model is the best-suited process for all of the sample data. For all stock indexes, there are significant volatility periods at the start and end of our estimation period. Singh et al.(2008) 15 world indices for the period of January 2000 to February 2008 have been considered AR-GARCH, bivariate VAR, Multivariate GARCH (BEKK) model. There is significant positive volatility spillover from other markets to Indian market, mainly from Hong Kong, Korea, Japan, Singapore, and US market. Indian market affects negatively the volatility of US and Pakistan. Chang et al. (2011), GJR-GARCH model for the Taiwan Stock Exchange (TAIEX), the S&P 500 Index, and the Nasdaq Composite Index from January 2000 to January 2004. (1,1) The TAIEX, the US spot index, and US index futures all have a considerable price transmission effect and volatility asymmetry.

Athukoralalage (2011) weekly stock market data of Australia, Singapore, UK, and the US for the period from Jan 1992 to June 2010. M-GARCH Model, Diagonal BEKK model ARCH, and GARCH techniques Positive return spill-over effects are only unidirectional and run from both US and UK (the bigger markets) to Australia and Singapore (the smaller markets). Shocks arising from the US market can impact on all of the other markets in the sample. Chen (2012) studied the New York, London, and Tokyo as well as those of Hong Kong, Shanghai, and Shenzen the period January 1993 to March 2010 Granger causality test, VAR model, VEC model, variance decomposition, impulse response function, co-integration, and GARCH models Evidence shows that five stock markets are in the process of increasing integration. The periodic breakdown of the co-integrating relationship is advantageous to foreign investors. Jebran & Iqbal (2016) in their paper they studied Pakistan, India, Sri Lanka, China, Japan, and Hong Kong as Asian countries. The data was collected daily from January 1999 to January 2014. The results of the GARCH model demonstrated that there was no volatility spillover impact between the Indian and Chinese stock markets. Other Asian markets, on the other hand, have generated bidirectional and unidirectional spillover effects. Pati et al. (2017) India NIFTY Volatility Index (IVIX) and CNX NIFTY Index (NIFTY), Australia S&P/ASX 200 Volatility Index (AVIX) and S&P/ASX 200 Index (ASX), and Hong Kong Hang Seng Volatility Index (VHSI) and HSI, consider the period of January 2008 to July 2016. GARCH family models. The study finds that the volatility index is a biased forecast but possesses relevant information in explaining future realized volatility. GARCH family models suggest that it contains relevant information in describing the volatility process.

Bhowmik & Wang (2018) BSE 30, SSE composite, DSEX, FBMKLCI, PSEi, KOSPI indices data of daily closing prices for the period of January 2007 to 2016. GARCH family models and VAR model. The returns and volatility linkages exist between the emerging Asian markets and the developed stock markets. The volatilities to unexpected shocks in various markets, especially, come from neighboring country markets and more developed country markets. Kumar & Biswal (2019) Brazil, India, Indonesia, and Pakistan stock markets return the average price (open, close, high, and low) for January 2014 to October 2018. GARCH family models, The result confirms the presence of volatility clustering and leverage effect that is that good news affects the future stock market more than bad news. Ozili and Arun (2020) examined the impact of a social distancing policy implemented to prevent the spread of the coronavirus (SARS-CoV-2), using data from four continents: North America, Africa, Asia, and Europe. The study focuses on how a 30-day social distancing strategy or lockout harms the economy by negatively impacting stock values. Azimili (2020) investigates the effects of covid-19 on the degree and structure of risk-return reliance in the United States. The findings reveal that in the higher quantiles of the COVID-19 occurrence, the degree of dependency between returns and market portfolio has increased, limiting the benefits of diversification. Osagie et al. (2020) discovered that the coronavirus (SARS-CoV-2) has a negative impact on stock returns in Nigeria, and that a stable political climate, incentives for local businesses, diversification of the economy, and a flexible exchange rate regime should be implemented to enhance the financial market. Shezad et al. (2020) used the Asymmetric Power GARCH model to investigate the nonlinear behavior of the financial markets in the United States, Italy, Japan, and China. The study found that the coronavirus (SARS-CoV-2) had a negative impact on the S&P 500's stock returns. The study, however, had no discernible effect on the Nasdaq Composite index

