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Indonesian Stocks' Volatility during COVID-19 Waves: Comparison between IHSG and ISSI

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Abstract

This study aims to compare Islamic and conventional stocks' performance amid a crisis. The performance was measured by analyzing the volatility of the Indonesian Sharia Stock Index (ISSI) and the Composite Stock Price Index (IHSG) during the COVID-19 pandemic. Based on the results of the different tests using the paired t-test and Wilcoxon rank test methods, it was uncovered that the ISSI and IHSG experienced significant changes before and after discovering the first case of COVID-19 in Indonesia. Significant changes in both values were also found when the Delta variance spread. Meanwhile, when the third wave occurred due to the presence of the Omicron variant, ISSI and IHSG could move more stable and did not experience significant shocks. Then, the estimation results of the GARCH model conclude that both Islamic and conventional stocks have an immense volatility power with an identical value of 0.94 or close to 1. The volatility is also significantly influenced by the previous volatility and the squared error, representing other previous events outside the model. Moreover, the volatility in Islamic and conventional stocks is not much different, even though both stocks have different characters in the debt and income ratio. Fundamental factors also cause this high volatility in the form of shocks in several macroeconomic variables, including the rupiah exchange rate, gold prices, and world oil prices. Besides, the contagion effect that occurred during the COVID-19 crisis also contributed to the spread of systemic risk in global stock indexes on stock volatility in Indonesia.

Keywords: Islamic Stocks, Conventional Stocks, Volatility, COVID-19 Pandemic, GARCH Model
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I. Introduction

The growth of stock investors has experienced a rapidly increasing trend over the last five years. As of September 2021, the number of stock investors has reached 2.8 million SID (Single Investor Identification) number. This amount covers 45.26% of the total capital market investors with a SID registered in the Indonesian Central Securities Depository (KSEI). Compared to the previous year, the number of stock investors throughout 2021 has grown by 72.69%. This number is greater than the total growth of investors in the capital market, which reached 61.86% (Puspitasari, 2021).

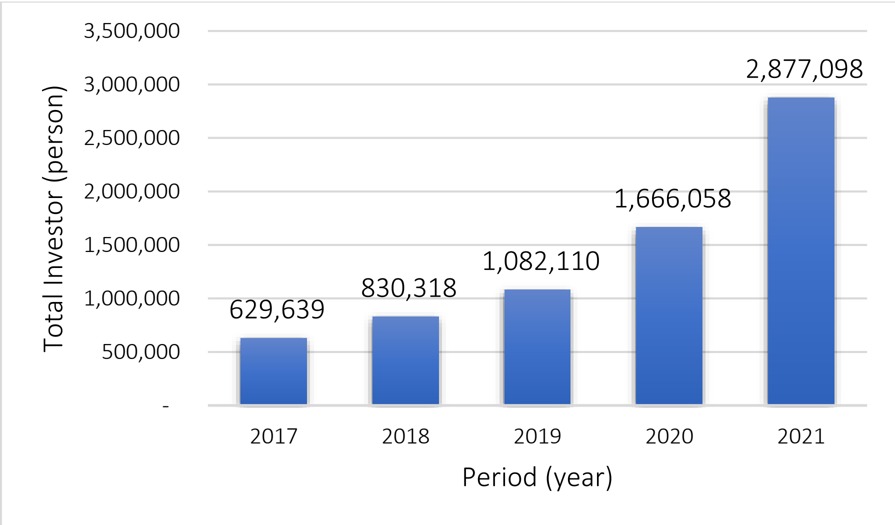

Figure 1. Number of Stock Investors on the Indonesia Stock Exchange

Source: Financial Services Authority (OJK) (2021)

Interestingly, Indonesia's stock investment trend experienced rapid growth during the COVID-19 pandemic. Based on Figure 1, the number of stock investors more than doubled during the pandemic compared to the previous 1.08 million SID in 2019. In this regard, millennials are the most dominating age group, with 59.23% of the total investors in the capital market (Sidik, 2021). Based on a survey conducted by the Katadata Insight Center of 806 stock investors, 41.3% of millennials stated that they had just started investing in stock in the last two years, particularly when the COVID-19 pandemic case was first identified in Indonesia (Siringoringo, 2021).

