Behaviour of Stock Returns During COVID-19 Pandemic: Evidence from Six Selected Stock Market in the World

Helma Malini[a,*]

[a] *Universitas Tanjungpura*

Abstract

This paper investigates the short term return behavior of six selected stock market around the world during the COVID-19 Pandemic. USA, Indonesia, India, South Korea, Saudi Arabia, and Singapore are selected based on the size of their stock market and the countries have taken a considerable amount of decision and policy to mitigate the risk of before, ongoing, and aftermath COVID-19 Pandemic. This study relies on two major time series investigation techniques, namely Econometric Modeling of returns; The Autoregressive model, Assumption of Linearity, Volatility Modeling, namely the GARCH and WBAVR Test. The results suggest that the stock return behavior in six selected countries occurs in different forms. Our findings suggest that the policymakers must understand how to shift their policy to mitigate the risk of COVID-19 in the financial sector, since we observe a strong correlation between the public health crisis and stock market performances.

Keywords: stock return; COVID-19 pandemic; stock market; volatilities; investor behavior
JEL Classification: G11; G12; G114; G01

*Corresponding Address: Fakultas Ekonomi dan Bisnis Universitas Tanjungpura, Jl. Prof. Hadari Nawawi, Pontianak, Kalimantan Barat 78121. E-mail: helma.malini@ekonomi.untan.ac.id.

1. Introduction

The world economy is currently going through a deep recession, with unemployment seeing record-high in some countries and global GDP experiencing a 20% decline. The COVID-19 outbreak is a phenomenon that the world did not expect to happen. It started with an outbreak in Wuhan in December 2019 and has since transformed into a pandemic that has infected more than 9 million people around the world (WHO, 2019). The virus moves around the world and ruins businesses and financial sectors and as consequences, financial sectors are severely impacted due to a huge decrease in the movement of capital, assets, and liquidity. Pandemic is a rare, but recurrent phenomenon. From 2002 to 2003, the world dealt with the SARS epidemic that started at the beginning of 2002 with a peak in fatalities and cases coming by 2003. However, only several countries during that time felt the calamity caused by the SARS, namely China, Taiwan, and Hongkong.

Contradicting the SARS epidemic, the COVID-19 virus has spread more quickly due to greater economic integration and mobility through international networks that have been knitted throughout the decades by the globalization process. As countries grow more interconnected with one another, risks of COVID-19 contagion and its subsequent economic impact are expected to surge, and such heightened risks may potentially disrupt capital flows and the trade of goods and services.

The COVID-19 outbreak has been followed by the increased instability of political and social-economic conditions around the world, and this has forced investors within the capital market industry to seek a stable portfolio platform. Stability despite both COVID-19 induced financial and economic crisis is observed among investment portfolios that are insulated against news and/or events happening in one country.

The financial crises that hit the world in 1997 and 2008 have been considered a setback for asset gatherers of all kinds in all marketplaces, but the stock market can derive a long-term benefit in the sense that it can serve as an alternative portfolio to others that are more prone to episodes of crisis (Price Water House Coopers, 2009).

However, the COVID-19 pandemic is relatively distinct compared to other world events that have hit the stock market throughout the decades – the Great Crash (10-11/1929), Great Depression (3/1933), Black Monday (10/1987), Global Financial Crisis (12/2008). The pandemic has caused a substantially larger downturn in the stock market, wherein the pandemic-induced crisis has engendered relatively sharper falls in stock markets and higher volatilities in exchange rates and commodity prices.

According to WHO (2020), until June 2020 there have been approximately 9 million people infected by the Coronavirus globally. The number would keep increasing with each passing day as an effective vaccine is yet to be distributed and businesses have re-opened (albeit with safety protocols) wherein higher cases might follow such reopening due to lack of compliance with social distancing measures. Table 1 displays the number of people infected by COVID-19 in 6 countries that are of interest to this study.

Table 1: Number of Infected COVID-19 of Six Selected Countries

Country	Number of Cases	Deaths
USA	2936890	132331
Indonesia	63749	3171
India	675453	19303
South Korea	13091	283
Saudi Arabia	209509	1916
Singapore	44800	26

Source: WHO (2020)

Stock return behavior depends on whether the news has incorporated all available information in the stock markets, and thus the depedency on news and events are very high. In the context of stock markets, the degree of volatility tends to reflect the current economic condition. There have been studies on the SARS epidemic experiences based on regional perspectives (Siu & Wong, 2004; Lee & McKibbin, 2004; Chen et al., 2007). The results of these studies cast doubt on the highly-interconnected nature of stock markets around the world.

Our study focuses on the impacts of the COVID-19 outbreak on six selected stock market around the world. The six selected countries contain stock markets with large, listed firms and hence high dependency toward volatilities should be observed. An important implication of this study is that it provides special treatment for the COVID-19 pandemic while at the same time acknowledging its big impact toward performances of stock market. Further, this study also discussed several stock market concepts, in aspects of fairness, transparency, protection to investor and reducing systematic risk, to help the market achieve efficiency in the future.

