doi: 10.31674/book.2022sseg.021

COVID-19 Pandemic and Stock Markets: The Case of Select Asian Economies

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ABSTRACT

Introduction: The present study attempts to capture the dynamic connection between the outbreak of the COVID-19 pandemic and stock indices of select Asian emerging economies like China, India, South Korea, Indonesia, Hong Kong, and Thailand, along with the volatility in the select stock markets occurring out of the COVID-19 pandemic. **Methodology:** The study period begins on January 1, 2019 and continues up to April 6, 2022. The Bai-Perron test for the identification of structural breaks and the Wald test for the determination of short-run causality are used. Granger causality test measures the existence of uni-directional or bi-directional causality. To capture the volatility, Dummy-GARCH (1,1) along with EGARCH are used. **Results:** The results reveal the existence of causality over the short-run among the indices and COVID-19, as well as the existence of ARCH and GARCH effects in most of the stock indices, which may have occurred due to the external shock of the pandemic. **Conclusion:** The stock markets across the globe are experiencing depressed sentiment, which is replicated in the numerous crashes in the stock indices in all parts of the world.

Keywords: *Stock Markets; Asian Emerging Economies; GARCH-Dummy; EGARCH Model; COVID-19*

JEL Classification: G10, G14, G15, C23

INTRODUCTION

As the world continues to grapple with ways to respond to the virus, the performance of Asian emerging economies remains murky and pretty bleak, and the stock markets of these emerging economies are certainly not immune to the convulsions of the current crisis. The marketplaces are expatriate, and the business segments and supply chains of numerous prominent nations will experience a wave, particularly because most of the nation's import grossly from China to implement their manufacturing procedure. The outbreak of the pandemic obligated the Chinese administration to declare the biggest quarantine instruction in history, upsetting 513 million humans globally. SARS-CoV-2 has wreaked havoc on the world's demographics, resulting in more than 6 million deaths worldwide as of March 2022, making it the most serious global health crisis since the 1918 influenza pandemic (Cascella *et al.*, 2022).

The influence of the pandemic on the emerging Asian economies is immense, and the estimated GDP growth in 2020 and 2021 is beyond ascertainment. There is no doubt, that the aftermath is severe. As per the IMF, the development in Asia remains at 0 per cent in 2020 which is unprecedented. Exhibit 1 displays the global financial crisis of 4.7% with the Asian Financial Crisis of 1.3% (Rhee, 2020). But, in spite of such occurrences, the IMF is of the opinion that Asian economies are still in a better position than other regions in the world in the context of their business and economic activity.

Source: International Monetary Fund Blog

Figure 1: Decline in output of Asia

Previously, authors like Guo, Kuai and Liu (2020), Alsaifi, Elnahass and Salama, (2020), Kowalewski and Śpiewanowski (2020), Bash and Alsaifi (2019), Shanaev and Ghimire (2019), Buhagiar, Cortis and Newall, (2018), Chen, Jang and Kim, (2007), Chen *et al*., (2009), Ichev and Marinč (2018) and others have studied the impact of different events like disasters, sports, news, political events, and the outbreak of epidemics like SARS (Severe Acute Respiratory Syndrome) and EBD (Ebola Virus Disease) on stock market returns. Very recently, Al-Awadhi *et al.* (2020) examined the influence of the pandemic on the returns of the stock market of Chinese enterprises using a panel regression model along with correlation analysis and found that the high spread of the pandemic has a substantial negative impact on Chinese enterprises' returns among all the sectors. Again, Chen, Qian, and Wen (2021) analyzed the effect of the Coronavirus on consumption by using daily data of businesses in 214 towns and opined that the expenditure on goods and services is severely affected. However, no literature has been found on the volatility and dynamic association among the COVID-19 contagion and the Asian emerging stock markets.

In this background, an attempt has been made to examine and evaluate the consequences of the COVID-19 pandemic on the Asian emerging stock markets, including the Shanghai Composite from China; KOSPI from South Korea; BSE Sensex from India; JKSE Composite from Indonesia; Hang Seng from Hong Kong and SET 100 from Thailand. The present paper delves into measuring the dynamic connection amongst the COVID-19 pandemic and stock indices of the Asian emerging economies as well as the volatility of the stock indices from the eruption due to the COVID-19 pandemic.

LITERATURE REVIEW

There is a dearth of studies made on the effects of the COVID-19 occurrence pertaining to the different stock markets along with the economy. So, the authors have decided to survey the existing research works on the different epidemics that occurred globally in the past which have been summarised below.