However, it is undeniable that the presence of COVID-19 has also affected the Indonesian economy since it first appeared in March 2020. Not to mention the capital market, the pandemic crisis caused the Composite Stock Price Index (IHSG) to reach its lowest point of decline in the last decade. The incident occurred on March 24, 2020, when the IHSG value fell 37% from the beginning of the year to 3,937. A drastic reduction followed this decline in stock market capitalization reaching IDR 1,907 trillion (Tamara, 2020). The impact of the

COVID-19 pandemic has also caused Indonesia to fall into a recession in the third quarter of 2020 due to negative economic growth for two consecutive quarters. The second quarter recorded economic growth of -5.32%, the lowest growth rate since 1998. Meanwhile, the third-quarter economic growth reached -3.49% (Fauzia, 2020). The negative economic growth extended until the first quarter of 2021, at the level of -0.74%.

The crisis consequently required the Indonesian government to adjust macroeconomic policies to maintain domestic economic stability. One of the implemented policies is to change the benchmark interest rate set by the central bank. Figure 2 shows that Bank Indonesia has made six changes to the benchmark interest rate or BI 7-Day Reverse Repo Rate during the last two years, from the initial 5.0% in early 2020 to 3.5% in February 2021. This level is the lowest in the history of applying the benchmark interest rate in monetary policy (Elena, 2021).

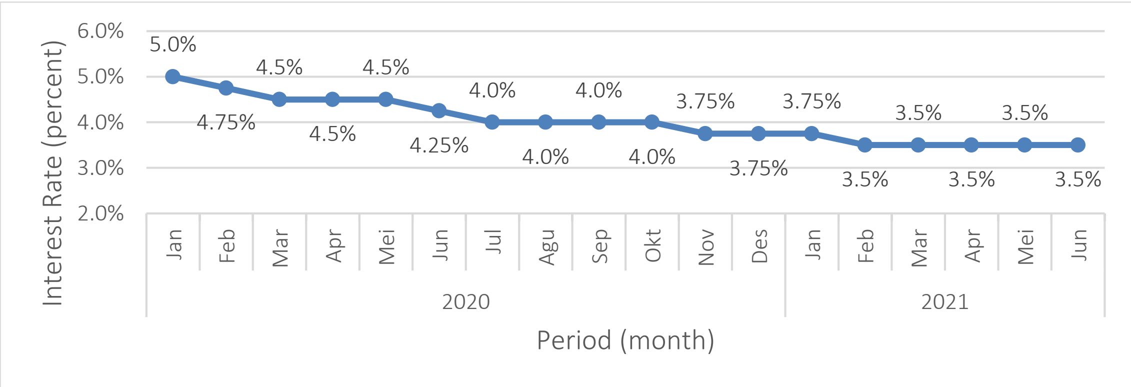

Figure 2. The Trend of BI 7-Day Reverse Repo Rate

Source: Bank Indonesia (2021)

Changes in these macroeconomic variables certainly impact capital market development since one of the macroeconomic variables affecting investment is interest rates (Mankiw, 2009). Therefore, changes in the benchmark interest rate set by the central bank will determine the public interest in investing, including in the capital market.

Apparently, several researchers have attempted to investigate the impacts of the COVID-19 pandemic crisis on stock markets from varied points of view. From the Islamic stock market point of view, the evaluation of the effect of COVID-19 on Islamic stock markets is crucial for several reasons. First, during the last decade, the Islamic finance industry has recorded tremendous growth, which is anticipated to reach 8% average yearly growth by 2025 to $4.95 trillion (Adil, 2022). Second, in recent times, the attractive risk-return characteristics and ethical issues of Islamic products tend to motivate non-Muslim investors, particularly ethical investors, to choose Islamic products for their portfolios. Third, the Islamic stock markets have empirically shown their outperformance over their conventional counterparts, especially in times of crisis, even though the portfolio size of the Islamic stock markets is smaller than the conventional (Al-Khazali et al., 2014).

In this paper, from a portfolio performance perspective, the researchers extended the current literature to examine whether returns earned by investors tracking the ISSI (Indonesian Sharia Stock Index) were significantly different from those of the IHSG (Composite Stock Price Index). Thus, the researchers conducted a comparative study regarding the volatilities of ISSI and IHSG during this pandemic crisis to provide a better avenue for investors to diversify their portfolios by considering the volatility of both stocks.