2. Literature Review

2.1. Theoretical Foundation of Stock Return Behaviour

The measurement of stock return behavior in stock market is an important endeavor, particularly during the period of COVID-19. The stock market behaviour will determine the pattern of the risk and how to mitigate such risk during period of pandemic-induced uncertainties. There are several issues that directly influence the movement and behaviour of stock prices; economic, political, social and security. However, due to the different scales, some issues trigger smaller stock-market shock relative to others. Studies have argued that market always reflects the current and real-life condition, and it incorporates the deviant behavior of investors that occur in response to current news and event (Ackert et al., 2003; Stracca, 2004).

Furthermore, studies on stock return behavior points to the stability of stock prices in times of crisis and/or other economic downturn. In stock market, the behavior of stock returns somewhat reflects investors' responses. Such behavior can also be described by equilibrium prices that are determined by supply and demand mechanisms. Ball (2009) asserts that the intrinsic value of stock prices should should decsribe its current conditions, while also predicting the return that would be received by the investors in the future.

As new information arrives to the stock market, investor automatically adjusts to that information by selling or buying stocks, which subsequently changes current price levels. Stracca (2004) stated that stock price frequently deviates due to investors' original motivation of avoiding risk. As Markowitz (1959) famously quipped, "high risk high return". However, such statement is an empirical one, and thus one may question whether higher risk will ultimately lead to higher return.

In their attempt to answer such question, Timmermann & Granger (2004) highlighted that new information arriving in stock markets will be taken into adjustment by investors, and therefore any such relationship between stock prices and information would be non linear. However, in reality, investor might be forced or compelled to buy stocks despite having less information, and as such, they might have to mitigate the risk. In stock markets, high degree of stock returns' or asset prices' mobility is crucial for identifying exogenous factors driving the movements and their subsequent impacts on the stock market. Hsieh (1991) noted that some news/events can influence stock price behavior to a great degree. An example of such events is the 1987 financial crisis, which brought extreme bearish or bullish sentiments to the stock market. Hsieh's (1991) work also marked the beginning of the non-linear hypothesis that have been widely proposed in the stock returns literature. Hsieh (1991) asserts that large movements in stock prices/returns due to chaotic dynamics will always be followed by self-repeating nonlinear dynamics.

Excessively volatile stock market has been a major challenge in measuring the real value of stock prices. LeRoy & Porter (1981) asserts that stock markets exhibiting 'excess volatility' reject the efficient market hypothesis. They proposed an alternative to test return behaviour in volatile markets by using the same test that was used by Samuelson (1965) – that is, they consider the present value relation that is equivalent to the null hypothesis tested in the return test.

Shiller (1981) suggests that excess volatility occurs as a result of internal factors leading to commensurate changes in stock price. Other factors, such as financial crisis or other economic shocks, are also considered as factors that also exert both direct and indirect, significant impact to the volatility of stock prices.

2.2. Economic Impact of Virus Outbreak

The effect of the COVID-19 pandemic has propagated throughout most economic sectors. The outbreak started in Wuhan, China and has since spread all over the world. Previous experiences point to the ripple effects of epidemic outbreaks on the regional economies (Lee & McKibbin, 2004).

In a retrospect, one can conclude that Spanish flu, Ebola Virus, SARS and COVID-19 pandemics have brought major global and local impact. However, the SARS epidemic in 2002 have made the world realize that health crisis should be dealt with if they are to have a quick economic recovery (Siu & Wong, 2004). Smith (2006) explains that globalisation has been one of the key factors contributing to the rapid spread of the virus around the world.

The response of investors toward extreme, tail events has confirmed that stock markets has experienced a greater degree of integration. During the SARS outbreak, the economic impacts of the epidemic were not equal across sectors. There were several industries with declining performances, such as the airline and tourism industries. However, other sectors still managed to record positive performances, such as the telecommunication, food and beverages sectors. We see a different picture in the COVID-19 pandemic, wherein the integration of trading system in recent decades has caused the volatility impact to be propagated across all industries in stock market. Hsieh et al. (2013) finds that the volatility of stock prices increases substantially during crisis periods (such as the SARS outbreak, 2002 anti-terror war, as well as the Enron scandal).

As the world comes to a realization that current COVID-19 pandemic would pose a threat to the economy that has not been seen since the SARS epidemic, global authorities have also realized that the virus will jeopardize the whole process of global financial integration. The data from Maliszewska et al. (2020) shows that the COVID-19 pandemic has left a deep hole in the economy, where it is predicted that most country will lose around 7 percent of their investment. The data also suggests that most countries will experience a negative economic growth rate at an average of 2.5 percent. Broader studies have pointed to the fact that epidemics, such as the SARS epidemic, did not exert positive influence on global investment, particularly in the stock market (Chen et al., 2007). However, further research is needed to confirm this hypothesis.

