Theoretical and Applied Economics
Volume XXX (2023), No. 4(637), Winter, pp. 243-256

The Asian Stock Market's reaction to Covid outbreak: an empirical Insights from ARDL approach

Dr. Neha SETH
Symbiosis International (Deemed) University, Noida, Uttar Pradesh, India
neha_seth01@yahoo.com
Deepti SINGH
Central University of Rajasthan, Ajmer, Rajasthan, India
ddeepti712@gmail.com

Abstract. *This paper examines the impact of COVID-19 on select Asian countries and the cointegration between the countries with high covid recovery rates and the countries with the least recovery rate. For this purpose, the daily closing values of ten Asian countries were taken from July 2018 to June 30, 2022. For this purpose, the paper employed Unit-root, Correlation analysis, Autoregressive Distributed Lag bound test, and Granger's Causality. The result implies that as an effect of Covid-19, all the markets were found to be strongly and positively correlated with each other. The results of the ARDL bound test depict that cointegration between the markets has significantly increased. Further, the pandemic has accelerated the bidirectional causality between the indices; hence, the markets affect each other even in the short run. The study results will help investors diversify their securities and hedge against adverse shocks like this pandemic.*

Keywords: Covid-19, Asian Stock Market, ARDL Cointegration, Covid Recovery Rates, Causality.

JEL Classification: C10, C40.

1. Introduction

The economic development of the world has a major contribution from the stock market, which has come to a halt due to the outbreak of infectious coronavirus leading to the worldwide lockdown and fall in the world economy. In today's era, no growing economy is deprived of a well-established stock market (Seth & Singh, 2023). It is a source to put the under-utilized and saved wealth into productive use. It has proved to be an essential sector of the financial system. With the passage of time, stock market integration is gaining more and more recognition. It is mainly because the degree of integration between markets significantly impacts the diversification opportunities for investors. Economic globalization or the increasing interdependency among the economies leads to an upsurge of this stock market integration. Numerous shreds of evidence exemplify this, mainly the wall street crash of 1929, black Monday (1987), and the financial crisis of 2007-2008, which led to a sudden fall in equity values and dangerously affected the economic system of the whole world.

The sudden outbreak of COVID-19 in China created a worldwide alarming situation. It has emerged as a significant phenomenon around the globe (Bloomberg, 2020). The coronavirus first appeared in Wuhan city of China, in December 2019. The pandemic first affected the Chinese economy, and it spread around the globe in just a couple of months. While the pandemic was transmitted to all countries, the degree of infection varied from country to country. On 30th January, WHO announced it as a global health emergency, and just after one and a half months, it was announced as a pandemic[(1)]. A series of nationwide lockdowns increased fatality rates; unusual drop-in economic activities led to a global economic recession. This global crisis has affected both developed and emerging economies (Hevia & Neumeyer, 2020) and has brought economic affairs to a standstill (Carlsson-Szlezak et al., 2020).

As the pandemic emerged from China, the countries nearer to China were affected earlier than the others. Thus, Southeast Asian countries were the most affected by the Covid-19 pandemic (Kartal et al., 2021). The countries took preventive measures to reduce the pandemic effect; still, the fatality rates, unemployment, and high volatility in share prices have occurred due to uncertainty. The pandemic has caused a dramatic fall in the stock market as the stock market always responds to the global situation. The beginning of the coronavirus pandemic demonstrated a stock market crash in March 2020 and faced huge losses. Consequently, the investors were compelled to look for safe options (Kinateder et al., 2021). As the investors feared loss, they sold their holdings, and the value of stocks fell sharply. Even the major stock indices were affected during the pandemic.

This paper examines the impact of the Covid-19 pandemic on select Asian countries and the cointegration between the countries with high covid recovery rates and the countries with the least recovery rate using the Autoregressive Distributed Lag model. As history proves, the stock market always recovers from shocks hence the countries with low values will eventually reach their normal levels. Therefore this paper contributes to providing better diversification opportunities to the investor, which will also help in the growth and development of low-rate countries. Although there is limited literature examining the impact of pandemic on the Stock market, but researchers around the globe made significant conclusions. Kartal et al. (2021) took the initiative to explore the reaction of East Asian Stock markets to a pandemic and concluded that there was a negative effect of this outbreak on the financial markets.