Several previous studies have analyzed comparing Islamic and conventional stocks' performance amid a crisis. Siregar (2020) compared the performance of LQ45 with JII (Jakarta Islamic Index) at the beginning of the spread of COVID-19 cases and explained that LQ45 experienced a 1.22% decline in stock prices on average, while JII, on average, experienced an increase of 0.14%. Globally, Al-Khazali et al. (2014) found that the Dow Jones sharia index performed better than the conventional index during the global economic crisis. For this reason, the current study aims to fill the gap in previous research by using inferential statistical analysis to compare the performance of the ISSI (Indonesian Sharia Stock Index) and the IHSG during the COVID-19 pandemic. It is based on the recommendation of Nurdany et al. (2021), which only examined ISSI's volatility during the COVID-19 pandemic with GARCH analysis.

Following the problems described, this study aims to compare the ISSI values before and after the COVID-19 virus spread, compare the IHSG values before and after the COVID-19 virus spread, and measure the ISSI and volatility IHSG during the COVID-19 pandemic. This study further attempts to verify the stock index endurance during the pandemic and indicates that the stock market volatility may last if the crisis is not over. In addition, fundamental factors also cause this high volatility in the form of shocks in several macroeconomic variables, including the rupiah exchange rate, gold prices, and world oil prices. The results of this research are expected to benefit various interested parties in the capital market industry in Indonesia. For capital market regulators, this research can become a reference for evaluating policies implemented to develop the stock market and sustain macroeconomic stability. The results of this study can also be deemed to determine the strategic steps to maintain stock price stability during an economic crisis for stock issuing companies. As for investors, the research findings can help predict stock prices in the future, especially in times of crisis, by considering the volatility when choosing investment products since the stocks have experienced high volatility throughout the pandemic.

II. Literature Review

2.1. Volatility

Volatility is a statistical measure used to gauge the movement and distribution of a security product or market index prices at a specific time (Hayes, 2021). The greater the volatility of the value of an asset, the greater the risk of investing in it (Nugroho & Robiyanto, 2021). In this regard, price fluctuations that occur in a short period have high volatility, whereas if the price movement is slow, the volatility is low (Mamtha & Srinivasan, 2016). In other words, volatility can be an indicator to assess financial market stability. Volatility, in general, can be measured by calculating the variance or standard deviation of the data set of price movements of an asset.

According to Thampanya et al. (2020), stock price volatility is broadly influenced by two determinants: fundamental and behavioral factors. Fundamental factors are derived from conventional financial theory, assuming that investors follow fundamental financial theories and design investment strategies based on risk and profit calculations. Meanwhile, behavioral factors emphasize that investors are ordinary people easily influenced by sentiment and psychological conditions, so investment decisions are made more based on good or bad news circulating.

Fundamental factors also consist of indicators that can be measured clearly and unbiased, such as macroeconomic variables, including inflation rates, interest rates, exchange rates, and GDP (Francis & Soffer, 1997), as well as company financial ratios such as ROA (Return on Assets), ROE (Return on Equity), and cash flow (Chang & Dong, 2006). On the other hand, several studies have also proven that behavioral factors determine stock volatility driven by investor sentiment based on their beliefs about future conditions (Baker & Wurgler, 2007). Based on the theory of capital market behavior, investors will buy more shares, and asset prices will be pushed above their fair value when bullish sentiment dominates the market. Meanwhile, when bearish sentiment dominates, investors will sell or hold their shares, so prices are dragged below the fundamental value (Shefrin & Statman, 1994).

2.2. Previous Studies

Numerous studies have been conducted on the impacts of the economic crisis on both conventional and Islamic stocks. Chebbi et al. (2021) researched the stock liquidity conditions of S&P 500 index companies during the COVID-19 pandemic-induced economic crisis. The S&P 500 is a collection of the 500 largest publicly traded companies in the United States by market capitalization. The study's findings demonstrated a significant negative correlation between COVID-19 cases and company liquidity. Those indicate that the company's liquidity would decrease if daily COVID-19 cases increased. Moreover, Li et al. (2021) comprehensively analyzed the relationship between the COVID-19 pandemic and the stock market in G20 member countries. They concluded that the volatility linkage between stock markets in G20 member countries increased significantly during the COVID-19 crisis. This volatility linkage was primarily transmitted by developed country stock markets, affecting developing country stock markets.