3. Data and Methodology

The data that I use in this study was taken from the Thomson-Reuters data stream. I collect the data on daily closing prices for weekdays (Mondays to Fridays). The analysis period for this study was restricted due to data availability issues. The data consists of daily closing price of six selected countries for the period of December 2019 – June 2020. I further divide the observation period into three stages of COVID-19 outbreak that influenced the six selected stock market:

1. December 2019 – Early February 2020: This period can be considered as the early stage of COVID-19 transmission; a key moment in this period is the emergence of the COVID-19 virus in Wuhan, China
2. End February 2020 – April 2020: This period can be considered as the stage where the COVID-19 virus began to be transmitted rapidly from Italy to

other continents, owing to the mobility of people around the world
3. May 1 2020 – June 2020: This period is the stage where COVID-19 has been acknowledged as a global pandemic, as it had infected more 10 million people worldwide, wreaking havoc on various sectors of the economy

I use daily index data obtained from the data stream. Using daily data helps capture the dynamic evolution of stock returns. In addition, it also helps capture the volatility in returns, which may be overlooked when using monthly observations.

Table 2: Selected Countries

Country	Stock Exchange	Number of Listed Firms
United States of America	NYSE Composite Index	2.8
Indonesia	Indonesia Composite Index	695
India	Bombay Composite Index	4.744
South Korea	Korea Composite Index	2.111
Saudi Arabia	Saudi Composite Index	188
Singapore	Singapore Composite Index	640

I select these stock markets based on several considerations. First, the chosen stock markets cover a wide geographical area which is line with the objectives of this study. In particular, the selected stock markets represent six major markets across the globe, not only in terms of market capitalization, but also in terms of the number of listed companies according to their respective continents. Second, the selected stock markets are heterogeneous, both in terms of the severity of COVID-19 induced crisis as well as the political, economic, and cultural characteristics of the countries underlying these stock markets.

3.1. Econometric Modeling of Returns

3.1.1. The Autoregressive Model

The methodology consists of fitting an AR(p) to the return series and checking the whiteness of the residuals. In the absence of autocorrelation, one can proceed by subjecting the residuals of the AR(p) process to a battery of tests to ensure that the residuals are independently and identically distributed (i.i.d).

Let Δ log Pt be stock returns: the AR (p) model is then:

$$\phi_p(L)\Delta \log P_t = \varepsilon_t \tag{1}$$

Where the AR polynomial in L of order ρ is:

$$\phi_p(L) = 1 - \phi_1 L - ... - \phi_p L^p \tag{2}$$

And εt satisfies the white noise properties:

$$E[\varepsilon_1] = 0, E[\varepsilon_1^2] = \sigma^2 \tag{3}$$

and

$$E[\varepsilon_t \varepsilon_n] = 0 \forall s \neq t \tag{4}$$

3.2. Testing the Assumption of Linearity

The interest toward non-linearity and chaotic processes has intensified after a high degree of stock-price movement due to severe crisis and stock market crash (Hsieh, 1991). Indications of high-degree stock market movement (in terms of capital flow) have triggered unanticipated decisions toward news and events, particularly those that are predicted to bear a huge shock and impact on the stock market.

3.2.1. Volatility Modeling

Modeling and forecasting stock return volatility is central to modern finance because risk volatility increases in response to heightened market uncertainty and the ensuing attempts from market participants to manage asset pricing, asset allocation and risk management. Two approaches that have been generally used are the GARCH and stochastic volatility (SV) models. In their standard forms, the ensuing volatility processes are assumed to be stationary and weakly dependent with autocorrelations that decrease exponentially (Lu & Perron, 2010).

Wild bootstrapped automatic variance ratio (WBAVR) test.

Let Yt be an asset return at time t, where $t = 1, 2, ..., T$. Choi's (1999) AVR test statistic takes the following form:

$$VR(k) = 1 + 2 \sum_{i-1}^{T-1} m\left(\frac{i}{k}\right) \hat{\rho}(i) \tag{5}$$

where $\hat{\rho}(i)$ is the sample autocorrelation of order I. These estimation follow Choi (1999) and use the quadratic spectral kernel for the weighting function so that:

$$m(x) = \frac{25}{12\pi^2 x^2} \left[\frac{\sin(6\pi x/5)}{6\pi x/5} - \cos(6\pi x/5) \right] \tag{6}$$

3.2.2. The GARCH Model and Its Extension

The GARCH model can capture volatility clustering and leptokurtosis, but as the underlying distribution is symmetric, the model fails to capture the leverage effect. The Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982), allows the variance of the error term to vary over time, in contrast to the standard time series regression models which assumes constant variance.

The mean equation of stock returns can be described as:

$$\Delta \log P_t = \omega + \sum \phi_i \Delta \log P_{t-i} + \varepsilon_t, \varepsilon_1 | \Omega_{t-1} \sim NID(0, h_t) \tag{7}$$

$$\varepsilon_t = z_t \sqrt{h_t}$$

Where, z is i.i.d with zero mean and unit variance. The conditional variance $[h_t]$ is:

$$h_t = \bar{\omega} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} = \bar{\omega} + \alpha(L)\varepsilon_t^2 + \beta(L)h_t \tag{8}$$