He *et al.* (2020) using conventional t-tests and Mann-Whitney tests tried to introspect the effect of COVID-19 on several stock markets and found no evidence of an adverse effect on the selected stock markets. Zhang, Hu, and Ji (2020) investigate to identify the overall forms of systemic risks and country-specific risks in the equity markets across the globe due to the outbreak of COVID-19. The paper furthermore studies the possible magnitude of various strategy interferences. Sharif, Aloui, and Yarovaya (2020) attempt to explore the connection between volatility in the prices of oil including

stock markets, economic policy uncertainty, and geopolitical risks amid the COVID-19 outbreak in the United States by using the coherence wavelet method. Ashraf (2020) analyses the response of stock markets to the outbreak of novel coronavirus in sixty-four nations and witnessed that the stock markets respond adversely to the surge in COVID-19 confirmed cases. Huo and Qiu (2020) examine how China's stock market counters the sudden outbreak of COVID-19 mainly to the declaration of the pandemic lockdown. Moser and Yared (2021) measured the rate of success that can be achieved by introducing lockdown at the cost of a comparatively lower economic output. Huang *et al*. (2020) have tried to analyze coronavirus eruption in China and the government's answer. Again, authors like, Ru, Yang, and Zou (2020) proposed that the impression of the early familiarity with similar viruses is a basic mechanism causing timely responses to COVID-19. Caballero and Simsek (2020) in their paper presented a model of endogenous asset price twist and stern combined demand reductions subsequent to a huge real (non-financial) setback.

METHODOLOGY

Dataset and econometric modelling

The present study is centred on daily frequency data of the closing Asian emerging stock market indices like the Shanghai Composite from China; KOSPI from South Korea; BSE Sensex from India; JKSE Composite from Indonesia; Hang Seng from Hong Kong and SET 100 from Thailand. The daily data of these stock indices has been retrieved from the DataStream database. The authors also created a dummy variable that specifies the occurrence of the pandemic. Hence, the phase of the occurrence of the COVID-19 pandemic is denoted using a dummy variable, '1' inferring the phase from December 31, 2019, and '0' otherwise, because the disease erupted on December 31, 2019. To get a clear view of the movement of stock indices before and after the outbreak of the pandemic, the authors commence the period one year prior to the occurrence, i.e., from January 1, 2019, to April 6, 2022. The authors observe several analyses of the COVID-19 pandemic where the literature up to January, 2019 has been considered. The structural breaks in the study period are identified through the Bai-Perron Test. Subsequently, the Granger Causality Test and Wald Test are implemented to measure the short-run dynamic association between the variables used in the study. To capture the impact on volatility, dummy models like GARCH (1,1) and EGARCH are used.

The GARCH-dummy variable model

The GARCH models with dummy variables are framed by Lu and Chen (2011). Though, there is a limitation of short event windows, the GARCH-dummy methodology delivers valuable advice and statistical implications.

Opposing to CLRM which undertakes volatility as constant and time-invariant, GARCH models reflect that one-step-ahead restricted variance is reliant on prevailing accessible indications (Lu & Chen, 2011). The mean model as propounded by Lu and Chen (2011) is provided hereunder:

$$Xt = \beta 0 + \sum_{I=1}^{k} \beta i\, Yit + \mu t, \mu t \mid It\text{-}1 \sim M(0, ht) \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where, Y's are lagged endogenous and/or exogenous variables; I_{t-1} is the information accumulated up to time t-1. Then, GARCH (q, p) regression model additionally postulates a restrictive variance regression model which is as follows:

$$Nt = \gamma 0 + \sum_{j=1}^{q} \gamma i \mu 2t\text{-}j + \sum_{k=1}^{p} \delta k Nt\text{-}k \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where, Y's are lagged endogenous and/or exogenous variables; I_{t-1} is the information accumulated up to time t-1. Then, GARCH (q, p) regression model additionally postulates a restrictive variance regression model which is as follows:

$$N_t = \gamma_0 + \sum_{j=1}^{q} \gamma_i \mu^2 t\text{-}j + \sum_{k=1}^{p} \delta_k N_{t-k} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

In eqn. 8.γ_i and δ_k are subject to the constraints: $\sum_{j=1}^{q} \gamma i + \sum_{k=1}^{p} \delta k < 1$ and $\gamma_i \zeta > 0$. French, Schwert, and Stambaugh, (1987), Franses and Van Dijk (1996), and Chong, Ahmad, and Abdullah, (1999) have already demonstrated the effectiveness of the GARCH (1, 1) model in measuring economic time series data. At par with the above-mentioned studies, Lu and Chen (2011) also used this model in defining commercial and financial time-series data. Researchers like Edison and Reinhart (2001), Bologna and Cavallo (2002), Mazouz and Bowe (2009), and Lu and Chen (2011) applied a dummy model in studying the events.

$$X_t = \lambda_0 + \sum_{i=1}^{1} \lambda i\, Yi + \mu t, \mu t \,|It - 1 \sim M(0, ht) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$N_t = \gamma_0 + \sum_{j=1}^{pq} \gamma_i \mu^2 t\text{-}j + \sum_{k=1} \delta_k N_{t-k} + \beta d_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

where, d_t is defined as the dummy variable for a specific event window $\{s_1, s_2\}$ ($d_t = 1$, if $s_1 \leq t \leq s_2$; = 0 else).