The paper is organized in the following manner: section 2 presents the insights of the reviewed literature, Section 3 depicts the Data and Research Methodology, followed by the Analysis and Interpretation. At last, the Study is Concluded with implications and the scope of future research.

2. Literature Review

This section deals with the empirical studies conducted around the world to show the impact of the Covid-19 on the stock market. According to an analysis by Nitha et al. (2021), examining the effects of Covid nineteen on Indian stock indices, i.e., Sensex and other sectoral indices, economic factors like crude oil also influenced the investor's decisions. It was a crucial factor in determining sectoral indices during the covid phase. Ahmed et al. (2021) analyzed the performance of the stock market and commodity market of South Asian countries as an effect of Covid-19. The study concluded that the Covid-19 outbreak significantly affected the markets of South Asian countries for a short duration, but the effect reduced in the second wave. The results also depict a significant negative impact on oil prices and India's stock market. He et al. (2020) examined the spillover and direct effect of Covid-19 on eight stock markets. The study used conventional t-tests and Mann and Whitney tests and concluded that a bidirectional spillover effect was observed between Asian, European, and American markets. The results also depicted that the pandemic had a short-term negative impact on these markets. In the same line, it was observed that compared to the European market, the Asian market was significantly and negatively affected due to this pandemic (Topcu & Gulal, 2020). Studies like Sharma (2020), Liu et al. (2020), and H. Y. Liu et al. (2020) also presented Similar results. Kumarapperuma et al. (2021) studied the effect of Covid-19 on Asian stock markets taking each developed, emerging, and frontier market into consideration. The study observed an Immediate negative impact but found that long-term impact was discovered only on emerging and frontier markets as indicated by two event windows.

Cutcu (2021) analyzed the relationship between number of death and stock indices using Panel data analysis with breaks of the ten most affected countries. Separate break dates were observed as per the conclusion for different countries due to some remarkable incidents which have been mentioned adequately. The global problem affects individuals' social life and health and has also significantly impacted the financial market (Zhang et al., 2020; Ali et al., 2020; Sansa, 2020). It has been observed that although the earlier epidemic outbreaks like the spread of Ebola virus disease (2013), MERS-Middle East respiratory syndrome (2012), and severe acute respiratory syndrome (2003) disease affected the market and indices in a significant manner, the COVID-19 has shown highest volatility and lead to difficulty in recovering for the countries (David et al., 2021). The recovery rate for every country has been visibly different, backed by an undefined number of reasons. In their study, Seven & Yılmaz (2020) analyzed the reasons for variation in equity market recovery. Fiscal rescue packages have proved to be significant in supporting stock recovery. The main factor, which is a nation's dependency rate on natural resources and tourism, has proved to be the reason for the slow recovery rate. Anh & Gan (2020) contributed to the existing literature on Covid-19 and the stock market by using panel-data regression model and depicting that the pre-lockdown period of the pandemic negatively and significantly affected the stock prices of the Vietnamese market. However, the lockdown period affected the market positively.

The above literature gives a glimpse of research conducted in the past year measuring the Covid-19 pandemic effect on different markets, either individually or in groups. The extensive review highlights a gap in analyzing the relationship between such markets. So that the investors could grab the opportunity of investing in countries where prices are still favourable because eventually, when everything would be in place and there would be no pandemic, the market will return to its original and these investors will gain in that situation. This foreign investment will also benefit the less recovering countries in creating stable economic conditions. So, this gap is the motivation of the present research work.

3. Data And Research Methodology

3.1 . Data

The paper examines the impact of COVID-19 on selected Asian countries and the relationship between countries with high recovery and lowest recovery rates. The study uses the Nikkei Covid-19 recovery index to select countries with the highest and lowest recovery rates(2). The daily closing values of the index for the period July 2018 to June 30, 2022, have been used from the web portal investing.com and Yahoo finance.

Table 1. *Summary of data*

Country	Index	Acronym
China	Shanghai Composite	SHCOMP
Qatar	QE All Share Index	QEAS
Singapore	FTSE Straits Time	STI
Israel	Tel Aviv-125	TA125
Turkey	Bursa Istanbul Stock Exchange 100	BIST100
Indonesia	IDX Composite	IDX
Bangladesh	Dhaka Stock Exchange	DS30
Malaysia	FTSE Bursa Malaysia	FBMKLCI
Vietnam	Vietnam Stock Exchange	VNI
Thailand	Stock Exchange of Thailand Index	SET

Note: The above table provides the abbreviations used in this study to represent various indices.
Source: Author's Calculation.