The condition:

$$\sum_{i=1}^{q} \alpha_1 + \sum_{j=1}^{p} \beta_j \tag{9}$$

implies that GARCH process is weakly stationary since the mean, variance, and auto covariance are finite and constant over time. However, this condition is not sufficient for weak stationary in the presence of autocorrelation. When the GARCH process is stationary, the unconditional variance of ε^t, is computed as:

$$v(\varepsilon_t) = \frac{\omega}{\left(1 - \sum_{i=1}^{q} \alpha_1 \sum_{j=1}^{p} \beta_j\right)} \tag{10}$$

$$(1 - \alpha(L))(1 - L)^d \varepsilon_t^2 = \omega + (1 - \beta(L))V_t \tag{11}$$

With a (L) and, $\beta(L)$ being polynomials of order q and p, and $0 < d < 1$ is the fractional integration parameter. Defining $V_t = \varepsilon^{t2} - h^t$ and rearranging the IGARCH (p, d, q) model can be expressed as:

$$h_t = \omega + \beta(L)h_t + (1 - \beta(L) - (1 - \alpha(L))(1 - l)^d)\varepsilon_t^2 \tag{12}$$

$$\Delta \log P_t = \mu + \sum \phi_1 \Delta \log P_{t-i} + \delta \sqrt{h_t} + \varepsilon_t \tag{13}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{P} \beta_i h_{t-i} \tag{14}$$

Where,

$$I_{t-1} = \text{lif}\varepsilon_{t-1} < 0$$

$$= 0 \text{ otherwise}$$

The EGARCH is specified as:

$$In(h_t) = \omega + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{q} \beta_j \ln(h_{t-j}) \tag{15}$$

Where

$$g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|], z_t = \frac{\varepsilon_t}{\sqrt{h_t}}$$

The coefficient of the second term in $g(z^t)$ is set to be $1(\gamma = 1)$ in the formulation. Note that $E|Z^t| = \left(\frac{2}{\pi}\right)^{1/2}$ if $Z^t \sim N(0,1)$. The function $g(Z^t)$ is linear in Z^t with slope coefficient $\Theta + 1$ if Z^t is positive and $\Theta - 1$ if Z^t is negative. Suppose $\Theta = 0$. Large innovations increase the conditional variance if $|Z^t| - E|Zt| > 0$ and decrease the conditional variance if $|Z^t| - E|Z^t| < 0$. Suppose that $\Theta < 1$. The innovation in variance, $g(Z^t)$, is positive if the innovations Z^t are less than $\frac{\left(\frac{2}{\pi}\right)^{1/2}}{(\Theta-1)}$. Therefore, negative innovations in return cause the innovations to the conditional variance to be positive if Θ is much less than 1.

3.2.3. Parameter Estimation of GARCH Models

To predict volatility of time series, the E-GARCH model has to be fitted into time series in question. The family of GARCH models is estimated by the maximum likelihood (ML) method. The ML method is the procedure of finding the most likely values of the parameters given the actual data. The log likelihood function is computed from the product of all conditional densities of the prediction errors. If we assume conditional normality, the likelihood function is specified as:

$$L(\theta) = -\frac{T}{2} In(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(In(h_t)) + \frac{\varepsilon_t^2}{h_t} \tag{16}$$

Where

$$\varepsilon_1 = \Delta \log P_t - \sum \phi_1 \Delta \log P_{t=i}$$

And h^t is the conditional variance. When the GARCH (p, q) – M model is estimated,

$$\varepsilon_1 = \Delta \log P_t - \sum \phi_1 \Delta \log P_{t=i} - \delta\sqrt{h_t} \tag{17}$$

Where $\Gamma(\bullet)$ is the gamma function and v is the degrees of freedom $(v > 2)$. Under a conditional t-distribution, the additional parameter $1/v$ is estimated. The log likelihood function for the conditional t-distribution converges to the log likelihood function of the conditional normal GARCH model as $1/v \to 0$.

4. Result and Discussion

The results reported in Table 3 strengthen the hypothesis that different events and/or news that are directly or indirectly related to the market generate distinct responses on the stock market. Looking at the standard deviation value, one can infer that the US stock market exhibits the highest volatility. However, the US stock market also offered highest daily average return as compared to other countries. The distributional properties of returns also point to the presence of extreme observations. The data suggests that the highest kurtosis in the sample occurs in South Korea. On the other hand, Indonesia has the lowest kurtosis value. If kurtosis in one country exceeds the threshold value of 3, this implies that the returns have fatter tails than would be expected from a normally distributed variable. With Indonesia as an exception, the distribution of return on all countries are positively skewed.

Deviations from normality can be decreased in part by temporal returns dependencies, especially the second moment temporal dependency, as it may indicate that assuming linear processes for the returns may leave important features of the data unexplained. The presence of second moment dependence is reinforced by Ljung-Box (LB) statistics calculated for 12 lags. The hypothesis that all autocorrelations up to the 12th lag are jointly zero is rejected.