3. DATA AND METHODOLOGY

Daily time series data was acquired from the stock exchange databases of eight Asian countries to perform this empirical study. Because China reported the first case of Covid-19 to the WHO's local office on December 31, 2019, the current Covid-19 period has been determined to span from 1st February 2020 to 30th April, 2021. This study takes into account the top ten covid-19 cases recorded and affecting stock market indexes in nations such the China (Shanghai Stock Exchange (SSE) Composite Index), India (Nifty 50), Hong Kong (Hang Seng Index (HSI)), Japan(Nikkei 225), Malaysia (KLCI Index), New Zealand (NZX 50), Australia(ASX All Ordinaries) and Philippines (PSEi Index) as of 30th April 2021. Firstly, returns for stock market indices were calculated as following: Rt = 100 * ln(St / St-1). Augmented Dickey-Fuller (ADF) test, Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) tests, and GARCH family of models were applied for the present research. The study has employed the E-views 11 package for investigation. Volatility is estimated on the daily returns of China (Shanghai Stock Exchange (SSE) Composite Index), India (Nifty 50), Hong Kong (Hang Seng Index (HSI)), Japan (Nikkei 225), Malaysia (KLCI Index), New Zealand (NZX 50), Australia(ASX All Ordinaries) and Philippines (PSEi Index).

Table 1. Covid-19 cases reported in observed Asian countries as on 28.05.2021

Country	Covid-19 cases	% of total world cases	Death cases	% of total deaths
India	2,75,55,457	16.24	3,18,895	9.05
Australia	30,074	0.02	910	0.03
China	91,045	0.05	4,636	0.13
Hong Kong	11,837	0.01	210	0.01
Japan	7,29,853	0.43	12,601	0.36
Malaysia	5,41,224	0.32	2,491	0.07
New Zealand	2,670	0.00	26	0.00
Philippines	12,00,430	0.71	20,379	0.58
Total Cases in observed countries	3,01,62,590	17.78	3,60,148	10.22
worldwide cases	16,96,48,062		35,25,426	

Source: https://www.worldometers.info

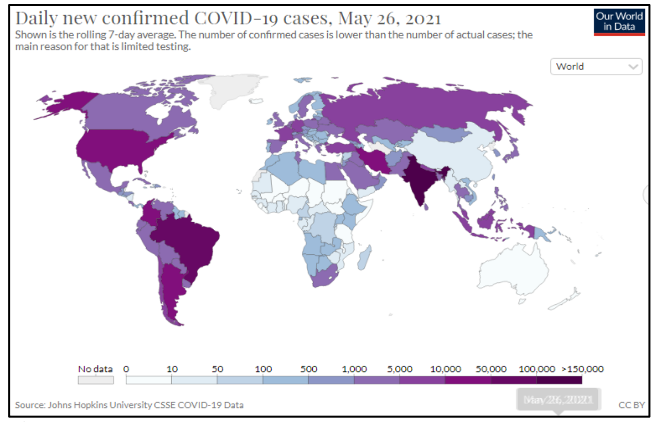

Figure 1. COVID-19 map as on May 26, 2021

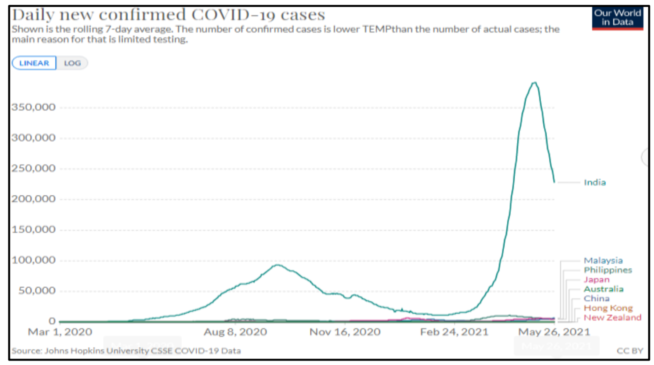

Figure 2. COVID-19 cases of observed countries

3.1 Augmented Dickey-Fuller (ADF) Test

The standard DF test is carried out by estimating the following Equation after subtracting yt-1 from both sides of the equation:

Dyt = ayt – 1 + xt ¢d + et,

Where a = r – 1. The null and alternative hypotheses may be written as,

H0: a = 0

H1: a < 0

Null Hypothesis: H0: There is a unit root; the time series is non-stationary.