A selected index has represented each selected country firstly, an exchange was chosen on the basis of maximum market capitalization, and then out of all the indices of the exchange, the one which has the highest listing was selected: Shanghai composite has been taken to represent China, Qatar All Share index to represent Qatar, Straits Time to represent Singapore, TA-125 to represent Israel, BIST-125 to represent Turkey 10X composite to represent Indonesia, DSE 30 from Dhaka, KLCI from Malaysia, VNI to represent Vietnam and SET index to represent Thailand. The study uses the daily closing values of the indices for the days when Shanghai Composite was open for trading. The study period of 1st July 2018 to 30th June 2022 has been divided into two parts, i.e., from 1st July 2018 to 30th Jan 2020 is taken as a pre-covid period. On 30th Jan 2020 World Health Organization (WHO) declared a global health emergency because of the pandemic (He et al., 2020). Hence 1st Feb 2020 to 30th June 2022 is taken as the Covid period to study the impact for the purpose of this study.

Table 2 and Table 3 depict the descriptive statistics of data, which will help the readers gain a better understanding as it includes the major data points. According to Table IDX, the representative of the Indonesian Market was the most volatile index in both periods. The considerable information to be considered here is that the average returns of all the markets were positive in both the periods, as substantiated by the mean values. The Skewness and Kurtosis values highlight that the data is not normal, which has been further confirmed by Jarque-bera statistics.

Table 2. *Descriptive Statistics (Pre-Covid period)*

	BIST100	DS30	FBMKLCI	IDX	QEAS	SHCOMP	STI	TA125	VNI	SET
Mean	989.4290	1829.110	1659.600	6162.680	3026.740	2851.110	3195.656	1476.515	963.3226	1639.498
Median	973.5150	1851.045	1652.520	6195.695	3041.000	2890.120	3205.775	1472.930	968.9050	1636.815
Maximum	1235.560	2049.000	1826.900	6540.950	3245.540	3270.800	3407.020	1682.440	1024.910	1756.410
Minimum	836.7500	1361.640	1551.230	5633.940	2645.250	2464.360	2966.450	1287.620	878.2200	1531.000
Std. Dev.	75.6349	135.1069	67.1072	224.0293	116.0726	181.4027	95.1056	72.9749	31.6152	54.0928
Skewness	0.8721	-1.1379	0.6452	-0.2750	-1.0452	-0.1176	-0.1417	0.5005	-0.6656	-0.0273
Kurtosis	3.6930	4.3327	2.6178	1.9796	4.2597	2.3388	2.4367	3.1739	2.7665	2.5278
Jarque-Bera	56.3638	111.2929	28.9848	21.5034	95.3118	7.8814	6.3636	16.5221	29.2296	3.6142
Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0194	0.0415	0.0002	0.0000	0.1641

Source: Author's Calculation.

Table 3. *Descriptive Statistics (Covid Period)*

	BIST100	FBMKLCI	DS30	IDX	QEAS	SET	SHCOMP	STI	TA125	VNI
Mean	1241.64	1541.063	1790.715	5518.409	3056.745	1409.329	3262.514	2818.206	1505.565	1000.489
Median	1191.990	1573.765	1811.000	5742.330	3041.000	1415.870	3358.880	2826.475	1490.000	938.4150
Maximum	1570.420	1684.580	2236.770	6435.210	3466.320	1636.560	3696.170	3231.550	1775.660	1410.040
Minimum	842.4600	1219.720	1203.430	3937.630	2488.290	1024.460	2660.170	2233.480	1105.950	659.2100
Std. Dev.	194.0755	86.07081	251.9463	590.6139	219.2967	141.7615	270.5273	265.5227	140.8980	183.4145
Skewness	0.0534	-1.3464	-0.1268	-0.3805	-0.1992	-0.4431	-0.5890	0.0609	0.0116	0.4371
Kurtosis	1.8744	4.4593	2.3928	1.9758	2.6848	2.3905	1.9825	1.5263	2.6941	2.1100
Jarque-Bera	18.3228	134.4545	6.2077	23.3363	3.6993	16.5823	34.7287	31.3403	1.3488	22.3069
Prob.	0.0001	0.0000	0.0449	0.0000	0.1573	0.0003	0.0000	0.0000	0.5095	0.0000

Source: Author's Calculation.