Table 3: Descriptive Statistic (Logarithmic Returns)

Country	Mean	Median	Standard Deviation	Skewness	Kurtosis
Period 1 (December, 2019–February, 2020)					
USA	0.1411	0.1898	0.8608	0.3597	0.3918
Indonesia	0.4500	0.3872	0.3300	-0.3700	0.2412
India	0.4900	0.3700	0.8608	0.0211	0.3124
Saudi Arabia	0.0956	0.4800	0.3700	0.3323	0.4839
South Korea	0.0426	0.3300	0.0182	0.7650	0.2412
Singapore	0.0206	0.9224	0.3700	0.3920	0.7650
Period 2 (February–April, 2020)					
USA	0.3453	0.3360	0.4890	0.4632	0.4638
Indonesia	0.3673	0.7003	0.0232	-0.1132	0.5733
India	0.2272	0.0201	0.4121	0.3322	0.4783
Saudi Arabia	0.2562	0.0048	0.6473	0.8843	0.4733
South Korea	0.1462	0.5280	0.4849	0.5433	0.5553
Singapore	0.3372	0.6590	0.4321	0.7831	0.6483
Period 3 (May–June, 2020)					
USA	0.1209	1.2532	0.4062	0.3009	0.2945
Indonesia	0.0975	0.3543	0.1722	-0.5087	0.6432
India	0.4143	0.4522	0.1496	0.7175	0.8254
Saudi Arabia	0.5232	0.5343	0.8832	0.8445	0.6156
South Korea	1.7643	0.6243	0.2844	0.8288	0.7577
Singapore	0.4865	0.3843	0.2865	0.4865	0.4554

4.1. Preliminary Evidence: AR (p) Model

An AR (p) model was fitted to the returns of six selected stock market to ensure the pre-whiten residual before testing the evidence of non-linearity. Stock market returns are modeled as autoregressive time series with random disturbances having conditional heteroscedastic variances, particularly with GARCH type processes. This research analyzes two sets of stock prices data, and fitting an AR (p) model to the series by OLS regression yielded the results in Table 4.

The majority of volatility studies in stock market apply the GARCH estimation. However, due to the large number of parameters to be estimated in the five countries of interest to this study, the order of lags cannot be restricted only to the variance model of GARCH. As such, Table 4 also estimates the volatility of

Table 4: Results of Fitting GARCH Models

	GARCH	EGARCH-M	GJR-GARCH-M	GARCH	EGARCH-M	GJR-GARCH-M
USA	0.064(1.222)	0.024*	0.02(0.33)	0.325**(6.67)	0.012(0.01/0	0.61(0.05)
Indonesia		0.022*	0.71(0.66)	0.22475.87)	0.022(0.01/0	0.041(0.07)
India	0.1202(4.404)	0.1125(1.365)	0.657(3.21)	0.1701(4.405)	0.8761(1.165)	0.221(0.21)
Saudi Arabia	0.064**(0.61)	0.283(6.231)	0.0344	0.05281	0.87645	0.876**
South Korea	0.327***	0.211***	0.681***	0.897***	0.545***	0.7865
Singapore	0.7801*	0.42377	0.54222	0.54907	0.6712**	0.9873**

***,**,* indicates significance at 1%, 5%, and 10% levels respectively.

models used in this research by assuming student t-distribution for the normalized residuals to account for fat tails. Estimation of the parameters is obtained by maximizing the likelihood function over the sample period. Given that the likelihood function in GARCH models cannot be maximized using analytical methods. Table 4 provides evidences of second moment time dependencies, and these results suggest that asymmetric volatility is not detected in our sample. The result from the table also shows that the GARCH model specification captures volatility in US stock market returns, while for South Korea the volatility is ranging and hence the GARCH model specification cannot provide forecasting tools in the future.

Table 5: AR (p) Pre-Whitening Model

Country	AR (p) Pre-Whitening MODEL	
USA	μ	0.191(42)
Indonesia	$\mu 1$	0.1033.756
India	$\mu 2$	0.0000
Saudi Arabia	$\mu 3$	0.1809.230
South Korea	$\mu 4$	0.054238
Singapore	$\mu 5$	0.19199

The six selected stock market follow the low order autoregressive process. Having fitted an AR (p) model, it is now necessary to examine an adequate and useful functional form of the data generating process. In the case of stock price during COVID-19 pandemic, the dynamic volatility of the stock price can be measured with integrated measurement toward whole industry listed in the selected stock markets. In order to further examine the data properties, I employ the nonlinear diagnostic tests outlined in Table 3.

The evidences for linearity in six selected stock market that are of interest to this research show that these stock markets are open to the possibility of gaining abnormal returns. Moreover, the existence of linearity in these stock markets also demonstrates how return predictions can lead to market inefficiencies. The case of COVID-19 can be considered as an event study and this may open up possibilities for investors to gain abnormal returns[1].

[1]Abnormal return, also known as "alpha" or "excess return," is the fraction of a security's or

Table 6: Nonlinearity Test on AR (p) Residuals

Country	EPS= 1	EPS=2	EPS=3	EPS=4	EPS=5
Bootstrap					
USA	0.000	0.000	0.000	0.000	0.000
Indonesia	0.000	0.000	0.000	0.000	0.000
India	0.000	0.000	0.000	0.000	0.000
Saudi Arabia	0.000	0.000	0.000	0.000	0.000
South Korea	0.000	0.000	0.000	0.000	0.000
Singapore	0.000	0.000	0.000	0.000	0.000
Asymptotic					
USA	0.000	0.000	0.000	0.000	0.000
Indonesia	0.000	0.000	0.000	0.000	0.000
India	0.000	0.000	0.000	0.000	0.000
Saudi Arabia	0.000	0.000	0.000	0.000	0.000
South Korea	0.000	0.000	0.000	0.000	0.000
Singapore	0.000	0.000	0.000	0.000	0.000

Notes: only p-values are reported under the null hypothesis that the time series is a serially iid process.
All calculations are done using the non-linear toolkit by Patterson & Ashley (2000).