Aside from the crisis phenomenon during the COVID-19 pandemic, there have previously been numerous studies analyzing stock market conditions during the economic crisis. Dang & Nguyen (2020) analyzed the relationship between liquidity risk and stock performance during the 2008-2009 global financial crisis from 17,493 companies across 41 countries. The study found that stocks that made more profits before the crisis experienced a more significant price decline when there was a liquidity shock on global financial markets during a crisis. In particular cases in Indonesia, Haryanto (2020) examined the relationship between the number of COVID-19 cases and the IHSG value. Using the multiple linear regression analysis techniques, the study results concluded a significant negative effect of the COVID-19 case on the IHSG value. Hence, every 1% increase in COVID-19 cases would cause a decrease in the value of the IHSG by 0.03%. Alfira et al. (2021), examining the impact of COVID-19 on the share price of Islamic banks in Indonesia, also discovered comparable findings. Their research revealed that the share prices of Bank Rakyat Indonesia Syariah (BRIS) and State Pension Savings Bank Syariah (BTPS) had decreased since the first case of COVID-19 was reported in Indonesia.

On the other hand, Mirza et al. (2022) revealed the condition of Islamic stock mutual funds when the COVID-19 crisis occurred. This study took samples from six countries: Malaysia, Pakistan, Saudi Arabia, Qatar, Kuwait, and the United Arab Emirates. Using the Sharpe Ratio, Sortino Ratio, and Jensen's Alpha measurements, the study results demonstrated that Islamic equity mutual funds in the six countries could show positive performance amid economic pressure due to COVID-19. This study also concludes that Islamic stock mutual funds are investment products with haven properties during a crisis. Before the emergence of the COVID-19 crisis, Kenourgios et al. (2016) analyzed the condition of the Islamic stock market during the global financial crisis in the case of the subprime mortgage and eurozone sovereign debt crises. This study took the period 2007-2015, which included both crisis phenomena, and used a sample of Islamic stock indices in European countries, G7 members, and BRICS (Brazil, Russia, India, China, and South Africa). The study unveiled that most Islamic stock indices were unaffected by financial system shocks or transmission risks during the global financial crisis.

In Indonesia, Muhaimin et al. (2021) scrutinized the movement of shares listed on JII during the COVID-19 crisis. By using descriptive analysis, the research results revealed that JII experienced positive performance trends following the implementation of Large-Scale Social Restrictions (PSBB) in Indonesia in the April-July 2020 period. According to Nuryani et al. (2021), JII's performance during the COVID-19 crisis was influenced by exchange rate variables, the SCI index (Shanghai Composite Index), and the DJIA index (Dow Jones Industrial Average). Meanwhile, another index, the ISSI, also experienced relatively high volatility from positive and negative shocks during the COVID-19 crisis (Nurdany et al., 2021). Also, positive shocks had a more substantial effect than adverse shocks on the ISSI stock return rate.

From the results of these studies, it can be concluded that the crisis impacts the volatility of both Islamic and conventional stocks. For an in-depth analysis of this phenomenon, developing studies also compared the impact of the crisis on Islamic and conventional stocks. Hasan et al. (2021) compared the conditions of Islamic and conventional stocks during the COVID-19 crisis. Their study aimed to assess the impact of COVID-19 on Islamic stock markets and compared market reactions to comparable conventional stock markets to understand stock market reactions during crisis periods better. The study used the Dow Jones index and the FTSE as a sample for January-November 2020, each of which has a particular index for conventional and Islamic stocks. The study uncovered that the pandemic caused identical volatility in both stock market categories. This study also stated that Islamic and conventional stocks experienced a reasonably strong relationship in their movements during the COVID-19 crisis.

A study on the performance of Islamic and conventional stocks was also carried out by Siregar (2020) in Indonesia in the March-July 2020 period, or when the COVID-19 case first entered Indonesia. The study compared the passion for conventional stock transactions and Islamic stocks in the capital market to find out the differences and advantages of these Islamic stocks. The study employed the LQ45 and JII indexes as a representative sample of conventional and Islamic stocks. The study results revealed that LQ45 and JII experienced fluctuations during the crisis. However, this study found that JII performed better with an average increase in the share price of 0.14%, in contrast to LQ45, which experienced a decrease in the average share price of 1.22%.