3.2. Methodology

3.2.1. Unit-Root test: This test examines the stationarity in a time series. A stationary time series does not have a trend or seasonal effect or whose mean and variance remain constant over time (Seth & Singh, 2022). A non-stationary time series is affected by random shocks and follows the random walk theory (Nelson & Plosser, 1982). In order to find the long-run relationship between variables or cointegration, it is a prerequisite condition to make the series stationary. The Augmented Dickey-Fuller test (1979) has been used in the study to examine the presence of unit root. ADF is based on the following equation:

$$\Delta Y_t = \alpha + \sum_{i=1}^{q} \beta_i \Delta Y_{t-1} + \varepsilon_t \tag{1}$$

The Δ denotes the first difference, α symbolizes the constant variable, Y_t stands for the series being tested, q denotes the lag and ε_t represents the error term.

3.2.2. Correlation Analysis: Correlation refers to the degree of association between the variables considered for the study.

3.2.3. Autoregressive Distributed Lag: ARDL model is used to examine the long-run relationship between the variables. This model is feasible and provides unbiased results when applied to small sample size. To run an ARDL bound test, a series may be integrated at level, first difference or a combination of I(0) and I(1) and therefore overcome the limitation of conventional methods, which have a pre-condition that the series must be stationary of the same order.

3.2.4. Granger's Causality Test: Granger causality examines whether the variables under study have a cause-and-effect relationship. Discovered in 1969, this test shows a connection between two series in such a manner that if x granger causes y, a change in the value of x will lead to a change in y and vice-versa. It is used to examine the short-run relationship between the variables.

4. Analysis and Interpretation

The analysis section starts with examining association between variables through correlation analysis. The unit root test is used for ensuring the stationarity of the series, first at level, then at first difference. Further similar to previous studies, like Albulescu (2020); C. T. Albulescu (2020); Erokhin and Gao (2020), based on examining the linkage between markets during covid-19, ARDL bound test is used to check for cointegration and at last Granger Causality results (Mamaysky, 2021) is employed to study the cause-and-effect relationships among the said Indices.

4.1 . Correlation Analysis

Correlation attempts to find the degree of association between two variables. The pairwise matrix shows the results described by 'r', the value of which ranges from -1 to +1. The values greater than 0.5 indicate a high positive relationship between variables, and the zero correlation indicates that hardly any connection exists between the said variables.

Table 4 exhibits that BIST100 has a negative relation with DS30 (-0.5607), FBMKLCI(0.3313), SET(0.2113). DS30 has a negative relation with QEAS(-0.1208), SHCOMP(-0.3750), TA125(-0.8314) and VNI(-0.2719). In the same line, FBMKLCI and SET also signify negative relations with six other markets, that are BIST100, IDX, QEAS, SHCOMP, TA125, and VNI.

In contrast, the pandemic period shows an enhanced association between indices. Most markets are strongly and positively related, and all the markets have a positive relationship (Table 5). The market, like BIST100, which had a negative relation with DS30, FBMKLCI, and SET, shows a positive association during covid. DS30, which was negatively correlated with QEAS, SHCOMP, TA125, and VNI, depicted a positive correlation during the second period. As an effect of Covid-19, the correlation has significantly increased.