The results presented in this study are consistent with those of Siu & Wong (2004), in which they find that abnormal returns observed during the pandemic are concurrent returns, and such returns depend on the ability of the stock market to provide information to its investors.

Table 7: Abnormal Return for the Six Selected Stock Market during Selected Periods

Country	Abnormal Return		
	December, 2019–February, 2020	February–April, 2020	May 1–June, 2020
USA	0.0032	-0.0009313	0.0093
Indonesia	0.0042	-0.0059545	1.4775
India	0.0046	-0.0118903	1.7085
Saudi Arabia	0.0043	-0.0000451	0.0163
South Korea	0.0038	-0.0024564	1.2512
Singapore	0.0095	-0.0080299	1.8952

Figure 1 and 2 display the trend of average volatilities in the selected stock market. Figure 1 exhibits a somewhat steady trend during the first period – that is, following the outbreak. Such steadiness was caused by the reaction of investors toward the virus during the early outbreak period, when world had been aware of the virus but it had not yet caused widespread panic since the virus spread were confined within the boundaries of Wuhan, China. On the contrary, second period exhibits somewhat increased volatility as the virus had grown to become more widespread, and consequently, widespread panic began to grow among

portfolio's return not explained by the rate of return of the market. Instead, it is a result of the investor's expertise.

Table 8: Fractional Differencing Parameter (*d*) for the Six Selected Stock Market

Country	d December, 2019–February, 2020	d February–April, 2020	d May 1–June, 2020
USA	0.-0165(-0.29)	[2.541]**	[-5.509]*
Indonesia	0.932***(4.302)	9.36E-06	[-9.027]*
India	[1.715]***	-0.00015	-0.0202
Saudi Arabia	[2.172]**	[-0.505]	-0.0105
South Korea	-0.00085	[-9.027]*	0.9821
Singapore	-0.00042	-0.058	-0.0033

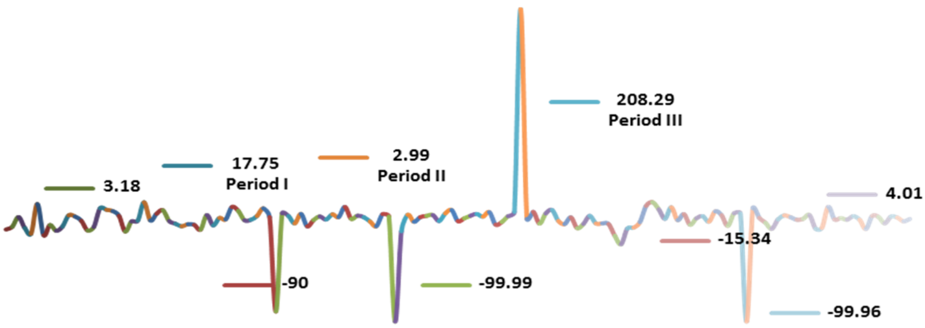

Figure 1: Abnormal Return (AR) of Six Selected Stock Market

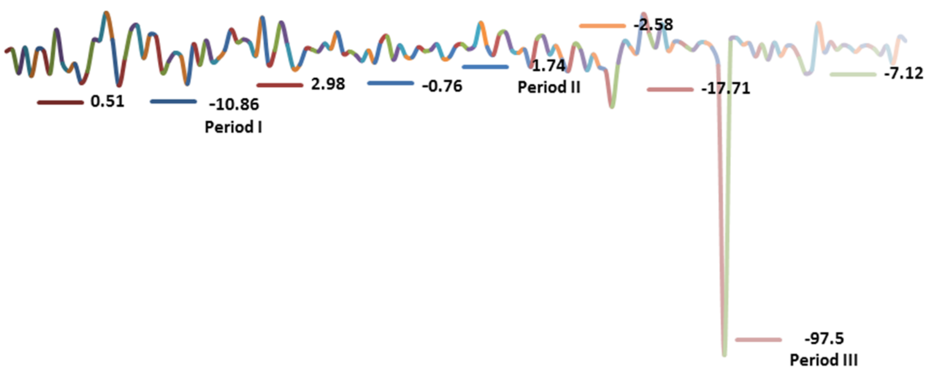

Figure 2: Cummulative Abnormal Return (CAR) of Six Selected Stock Market

investors. This is reflected in the increased volatility among the selected stock markets in the second period – particularly USA, South Korea, Singapore, and Saudi Arabia.