Alternate hypothesis: Ha: There is no unit root; the time series is stationary

3.2 Tools for measuring Volatility

When compared to downward movements of a similar sort, increasing moves in the stock market are generally followed by modest variations. The leverage effect is the name given to this unbalanced moment. As a result, the symmetrical Generalized ARCH (GARCH) methodology will not be suited for evaluating unpredictability in time series. The Exponential GARCH (EGARCH) approach proposed by Nelson (1991) and the Threshold GARCH (TARCH) technique championed by Glosten, Jaganathan, and Runkle (1993) and Zakonian (1994) are used to capture the asymmetrical data.

Table 2. Overview of the GARCH-family models used

Model	Short Description	Formula
GRACH (1,1)	the indicator about the time a shock will persist	$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ $\alpha_0 > 0,\ \alpha_1 \geq 0,\ \beta_1 \geq 0,$ $\alpha_1 + \beta_1 < 1$ (Stationarity constr.)
Exponential GARC H (EGARCH) (1,1)	Capture the asymmetry of the volatility	$\ln(\sigma_t^2)=\omega+\beta\ln(\sigma_{t-1}^2)+\gamma\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}+\alpha\left[\frac{\lvert u_{t-1}\rvert}{\sqrt{\sigma_{t-1}^2}}-\sqrt{\frac{2}{\pi}}\right]$
Integrated GARCH (IGARCH) (1,1)	Any shock to volatility is permanent and the unconditional variance is infinite	$\sum_{i=1}^{q}\alpha_i+\sum_{j=1}^{p}\gamma_j=1.$

Table 3. Descriptive statistics of observed stock market indices

	Nifty	SSE Composite Index	Hang Seng Index	Nikkei 225	PSEi Index	ASX All Ordinaries	KLCI Index	NZX 50
Mean	0.073845	0.000745	0.034516	0.074520	-0.031700	0.021140	0.018075	0.027463
Median	0.040730	0.000839	0.111093	0.040730	0.032052	0.161766	0.039600	0.058413
Std.Dev.	1.911555	0.011790	1.447665	1.554435	1.972653	1.725338	1.151035	1.142924
Skewness	-1.655288	-0.107546	-0.44110	0.111319	-1.869549	-1.669888	-0.189908	-0.25999
Kurtosis	15.39430	5.447428	4.798887	7.210962	15.73544	10.59453	8.806528	10.70453
Jarque-Bera	2112.091	76.70963	10.34942	225.2357	2209.493	903.4069	431.7154	926.7532
Probability	0.0000	0.00000	0.0000	0.00000	0.0000	0.0000	0.0000	0.0000

4. DESCRIPTIVE STATISTICS

The descriptive statistics of the data set of the eight stock markets affected by the Covid-19 epidemic are shown in Table 3. When compared to other chosen stock market indices during the Covid-19 epidemic, the result indicates that stock prices in the Philippines (PSEi Index) and India (Nifty 50) are the most volatility, as indicated by standard deviations of 1.97 and 1.91, respectively, while stock markets in the China-SSE and New Zealand (NZX 50) are the least volatility, with standard deviations of 0.012 and 1.14, respectively. All of the observed indices in the Covid-19 pandemic have a negative skewness coefficient, indicating that it has a long left tail and that all of the selected stock market indexes exhibit non-symmetric returns. All of the indices have an excess kurtosis, indicating that the returns are not normally distributed across the whole research period. The Jarque-Bera test statistic is used to test the hypothesis that log returns are regularly distributed, and the results show that the null hypothesis of normality is rejected at a significance level of 5%.

4.1 GARCH (1, 1) test results

Table 5 shows the results of the GARCH (1,1) test on the daily stock prices of the Asian impacted stock markets during the Covid-19 era. The GARCH (1,1) indicates that conditional variance changes away from the long-run mean take a long period. GARCH outcomes have been almost entirely positive during the Covid-19 outbreak. The GARCH effect is highly strong in the (Shanghai Stock Exchange (SSE) stock market indices in China and low in the NSE Nifty stock market indices in India. In general, the volatility is computed by summing the values in the GARCH (1,1) model, and the combined value of and during the Covid-19 period ranges from 0.9767 Australia(ASX All Ordinaries) to 0.84665 India (Nifty). The findings of the tests demonstrate that during the Covid-19 epidemic, all of the observed stock market indexes had a greater ARCH and GARCH influence. The fact that the GARCH coefficient is higher than the ARCH coefficient indicates that conditional variance is heavily reliant on forecast variance from the preceding period rather than knowledge about prior period volatility.