Table 4. *Correlation Analysis (Pre-Covid period)*

	BIST100	DS30	FBMKLCI	IDX	QEAS	SHCOMP	STI	TA125	VNI	SET
BIST100	1	-0.5606	-0.3312	0.2847	0.2563	0.3987	0.2036	0.6241	0.2939	-0.2113
DS30	-0.5607	1	0.5807	0.01020	-0.1208	-0.3750	-0.0019	-0.8314	-0.2719	0.3516
FBMKLCI	-0.3313	0.5807	1	-0.3210	-0.3534	-0.4429	0.0900	-0.5027	-0.1971	0.4998
IDX	0.2847	0.0102	-0.3210	1	0.6041	0.4267	0.4218	0.0853	0.2074	-0.0760
QEAS	0.2563	-0.1208	-0.3534	0.6041	1	0.1098	0.0437	0.1838	-0.0305	-0.1750
SHCOMP	0.3987	-0.3750	-0.4429	0.4267	0.1098	1	0.5654	0.4773	0.6128	-0.0181
STI	0.2036	-0.00189	0.0900	0.4218	0.0437	0.5654	1	0.1295	0.3309	0.2786
TA125	0.6241	-0.8314	-0.5027	0.0853	0.1838	0.4773	0.1295	1	0.4997	-0.1508
VNI	0.2934	-0.2719	-0.1971	0.2074	-0.0305	0.6128	0.3309	0.4997	1	0.2094
SET	-0.2113	0.3516	0.4998	-0.0760	-0.17502	-0.01819	0.2786	-0.1508	0.2094	1

Source: Author's Calculation.

Table 5. *Correlation Analysis (Covid Period)*

	BIST100	FBMKLCI	DS30	IDX	QEAS	SET	SHCOMP	STI	TA125	VNI
BIST100	1	0.7564	0.5970	0.8627	0.7716	0.8081	0.8151	0.6929	0.7224	0.8501
FBMKLCI	0.7564	1	0.2247	0.7366	0.7045	0.7344	0.7640	0.5400	0.5726	0.6269
DS30	0.5970	0.2247	1	0.5268	0.6407	0.4472	0.5323	0.4521	0.6106	0.6714
IDX	0.8627	0.7366	0.5268	1	0.7190	0.79117	0.7143	0.7933	0.742	0.7926
QEAS	0.7716	0.7045	0.6407	0.7190	1	0.7055	0.7774	0.5948	0.7943	0.8032
SET	0.8081	0.7344	0.4472	0.7911	0.7055	1	0.6398	0.8295	0.8044	0.8307
SHCOMP	0.8151	0.76400	0.5323	0.71437	0.7774	0.6398	1	0.4464	0.5667	0.77606
STI	0.6929	0.5400	0.4521	0.7933	0.5948	0.8295	0.4464	1	0.7943	0.7692
TA125	0.7224	0.5726	0.6106	0.7422	0.7943	0.8044	0.5667	0.7943	1	0.7733
VNI	0.8501	0.6269	0.6714	0.7926	0.8032	0.8307	0.7760	0.7692	0.7733	1

Source: Author's Calculation.

4.2 . Unit Root Test

In order to establish a long-run linkage between the variables or, in other words, to establish a cointegration between variables, it is essential that the series are stationary. Hence Augmented-Dickey fuller method has been applied to check the stationarity of time-series data. Table 6 presents the results of the ADF test, which exhibits that all the indices were non-stationary at level showing probability values more than 0.05 except for FBMKLCI having a probability value of 0.01, which is less than 0.05 level of significance. Hence all the other indices except FBMKLCI, which is found to be stationary at level only, fail to reject the null hypothesis, which is as follows:

$\mathbf{H_0}$ = x has a unit root, or x(variable) is not stationary.

As all the series were found non-stationary at level hence, they were differenced once. Consequently, the series became stationary at I(1), or statistically, all the variables rejected the null hypothesis.

In table 7 also, which shows the result of ADF for the Covid period, all the variables became stationary after first differencing except QEAS, which was found to be stationary at level only. From the mentioned results, it has been depicted that the series are a combination of I(0) and I(1). Hence to check for the presence of cointegration, Auto Regressive Distributed Lag will be the most appropriate method.

Table 6. *Unit Root Test (Pre-Covid period)*

Index	At level		At first difference	
	Adf statistic	Prob.	Adf statistic	Prob.
SHCOMP	-2.2909	0.4543	-7.1183	0.01
QEAS	-3.289	0.07302	-8.2115	0.01
STI	-3.2062	0.08708	-7.7354	0.01
TA 125	-1.7978	0.6625	-9.0558	0.01
BIST100	-2.3293	0.4381	-9.3624	0.01
IDX	-2.487	0.3715	-9.931	0.01
DS 30	-1.897	0.6206	-10.047	0.01
FBMKLCI	-4.0557	0.01	-7.8092	0.01
VNI	-3.2154	0.0855	-6.8755	0.01
SET	-3.045	0.1359	-10.028	0.01

Source: Author's Calculation.