The increased volatility occurred as a form of market response towards the drop in demand for particular industries, which was triggered by pandemic-induced income shocks. In the US, one of such heavily affected industries is airlines, while in the context of South Korea, tourism is among the hardest-hit sectors. Similarly, tourism and/or other services industries have also experienced a substantial performance decline in Singapore. Performance declines in these sectors triggered greater perceived uncertainty and hence higher volatility in the stock market, where the average volatility in the six selected stock markets amounts to -99.99. During the third period, the six selected stock market showed, on average, different responses due to between-industries heterogeneity in terms of performances. Several industries, such as telecommunication and pharmaceuticals industries, were thriving during the outbreak and positive performances among these sectors contributed to the increase in stock market returns in the US and South Korea.

Figure 2 showed the cumulative average return of the six selected stock market. From the graph, one can observe a decrease in average returns during the third period, as most industries were announcing the impacts of COVID-19 on their businesses. In response to such information, investors postponed their stock market activities and sold their current holdings of the impacted stocks (Hsieh et al., 2013).

Table 9: Cumulative Abnormal Return in the Event Window

Stock Market	Index	CARi	t-test	p-value
December 2019 – February, 2020				
USA	NYSE Composite Index	0.0525208	0.0740676	0.0608488
Indonesia	Indonesia Composite Index	0.0192188	0.066233	0.0959838
India	Bombay Composite Index		-0.0482862	
Saudi Arabia	Saudi Composite Index	-0.0446717*		
South Korea	Korea Composite Index	0.7878957	0.0959838	0.1543534
Singapore	Singapore Composite Index	0.0525208	0.4037271	0.7878957
February 2020 – April, 2020				
USA	NYSE Composite Index	-0.0243261	-0.0313121	-1.874593
Indonesia	Indonesia Composite Index	0.066233	-0.0255788	-0.0258508*
India	Bombay Composite Index	-0.0796273	-0.0482862	-0.0890671
Saudi Arabia	Saudi Composite Index	0.9365125	-0.0446717*	0.4037271
South Korea	Korea Composite Index	0.066233	-0.0443531	0.0482178
Singapore	Singapore Composite Index	0.0740676	0.0340714	0.5680507
May 1 2020 – June, 2020				
USA	NYSE Composite Index	-0.7100	-0.6374	-0.0220
Indonesia	Indonesia Composite Index	-0.4865	-0.0233192	0.56939
India	Bombay Composite Index	-0.0140	-0.0233915	0.1210778
Saudi Arabia	Saudi Composite Index	-0.7100	-0.0112227	0.6529
South Korea	Korea Composite Index	0.693472	0.021077	0.00236818
Singapore	Singapore Composite Index	0.2546	-0.3231	0.65272

The result in Table 6 suggests that the COVID-19 pandemic is an extraordinary event to which stock markets around the world give out different responses. Among the six selected stock markets, the US and South Korea stock markets are among the fastest-responding markets, recording an estimated CAR of 0.0525208 and 0.7878957 for the US and South Korean markets (respectively) during the first period of observations – which marked the start of the COVID-19 outbreak around the world. Both countries also had large numbers of multinational companies, and as such, their volatility responses during the second and third period were also rapid. On the other hand, the Saudi Stock Exchange apparently responded to the pandemic in a rather slow manner, with CAR values of -0.0446717*, 0.9365125, -0.7100. One plausible explanation for such slow response might be the fact that its stock market had been closed for foreign investors (Timmermann & Granger, 2004).

5. Conclusions

After COVID-19 was declared as a pandemic, the impact was very pronounced in various economic and business sectors. The pandemic had exerted influence on the investor behaviors, particularly in terms of consumption and purchases, as investors may exhibit panic behavior and respond to the pandemic by making irrational decisions. Based on the standard deviation, one can observe that the US stock market exhibited highest volatility while also offering highest daily average return as compared to other countries. Kurtosis values indicate the presence of extreme observations. The highest and lowest kurtosis values in the sample are seen in the South Korean and Indonesian stock markets, respectively. If kurtosis in one country exceeds the threshold value of 3, it implies that the returns possess fatter tails than what one would expect from a normally distributed variable. With Indonesia as an exception, all the return series are positively skewed.

This study aims to investigate the impact of the COVID-19 pandemic towards six selected stock market around the world. The result suggests that the COVID-19 pandemic is significantly associated with and exert significant impact on the behavior of stock return – in terms of volatilities and abnormal return – due to investors' reactions towards the shock. The COVID-19 can be categorized as a major shock due to level impact that it has created. During the first period of the virus outbreak, most of the countries under study were still undergoing early stages of virus spread in their countries. I begin to observe substantial plunges in the six-selected stock markets during the second stage of the pandemic, which is reflected by the significant changes in the AAR and CAAR values, as most industries began experiencing the pandemic-induced performance decline. During the third period, though, stock market seems to have bounced back and revert to a steady pattern as investors began to develop a new sense of normalcy despite the continued spread of the COVID-19 pandemic. I argue that investors had responded to the initial pandemic news during the first and second period by developing fear sentiment towards the pandemic and then chanelled it to the stock market.