Table 4. Augmented Dickey-Fuller Test (ADF)

Indices	Augmented Dickey Fuller Test (ADF) Level with Intercept	
	T-Statistics	Prob. Value
India -Nifty	-5.242465	0.00000*
China- SSE Composite Index	-16.96352	0.00000*
Hong Kong- Hang Seng Index	-19.74323	0.00000*
Japan- Nikkei 225	-16.23120	0.00000*
Philippines- PSEi Index	-6.952075	0.00000*
Australia- ASX All Ordinaries	-7.572980	0.00000*
Malaysia- KLCI Index	-17.94088	0.00000*
New Zealand- NZX 50	-16.35294	0.00000*
Note- H0: Variables have unit root Test critical values:* 1% level -3.432807 5% level -2.862511 10% level -2.567332		

H0: Variables have unit root

The Augmented Dickey-Fuller test is used in table 4 to determine whether or not the eight Asian countries covid-19 instances reported stock market indices time series attributes are stationary. The ADF test is statistically significant at the 1% level, according to the principal outcome of this test. This means that the null hypothesis is rejected and that the returns of all selected stock market indices throughout the Covid-19 epidemic are stationary. All of this demonstrates that autocorrelation does not occur. As a result, the null hypotheses of the ADF test are rejected, and the return series data are determined to be stationary at the level.

This shows that equities market volatility can be represented by a pattern of volatility that is predicted to persist over time. Perhaps the conclusions are drawn from the fact that certain financial markets are substantially more volatile, especially during the Covid-19 era.

Table 5. Parameters estimates of GARCH (1.1) model

	Nifty	SSE Composite Index	Hang Seng Index	Nikkei 225	PSEi Index	ASX All Ordinaries	KLCI Index	NZX 50
ω (constant)	0.209895 (0.0065)*	7.90E-06 (0.0555)	0.126409 (0.0526)	0.134318 (0.0399)*	0.201857 (0.0094)*	0.074916 (0.0470)*	0.134719 (0.0203)*	0.075278 (0.0123)*
α (arch effect)	0.307132 (0.0000)*	0.095677 (0.0059)*	0.102060 (0.0086)*	0.162748 (0.0008)*	0.207339 (0.0001)*	0.222582 (0.0001)*	0.159108 (0.0001)*	0.157722 (0.0000)*
β (garch effect)	0.654944 (0.0000)*	0.850180 (0.0000)*	0.837864 (0.0000)*	0.774824 (0.0000)*	0.744514 (0.000)*	0.754127 (0.0000)*	0.724629 (0.0000)*	0.774672 (0.0000)*
α + β	0.962076	0.945857	0.939924	0.937572	0.951853	0.976709	0.883737	0.932394

*Note: * Significance at 5%*

Table 6. Parameters estimates of EGARCH (1.1) model

	Nifty	SSE Composite Index	Hang Seng Index	Nikkei 225	PSEi Index	ASX All Ordinaries	KLCI Index	NZX 50
ω (constant)	-0.158916 (0.0000)*	-0.696454 (0.0324) *	-0.130490 (0.0205) *	-0.169257 (0.0001) *	-0.168933 (0.0000) *	-0.165809 (0.0014) *	-0.182953 (0.1378)	-0.225939 (0.0000) *
α (arch effect)	0.240759 (0.0000) *	0.190494 (0.0016) *	0.222507 (0.0074) *	0.250257 (0.0001) *	0.271158 (0.0000) *	0.231693 (0.0005) *	0.497268 (0.0000) *	0.296705 (0.0000) *
β (garch effect)	0.990823 (0.0000) *	0.937739 (0.0000) *	0.943849 (0.0000) *	0.968500 (0.0000) *	0.971933 (0.0000) *	0.982001 (0.0000) *	-0.613902 (0.0000) *	0.940083 (0.0000) *
α + β	1.231582	1.128233	1.166356	1.218757	1.243091	1.213694	-0.11663	1.236788
Leverage effect	0.279069 (0.0000) *	0.033144 (0.4850)	0.127338 (0.0018) *	0.093336 (0.0000) *	0.155608 (0.0001) *	0.199926 (0.0000) *	-0.113076 (0.0210) *	0.039808 (0.2274)