Table 7. *Unit Root Test (Covid period)*

Index	At level		At first difference	
	Adf statistic	Prob.	Adf statistic	Prob.
SHCOMP	-2.4844	0.3724	-7.7105	0.01
QEAS	-4.4804	0.01	-9.1215	0.01
STI	-3.1774	0.09201	-7.8344	0.01
TA 125	-3.5368	0.03938	-9.0558	0.01
BIST100	-2.6722	0.2931	-7.8507	0.01
IDX	-3.3596	0.06125	-9.3351	0.01
DS 30	-2.7584	0.2568	-9.819	0.01
FBMKLCI	-2.7059	0.2789	-8.1484	0.01
VNI	-3.0076	0.1516	-8.1035	0.01
SET	-3.6317	0.03025	-8.9756	0.01

Source: Author's Calculation.

4.3 . Auto-Regressive Distributed Lag

The indices are a combination of stationary at the level and first difference; therefore, the ARDL is the best feasible method to test the long-term relationship between these indices. The null hypothesis of the ARDL model is rejected when the value of f-statistics is greater than the higher bound critical value, i.e., I(1) and it symbolizes that cointegration exists between the said variables. No cointegration prevails between the variables if this value is below the lower bound value. Still, if the f-statistics lie between the upper and lower bound values, the results are indecisive (Pesaran et al., 2001).

As per the rule, as shown in Table 8, one variable is taken as a dependent variable and others as regressors at one time. Hence when IDX, SET, STI, TA125, and DS30 are taken as dependent variables and others as independent ones, it was ascertained that cointegration existed between the indices as the value of f-statistics and t-statistics were found to be greater than the highest bound value that is I(1) at 5% level of significance. All the other markets, when taken as regressors, did not show any cointegrating relationship. Whereas, as an effect of the pandemic, the variables with cointegrating relationships increased. However, the STI index, which earlier depicted long-run relation when taken as a dependent variable during the Covid period, the t-statistics value was -4.6321, which is less than the highest bound value. Hence cointegration ceases to exist. All the other indices except BIST100, STI, and VNI showed a long-run association during the covid phase, as shown in Table 9. Hence, as an impact of pandemic, the cointegration increased between the markets, reducing the diversifying opportunities for the investors.

Table 8. *ARDL Bound Test (Pre-Covid period)*

Dependent| Independent	F-Stats	t-Stats	Decision Rule(5%)
BIST100| SHCOMP,QEAS,STI,TA125,IDX,DS30,FBMKLCI,VNI,SET	2.5759	-4.359	No-Cointegration
FBMKLCI| SHCOMP,QEAS,STI,TA125,IDX,DS30,BIST100,VNI,SET	2.2467	-4.319	No-Cointegration
IDX| SHCOMP,QEAS,STI,TA125,BIST100,DS30,FBMKLCI,VNI,SET	4.8124	-6.225	Cointegration
QEAS| SHCOMP,BIST100,STI,TA125,IDX,DS30,FBMKLCI,VNI,SET	2.4328	-2.4	No-Cointegration
SET| SHCOMP,QEAS,STI,TA125,IDX,DS30,FBMKLCI,VNI,BIST100	3.834	-5.942	Cointegration
SHCOMP| BIST100,QEAS,STI,TA125,IDX,DS30,FBMKLCI,VNI,SET	1.5424	-1.935	No-Cointegration
STI| SHCOMP,QEAS,BIST100,TA125,IDX,DS30,FBMKLCI,VNI,SET	3.89909	-5.404	Cointegration
TA125| SHCOMP,QEAS,BIST100,STI,IDX,DS30,FBMKLCI,VNI,SET	3.5983	-5.523	Cointegration
VNI| SHCOMP,QEAS,BIST100,TA125,IDX,DS30,FBMKLCI,STI,SET	3.0035	-4.1021	No-Cointegration
DS30| SHCOMP,QEAS,BIST100,TA125,IDX,STI,FBMKLCI,VNI,SET	5.0215	-6.4799	Cointegration

Critical Values with Case 3:Unrestricted Constant and No Trend				
	f-Stats		t-Stats	
	I(0)	I(1)	I(0)	I(1)
At 10%	1.88	2.99	-2.57	-4.56
At 5%	2.14	3.3	-2.86	-4.88
At 1%	2.65	3.97	-3.43	-5.54

Source: Author's Calculation.