The findings of this study contribute to the policymakers' understanding on how to shift the focus of their policy towards mitigating the risk of COVID-19 in the performance of financial sector, as I observe a strong correlation between the public health crisis and stock market performances in the six selected markets that are of interest to this study. These selected stock markets consist of different sectoral indices, and each of these sectors responded differently towards the proliferation of the COVID-19 pandemic. Telecommunication, retail, food and beverages industries are among the industries that thrive during the pandemic. On the contrary, the COVID-19 pandemic have wreaked havoc on several sectors, particularly the service-related ones, such as airlines, tourism, and hotel industries. As such, the government needs to cooperate with its health care and economists counterparts to formulate an integrated approach to mitigating the COVID-19 risk.

Future research studying the COVID-19 pandemic should consider the behavior and sentiment of investors, and extant literature could benefit from longer-term period studies on such issues, as they provide further understanding of how perceived-uncertainties evolve as the pandemic progresses. I acknowledge that one of the main limitation of this study is the limited length of time period, as this study was written in the early stages of the pandemic to trigger discussion of immediate responses among policy-makers.

References

[1] Ackert, L. F., Church, B. K., & Deaves, R. (2003). Emotion and financial markets. *Federal Reserve Bank of Atlanta Economic Review, 88*(2), 33-41.

[2] Ball, R. (2009). The global financial crisis and the efficient market hypothesis: what have we learned?. *Journal of Applied Corporate Finance, 21*(4), 8-16. doi: https://doi.org/10.1111/j.1745-6622.2009.00246.x.

[3] Chen, M. H., Jang, S. S., & Kim, W. G. (2007). The impact of the SARS outbreak on Taiwanese hotel stock performance: an event-study approach. *International Journal of Hospitality Management, 26*(1), 200-212. doi: https://doi.org/10.1016/j.ijhm.2005.11.004.

[4] Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society, 50*(4), 987-1007. doi: https://doi.org/10.2307/1912773.

[5] Hsieh, D. A. (1991). Chaos and nonlinear dynamics: Application to financial markets. *The Journal of Finance, 46*(5), 1839-1877. doi: https://doi.org/10.1111/j.1540-6261.1991.tb04646.x.

[6] Hsieh, T. Y., Kuo, W. H., & Lee, H. I. (2013). The week effect of the returns and volatilities: The case of the Taiwanese stock and option markets. *Journal of Asian Business Strategy, 3*(10), 270-277.

[7] LeRoy, S. F., & Porter, R. D. (1981). The present-value relation: Tests based on implied variance bounds. *Econometrica: Journal of the Econometric Society, 49*(3), 555-574. doi: https://doi.org/10.2307/1911512.

[8] Lee, J. W., & McKibbin, W. J. (2004). Globalization and disease: The case of SARS. *Asian Economic Papers, 3*(1), 113-131. doi: https://doi.org/10.1162/1535351041747932.

[9] Lu, Y. K., & Perron, P. (2009). Modeling and forecasting stock return volatility using a random level shift model. *Journal of Empirical Finance, 17*(1), 138-156. doi: https://doi.org/10.1016/j.jempfin.2009.10.001.

[10] Maliszewska, M., Mattoo, A., & Van Der Mensbrugghe, D. (2020). The potential impact of COVID-19 on GDP and trade: A preliminary assessment. *Policy Research*

Working Paper, 9211. World Bank Group. doi: https://doi.org/10.1596/1813-9450-9211.

[11] Markovitz, H. M. (1959). *Portfolio selection: Efficient diversification of investments*. John Wiley. http://cowles.yale.edu/sites/default/files/files/pub/mon/m16-all.pdf.

[12] Patterson, D. M., & Ashley, R. A. (2000). *A nonlinear time series workshop: A toolkit for detecting and indentifying nonlinear serial dependence* (Vol. 2). Kluwer Academic Pub.

[13] Price Water House Coopers. (2009). *Shariah-compliant funds: A whole new world of investment*. https://www.pwc.com/gx/en/financial-services/islamic-finance-programme/assets/shariah-compliant-funds.pdf.

[14] Siu, A., & Wong, Y. R. (2004). Economic impact of SARS: The case of Hong Kong. *Asian Economic Papers, 3*(1), 62-83.

[15] Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review, 6*(2), 41-49.

[16] Shiller, R. J., (1981). Do stock prices move too much to be justified by subsequent changes in dividends?. *The American Economic Review, 71*(3), 421-436.

[17] Smith, T. (2006). *Globalisation: A systematic Marxian account*. Brill.

[18] Stracca, L. (2004). Behavioral finance and asset prices: Where do we stand?. *Journal of Economic Psychology, 25*(3), 373-405. doi: https://doi.org/10.1016/S0167-4870(03)00055-2.

[19] Timmermann, A., & Granger, C. W. (2004). Efficient market hypothesis and forecasting. *International Journal of Forecasting, 20*(1), 15-27. doi: https://doi.org/10.1016/S0169-2070(03)00012-8.

[20] WHO. (2019). *Coronavirus disease (COVID-19) pandemic*. World Health Organization. https://www.who.int/emergencies/diseases/novel-coronavirus-2019.

[21] WHO. (2020). *WHO Coronavirus disease (COVID-19) dashboard*. World Health Organization. https://covid19.who.int/.

this page intentionally left blank