RESULTS AND DISCUSSION

Granger Causality Test and Wald Test

Amongst the different VAR models, the Granger Causality test is quite popular. In this study, the Granger causality test is applied to conclude whether one cross-section time series is beneficial in estimating another thereby noting the way of the association between the variables of the study (Bagchi, 2016). However, while running this test we will only examine the existence of unidirectional causality if any, from COVID-19 to the Asian emerging stock indices, and not bidirectional causality. Therefore, in order to find out unidirectional causality from the explanatory variable COVID-19 to each of the dependent variables (Shanghai Composite, KOSPI, BSE Sensex, JKSE, Hang Seng, and SET 100), the following equation is estimated:

$$X_t = \lambda_0 + \sum_{j=1}^{n} \lambda_i X_{t-i} + \sum_{j}^{n} \delta_j COVID19_{t-j} + \mu_{2t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

In equation 5, X implies any variables like, Shanghai Composite, KOSPI, BSE Sensex, JKSE, Hang Seng, and SET 100. It is also anticipated that the turbulences μ1t and μ2t are not correlated. Equation 5 hypothesizes that each of the stock indices is related to lagged values as well as that of COVID-19.

Table 1 shows the values of F-statistics for Granger-causality tests using the lag length of 2. The null hypothesis is rejected in all the cases either at 1 per cent level or at 5 per cent level thus implying that COVID-19 Granger causes all the select stock indices.

Table 1: Granger Causality Test

Null Hypotheses	f-statistic	*p*-value	Remarks
COVID-19* does not Granger Cause Shanghai Composite	0.62428	0.0372	Reject
COVID-19 does not Granger Cause KOSPI	0.85410	0.0279	Reject
COVID-19 does not Granger Cause BSE Sensex	1.35662	0.040	Reject
COVID-19 does not Granger Cause JKSE Composite	1.46764	0.0341	Reject
COVID-19 does not Granger Cause Hang Seng	1.36985	0.0076	Reject
COVID-19 does not Granger Cause SET 100	1.12098	0.0089	Reject

**COVID-19 is a dummy variable with '1' representing the outbreak from 31 December, 2019 onwards and '0' otherwise.*

Now, to check the occurrence of the causality between COVID-19 and Asian emerging stock indices over a short-run time horizon, the Wald test has been applied. COVID-19 is taken as an independent variable and stock indices like Shanghai Composite, KOSPI, BSE Sensex, JKSE Composite, Hang Seng, and Set 100 are taken as dependent variables. It has been found that the values of F-statistic, t-statistic, and chi-square are significant for all the stock indices and hence short-run causality exists between COVID-19 and the Asian emerging stock indices and they move jointly over a short-run time horizon. Results of the Wald test are displayed in table 2 below.

Table 2: Wald Test

Dependent Var.	Independent Var.	f-statistic	t-statistic	Chi-square	*p*-value
Shanghai Composite	COVID-19*	173.471	13.170	173.471	0.000
KOSPI		171.327	13.089	171.327	0.000
BSE Sensex		170.649	13.063	170.649	0.000
JKSE Composite		168.510	12.981	168.510	0.000
Hang Seng		172.698	13.141	172.698	0.000
SET 100		166.246	12.893	166.246	0.000

**COVID-19 is a dummy variable with '1' representing the outbreak period from 31 December, 2019 onwards and '0' otherwise.*

Bai-Perron Test

Identification of multiple structural changes in Asian emerging stock indices that occurred due to the outbreak of COVID-19 is made through the Bai-Perron test. Shanghai Composite has a breakpoint in its structure on 14-Sep-20, KOSPI has a breakpoint on 20-Mar-20, BSE Sensex has a breakpoint on 24-Mar-20, JKSE Composite has a breakpoint on 25-Mar-20, Hang Seng has a breakpoint on 18-Feb-21, SET 100 has a breakpoint on 24-Mar-20 and the COVID-19 bears a breakpoint on 31st December, 2019. The variation in a time-series data specifies a modification in the character of a data occurring from the worldwide developments. Table 3 below showcases the results of the Bai-Perron Test.