Table 9. *ARDL Bound Test (Covid period)*

Dependent| Independent	F-Stats	t-Stats	Decision Rule(5%)
BIST100| SHCOMP,QEAS,STI,TA125,IDX,DS30,FBMKLCI,VNI,SET	2.1815	-2.0856	No-Cointegration
FBMKLCI| SHCOMP,QEAS,STI,TA125,IDX,DS30,BIST100,VNI,SET	6.6027	-7.2761	Cointegration
IDX| SHCOMP,QEAS,STI,TA125,BIST100,DS30,FBMKLCI,VNI,SET	4.6326	-6.2167	Cointegration
QEAS| SHCOMP,BIST100,STI,TA125,IDX,DS30,FBMKLCI,VNI,SET	5.9099	-7.0503	Cointegration
SET| SHCOMP,QEAS,STI,TA125,IDX,DS30,FBMKLCI,VNI,BIST100	6.3944	-7.1603	Cointegration
SHCOMP| BIST100,QEAS,STI,TA125,IDX,DS30,FBMKLCI,VNI,SET	3.3971	-3.9914	Cointegration
STI| SHCOMP,QEAS,BIST100,TA125,IDX,DS30,FBMKLCI,VNI,SET	4.1749	-4.6321	No-Cointegration
TA125| SHCOMP,QEAS,BIST100,STI,IDX,DS30,FBMKLCI,VNI,SET	4.8727	-4.8672	Cointegration
VNI| SHCOMP,QEAS,BIST100,TA125,IDX,DS30,FBMKLCI,STI,SET	3.7853	-4.7485	No-Cointegration
DS30| SHCOMP,QEAS,BIST100,TA125,IDX,STI,FBMKLCI,VNI,SET	5.0859	-6.3386	Cointegration

Critical Values with Case 3:Unrestricted Constant and No Trend				
	f-Stats		t-Stats	
	I(0)	I(1)	I(0)	I(1)
At 10%	1.88	2.99	-2.57	-4.56
At 5%	2.14	3.3	-2.86	-4.88
At 1%	2.65	3.97	-3.43	-5.54

Source: Author's Calculation.

4.4. Granger Causality Test

Granger's model attempts to examine the cause-effect relationship between various variables. It measures whether short-run relation exists between variables or not. Pre-covid results, as presented in Table 10, describe that BIST100 had bidirectional causality with two other indices, i.e., DS30 and TA125 and TA125 had a unidirectional relationship with FBMKLCI. On the other hand, many unidirectional relations were observed during this period. DS30 had a unidirectional causal link with four indices as it causes SET (0.009) and is caused by FBMKLCI (0.0410), SHCOMP (0.0241) and TA125 (0.0036). Similarly, QEAS had unidirectional relation with FBMKLCI (0.0060) and VNI (0.90). FBMKLCI had a unidirectional causality with all the markets except IDX, STI and VNI.

The Covid phase manifests very captivating results. Both unidirectional and bidirectional causal relationships have significantly increased compared to the pre-pandemic phase as presented in Table 11. BIST100 index had a unidirectional relation with all the indices, or it was in a position to affect all the selected Asian indices except QEAS or the Qatar market with which it shared bi-directional causality. Comparatively, all the markets were caused by VNI. QEAS has a bidirectional causality with BIST100, IDX, SET, and SHCOMP; SHCOMP with FBMKLCI and QEAS; IDX with SET and TA125; SET with STI and TA125; TA125 with STI. All the remaining markets shared unidirectional causality with each other.