Based on the literature above, it was found that the economic crisis impacted the occurrence of capital market volatility, including Islamic and conventional stocks. However, the volatility varies depending on the stock index sampled and the crisis period analyzed. This volatility can also cause performance differences in Islamic and conventional stocks depending on their respective strengths.

III. Methodology

3.1. Data

This study used time-series data. The time-series data consisted of daily stock prices listed on the ISSI and IHSG values. Data on the movement of stock prices could be obtained from the official portal of the Indonesia Stock Exchange. Because these data were not collected directly by the authors, the data used were included in the category of secondary data. In this case, the daily stock price means the ISSI and IHSG values at the closing of the stock exchange on that day according to the stock exchange operating hours. Then, the value of all stocks on the Indonesia Stock Exchange is represented by IHSG. Meanwhile, ISSI signifies only stocks of sharia-compliant companies. Each of their volatility would be estimated in a different equation.

Daily stock prices were used to compare stock performance before and after the spread of the COVID-19 virus. This study further compared stock prices between 30 days before and after the official announcement from the government regarding the COVID-19 variant. Daily stock price data were also utilized to measure volatility during a pandemic, but the data should be transformed to find the daily return measurement of volatility that began in March 2020 when the first COVID-19 case was found in Indonesia until March 2022 with a total period of 500 days.

3.2. Model Development

Time series data in the financial sector, such as stock prices, are prone to volatility clustering, which is if there is relatively high data variability at one time, the same trend will occur in the next period. The distribution of residuals from stock price data is also often fat tails, and it has a greater tendency for extreme events to occur in a certain period. Based on these properties, the GARCH model can explain data variance (Enders, 2004).

Bollerslev (1986) introduced the GARCH model of the simplest equation as follows:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

The model is a variance equation, stating that the conditional variance σ at time t depends not only on the square of the error in the previous period but also on the conditional variance in the previous period (Gujarati, 2004). Moreover, each IHSG and ISSI has its model and is not united in one equation.

The result obtained from the GARCH estimation would be compared to measure the difference between IHSG and ISSI in their volatility.

3.3. Method

Comparative analysis can be done using a different test method: Paired t-test or Wilcoxon signed-rank test. Paired t-test is carried out if the sample data are normally distributed. Meanwhile, Wilcoxon signed-rank test is conducted if the sample data are not normally distributed. Therefore, before performing a different test, it is necessary to test for normality. In this study, the difference test was conducted utilizing the software SPSS.

Meanwhile, in measuring the volatility of a variable, the most appropriate analytical method to use is the GARCH (Generalized Auto Regressive Conditional Heteroskedasticity) model (Enders, 2004). As the name implies, this model considers heteroscedasticity elements in different time series. Several previous studies that analyzed stock volatility also used the GARCH model, including Aliyev et al. (2020), Azakia et al. (2020), Mhd Ruslan & Mokhtar (2021), Naik et al. (2020), and Nurdany et al. (2021).

To test using the GARCH model, the data must first go through the stationarity test process. The stationarity test can be done by using unit roots and correlograms. If the data are stationary, it can be estimated using the ARMA (Autoregressive Moving Average) model to obtain the best model from the mean equation. The selection of the best ARMA model is shown from the smallest Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) values. Against the ARMA model formed, a heteroscedasticity test was conducted to identify the model's volatility element. When it was found that the existing model was not homoscedastic, the data processing continued to the GARCH analysis stage. A series of analysis processes would be carried out utilizing the software EViews.

IV. Results and Analysis

4.1. Comparative Analysis

4.1.1. Results

The presence of the COVID-19 pandemic undoubtedly impacts the movement of the country's economy, including the stock market. When compared between 30 days before and after the emergence of the first COVID-19 case in Indonesia, it can be seen that the movement of ISSI and IHSG values experienced a negative trend. The lowest value was recorded on March 24, 2020, or 22 days after the entry of the COVID-19 case in Indonesia, where ISSI touched 115.95 and the IHSG touched 3,937.63.