*Note: * Significance at 5% γ*

For analyzing the asymmetrical effect of news and data on volatility and leverage, the EGARCH (1,1) model is appropriate. The EGARCH (1,1) model's positive and statistically significant gamma (γ) establishes the truth of the leverage effect and shows that positive shocks have even less influence on the explanatory variables, implying that the leverage effect (gamma) is expected to be negative and statistically significant. Table 6 exhibits that during the Covid-19 outbreak, the sum of and in the EGARCH (1,1) model ranges between -0.113076 and 0.279069. When the total of and exceeds one, the ARCH and GARCH shocks have a larger impact on volatility, and conditional variance is volatile. The results demonstrate that during the Covid-19 era, the total of and are greater than one of seven stock market indexes (excluding Malaysia- KLCI Index, which is negative), indicating that there are ARCH and GARCH shocks on volatility and conditional variance is volatile. The gamma parameter (γ) is a measure of asymmetric volatility; however, during the Covid-19 outbreak, it was positive in all but one stock market Malaysia- KLCI Index, which was statistically insignificant. This means that during the outbreak, the leverage effect did not present in some stock market indices.

The leverage impact was present in the observed stock markets during the Covid-19 period, according to TGARCH test results. EGRACH findings show that during the Covid-19 era, the total of and are larger than one of seven stock market indexes (except for Malaysia- KLCI Index, which is negative), indicating that there are ARCH and GARCH shocks on volatility and conditional variance is volatile. A measure of asymmetric volatility is the gamma parameter (γ). During the Covid-19 outbreak, however, it was positive in all stock markets except one, which was statistically insignificant. This suggests that the leverage impact was absent in various stock market indices during the outbreak.

Table 7. Parameters estimates of TGARCH (1.1) model

	Nifty	SSE Composite Index	Hang Seng Index	Nikkei 225	PSEi Index	ASX All Ordinaries	KLCI Index	NZX 50
ω (constant)	0.041258 (0.1739)	7.90E-06 (0.0614)	0.102827 (0.0643)	0.088493 (0.0507)	0.152109 (0.0227)*	0.033233 (0.1992)	0.068435 (0.0240)*	0.068354 (0.0078)*
α (arch effect)	0.500792 (0.0000)*	0.101877 (0.0452)*	0.218086 (0.0084)*	0.224201 (0.0002)*	0.333722 (0.0001)*	0.350713 (0.0005)*	0.253349 (0.0001)*	0.184897 (0.0002)*
β (garch effect)	0.833052 (0.0000)*	0.848925 (0.0000)*	0.851508 (0.0000)*	0.833174 (0.0000)*	0.783681 (0.0000)*	0.834775 (0.0000)*	0.840990 (0.0000)*	0.810712 (0.0000)*
α + β	1.333844	0.950802	1.069594	1.057375	1.117403	1.185488	1.094339	0.995609
Leverage effect	-0.505335 (0.0000)*	-0.009259 (0.8829)	-0.205321 (0.0065)*	-0.181279 (0.0120)*	-0.276306 (0.0004)*	-0.321815 (0.0015)*	-0.275619 (0.0000)*	-0.115227 (0.0308)*

*Note: * Significance at 5% γ*

4.2 TGARCH (1,1) Test results

The findings of the TGARCH (1,1) test have been utilized to identify the asymmetric performance or leverage effect. Table 5 shows that over the Covid-19 period, the volatility, or the sum of and in the TGARCH (1,1) model, ranged from 0.950802 to 1.33384 (table.7). In the China stock market (SSE Composite Index), the sum is smaller than one, indicating that ARCH and GARCH shocks have a bigger impact on volatility, but the ARCH and GARCH coefficients are not statistically significant. However, the gamma parameter (γ) is negative and less than zero in all the observed stock market indices which were significant during the period of Covid-19. This means that leverage effects exist in the select stock markets during the outbreak of the pandemic. During the period of Covid-19, the Indian Nifty stock market disclosed higher α (ARCH effect) than the other seven stock market indices that designate the effects in earlier periods have a propensity to stay more or less for a longer time or less market efficiency than it does in other nine stock markets under study. The (GARCH impact) values across time reveal long-term implications on stock market volatility. During the Covid-19 period, the stock market of the Hang Seng indices revealed a higher (GARCH impact) than the other seven stock markets, which denotes a long-term impact on stock market volatility. The (leverage impact) value in the SSE Composite Index china stock market was higher than the other nine stock markets during the Covid-19 period.

5. CONCLUSIONS

The goal of this study was to see how the COVID-19 pandemic affects stock return volatility in the eight Asian countries afflicted by the virus. The descriptive study of the return data revealed that during the COVID-19 pandemic, stock returns in each country are very volatile, particularly in March 2020. The findings of the GARCH test demonstrate that during the Covid-19 pandemic, all observed stock market indexes had a greater ARCH and GARCH influence.

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