Table 10. *Granger's Causality Test (Pre-Covid Period)*

	BIST100	FBMKLCI	DS30	IDX	QEAS	SET	SHCOMP	STI	TA125	VNI
BIST100	-	⬆	⇅	✖	✖	✖	✖	✖	⇅	✖
FBMKLCI	↲	-	⬆		↲	⬆	↲	✖	↲	✖
DS30	⇅	↲	-	✖	✖	⬆	↲	✖	↲	✖
IDX	✖	✖	✖	-	✖	⬆	⬆	⬆	✖	✖
QEAS	✖	⬆	✖	✖	-	✖	✖	✖	✖	↲
SET	✖	↲	↲	↲	✖	-	✖	✖	✖	✖
SHCOMP	✖	⬆	⬆	↲	✖	✖	-	⬆	✖	✖
STI	✖	✖	✖	↲	✖	✖	↲	-	✖	✖
TA125	⇅	⬆	⬆	✖	✖	✖	✖	✖	-	⬆
VNI	✖	✖	✖	✖	⬆	✖	✖	✖	↲	-

Source: Author's Calculation.

Table 11. *Granger's Causality Test (Covid Period)*

	BIST100	FBMKLCI	DS30	IDX	QEAS	SET	SHCOMP	STI	TA125	VNI
BIST100	-	⬆	⬆	⬆	⇅	⬆	⬆	⬆	⬆	↲
FBMKLCI	↲	-	✖	⬆	⬆	↲	⇅	✖	⬆	↲
DS30	↲	✖	-	↲	✖	⬆	↲	↲	✖	↲
IDX	↲	↲	⬆	-	⇅	⇅	↲	⬆	⇅	↲
QEAS	⇅	↲	✖	⇅	-	⇅	⇅	↲	⬆	↲
SET	↲	⬆	↲	⇅	⇅	-	✖	⇅	⇅	↲
SHCOMP	↲	⇅	⬆	⬆	⬆	✖	-	✖	✖	✖
STI	↲	✖	⬆	↲	⬆	⇅	✖	-	⇅	↲
TA125	↲	↲	✖	⇅	↲	⇅	✖	⇅	-	↲
VNI	⬆	⬆	⬆	⬆	⬆	⬆	✖	⬆	⬆	-

Note: ↲ and ⬆ denotes unidirectional relationship; ⇅ shows bidirectional causality and ✖ indicates no causality.

Source: Author's Calculation.

5. Conclusion

Covid-19 is the major phenomenon that has significantly affected the stock market recently. Hence, the study analyzed the impact of the COVID-19 pandemic on select Asian markets and examined the relationship between the countries with the highest covid recovery rates and low recovering countries from 1st July 2018 to 30th June 2022. This period was further divided into pre- covid (1 July 2018-31 Jan 2020) and Covid phase(1 Feb 2020-30 June 2022). For this purpose, the study employed unit root test, Correlation analysis, ARDL Bound Test and Granger's Causality test. The results concluded that the degree of correlation between countries has significantly increased due to the pandemic. Unlike in the pre-covid phase, no index showed a negative correlation between them. The results of ARDL revealed that a long-run relationship between more markets was observed during the COVID phase. Due to increased cointegration and correlation between markets, the diversification opportunities are reduced for investors (Gamal et al., 2021). The Granger's causality depicts that the markets affect each other even in the short run (Chaouachi & Slim, 2020). In contrast to the Pre-covid period, bidirectional causality has increased, and remarkably all the other markets were found to be unidirectionally related. The interesting fact to be observed here is that both unidirectional and bidirectional relationship between markets has increased. The study results will help the investors diversify their securities and hedge against adverse shocks like this pandemic. It will also assist the investors in quitting or continuing their existing portfolios.

Our contribution to the existing literature includes the impact of Covid-19 on the highest-recovering countries and the least recovering countries covering pre and post-pandemic periods. The study uses a methodological technique (ARDL bound cointegration) applied in significantly fewer studies regarding this issue. The findings would facilitate the regulating authorities and policymakers to make appropriate decisions and find the factors influencing the prices of shares based on stock market cointegration. As the markets are cointegrated, investors can predict other countries' price fluctuations by observing one or two markets. Further, this study may also benefit the researchers who want to study the impact of such shocks. The major limitation of the study is that it focuses on very limited countries' contexts. Further, the study focuses on examining only cointegration and causality between countries. Future studies may focus on examining volatility and contagion between countries as an effect of crisis by employing more advanced techniques and including other developed nations.

Notes

(1) https://www.statnews.com/2020/01/30/who-declares-coronavirus-outbreak-a-global-health-emergency/

(2) https://asia.nikkei.com/Spotlight/Most-read-in-2021/Nikkei-COVID-19-Recovery-Index2

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