The same thing happened when the peak second wave of COVID-19 cases in Indonesia occurred due to the spread of the Delta variant. The ISSI and IHSG values decreased when compared between 30 days before and after the Delta variant's appearance in Indonesia. At first, the ISSI value was 184.29. This figure decreased to 171.29 after 30 days since the detection of the first Delta case. Likewise, the IHSG decreased from 6,356.16 to 5,996.25. Meanwhile, due to the Omicron variant, a different trend occurred in Indonesia's ISSI and IHSG values movement during the third wave of COVID-19 cases. The ISSI and IHSG values increased slightly when compared between 30 days before and after the emergence of the first Omicron variant case on December 16, 2021. The ISSI value increased from 186.22 to 188.36. Meanwhile, the IHSG increased from 6,586.44 to 6,645.51.

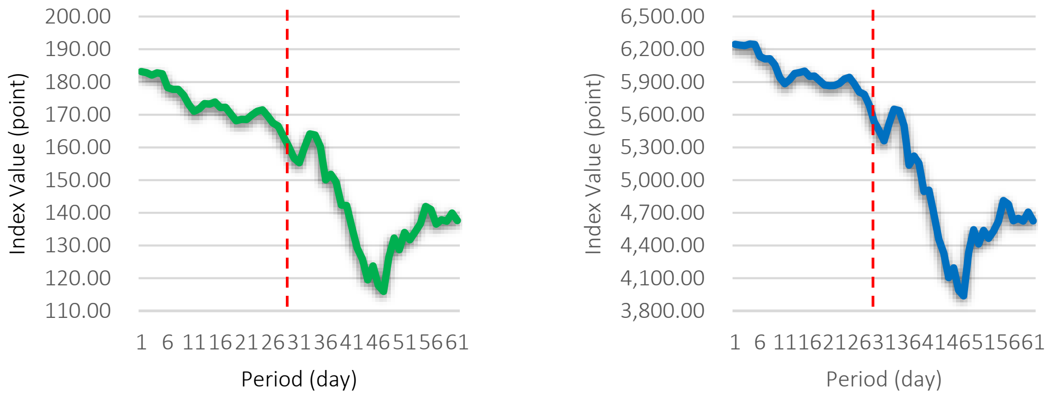

Figure 3. ISSI and IHSG Value Before and After the Emergence of the First Case of COVID-19

Source: Indonesian Stock Exchange (2020)

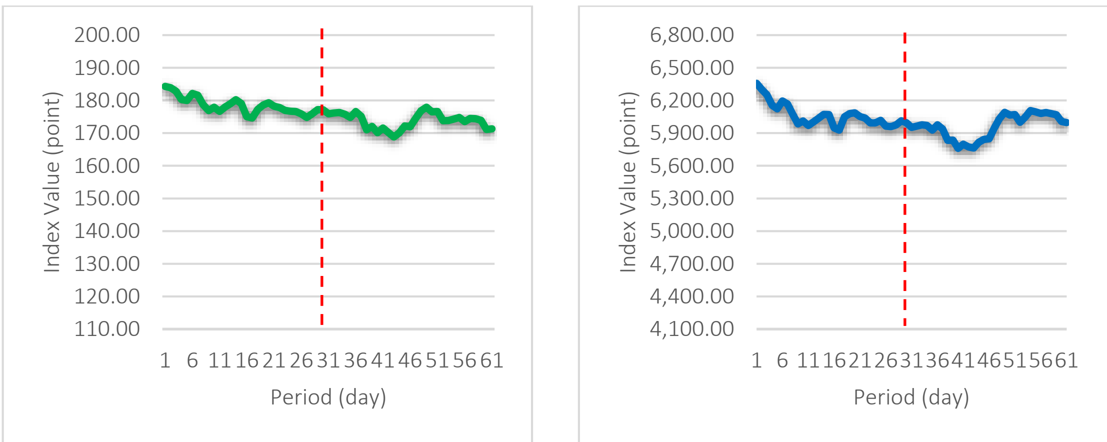

Figure 4. ISSI and IHSG Value Before and After the Emergence of Delta Variant

Source: Indonesian Stock Exchange (2021)