Shanghai Composite	KOSPI	BSE Sensex	JKSE Composite	HANG SENG	SET 100	COVID-19*
Sep 14, 2020	Mar 20, 2020	Mar 24, 2020	Mar 25, 2020	Feb 18, 2021	Mar 24, 2020	Dec 31, 2019

**COVID-19 is a dummy variable with '1' representing the outbreak period from 31 December, 2019 onwards and '0' otherwise.*

GARCH Estimates

The parameter estimates of the GARCH (1, 1) model are presented in table 4 below, which are all found to be statistically significant at 1% and 5%. α and β coefficients are positive for both indices. The summation of α and β in the model is nearer to 1 (one), which lies from 0.934 to 0.983 with an average value of 0.955, which implies the presence of ARCH and GARCH effects, as indicated by Lu and Chen (2011). This necessitates that the existing volatility of stock market returns can be explained by some external shocks which can be COVID-19 in our case.

Table 4: GARCH (1, 1) Test Results

	Shanghai Composite	KOSPI	BSE Sensex	JKSE Composite	HANG SENG	SET 100
ω (constant)	3.488**	3.339*	4.582*	3.767*	4.491*	3.170*
	(0.031)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α (arch effect)	0.045*	0.165*	0.167*	0.067**	0.121**	0.157*
	(0.000)	(0.001)	(0.000)	(0.034)	(0.019)	(0.000)
β (garch effect)	0.903*	0.818*	0.798*	0.882**	0.813**	0.793*
	(0.000)	(0.000)	(0.000)	(0.023)	(0.009)	(0.000)
α + β	0.948	0.983	0.965	0.947	0.934	0.950
AIC	4.644	0.444	3.593	3.327	3.341	2.840
SIC	4.727	0.526	3.675	3.410	3.423	2.923

** represent significance at 1%; ** represents significance at 5%*

EGARCH Estimates

To inspect the asymmetries of information on volatility and the leverage effect, this study implements EGARCH (1,1) model. The asymmetries restricted by the parameter (γ) in the EGARCH model are negative and statistically noteworthy values specify the presence of leverage effects to disclose that positive effects have a smaller amount of effect on the conditional variance when compared to the negative effects. Table 5 points out the purpose of volatility, as computed through the summation of α and β in the GARCH (1,1) model, ranges from 3.077 to 1.26 with an average of 2.009, which is greater than one, thus representing a robust existence of ARCH and GARCH influences on volatility. The test results of EGARCH (1,1) additionally approve that the sum of ARCH (α) and GARCH (β) is more than one in the incident of Asian emerging stock markets, which designates that the conditional variance is volatile and the coefficients of ARCH and GARCH are noteworthy at 1% and 5% levels. The gamma parameter (γ), which is regarded as the indicator for asymmetric volatility, it is negative and significant at the 1% level for all the stock markets, which implies that the leverage effect in Asian emerging stock markets is observed. Moreover, this signifies that the impact of a progressive return to the select stock markets and crude oil makes lesser volatility than the impact of a negative return, as suggested by Premaratne and Balasubramanyan (2003).

Table 5: EGARCH (1, 1) Test Results

	Shanghai Composite	KOSPI	BSE Sensex	JKSE Composite	HANG SENG	SET 100
ϖ (Constant)	2.202	2.132	2.775	2.399	2.698	2.056
p-value	0.006*	0.001*	0.009**	0.000	0.007**	0.002*
α (ARCH Effect)	1.148	1.067	1.069	2.068	1.165	1.163
p value	0.003*	0.005*	0.000	0.005*	0.008**	0.009**
β (GARCH Effect)	0.112	1.008	1.008	1.009	1.003	0.233
p-value	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
$\alpha + \beta$	1.26	2.075	2.077	3.077	2.168	1.396
γ (Leverage Effect)	-0.22	-0.072	-0.075	-0.073	-0.232	-0.174
p-value	0.000*	0.000*	0.004*	0.003*	0.000*	0.000*

**denotes significance at the 1%; ** denotes significance at the 5% level.*

CONCLUSION

The stock markets across the globe are experiencing a depressed sentiment which is reflected in the frequent crashes in the stock indices in all parts of the world. Due to noteworthy ambiguity about the economic outlook and the connected shortcomings, it is problematic to enumerate the monetary effect, and an unanticipated expansion in ambiguity can put both economic growth and monetary steadiness at threat.

Granger causality test results prove the uni-directional causality running from COVID-19 to all the select stock indices which are further supported by the Wald test results that reveal the existence of the short-run relationship between COVID-19 and the Asian emerging stock markets. Both GARCH and EGARCH estimates disclose the presence of ARCH and GARCH effects that has an influence on the unpredictability of stock markets. Furthermore, in EGARCH, the value of γ is negative and significant at the 1 per cent level implying the existence of a leverage effect in all the Asian emerging stock markets.

ACKNOWLEDGMENT

The authors are extremely grateful to the anonymous reviewers and the Respected Editors for their constructive recommendations and invaluable comments that have helped in shaping up the present article.

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