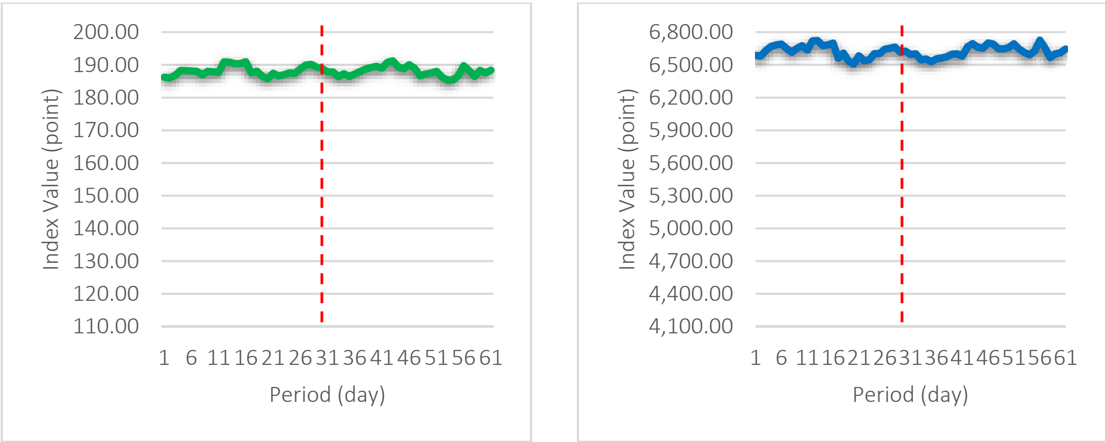

Figure 5. ISSI and IHSG Value Before and After the Emergence of Omicron Variant

Source: Indonesian Stock Exchange (2021)

Based on Figure 3, 4, and 5, it can be clearly seen that the highest volatility of the ISSI and IHSG value movements occurred during the first wave of COVID-19 cases in Indonesia. When compared between 30 days before and after the first case's appearance, the ISSI value fell to 24.86%, and the IHSG value fell to 25.93%. It was in stark contrast to the second wave, which only fell by 7.05% and 5.66%, respectively, and the third wave, which actually grew positively by 1.15% on the ISSI and 0.90% for the IHSG.

According to the prior discussion, every wave of COVID-19 has a similar movement tendency between ISSI and IHSG. However, this tendency does not adequately explain the comparison between ISSI and IHSG before and after the COVID-19 case. Given that the COVID-19 virus affected the stock market, the researchers had to divide the data into two categories: before and after the COVID-19 variants arrived in Indonesia.

Table 1. Descriptive Statistics of ISSI and IHSG

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	IHSG Pre-First Case	5955.8260	30	194.52154	35.51461
	IHSG Post First Case	4720.2557	30	458.89349	83.78211
Pair 2	ISSI Pre-First Case	172.5367	30	6.55064	1.19598
	ISSI Post First Case	138.2620	30	12.93999	2.36251
Pair 3	IHSG Pre Delta	6062.2040	30	105.22733	19.21179
	IHSG Post Delta	5959.9083	30	113.88358	20.79220
Pair 4	ISSI Pre Delta	178.4510	30	2.55470	.46642
	ISSI Post Delta	173.6917	30	2.42699	.44311
Pair 5	IHSG Pre Omicron	6628.9517	30	56.50490	10.31634
	IHSG Post Omicron	6623.6017	30	51.85356	9.46712
Pair 6	ISSI Pre Omicron	188.2253	30	1.53414	.28009
	ISSI Post Omicron	188.0177	30	1.49000	.27203

Table 1 reveals that each wave of COVID-19 reduced the average ISSI and IHSG values in 30 days. The first wave had the most significant decline in ISSI and

IHSG values. Meanwhile, the smallest drop happened in the third wave when the Omicron variety expanded to Indonesia. When comparing the two types of stocks, the IHSG's average value dropped more severely than the ISSI during the first wave of COVID-19. Before the arrival of COVID-19 cases in Indonesia, the average IHSG value declined by 20.75%, while the average ISSI value decreased by 19.87%. When the decline in values was compared to the change in the average value of the two during the Omicron variant wave, it was discovered that there was a very slight difference. The average IHSG value decreased by 0.08%, slightly less than the average ISSI value, which fell by 0.11%.

The data in the preceding table can also be used to compare volatility in the ISSI and IHSG based on their relative standard deviation values. Both the ISSI and the IHSG demonstrated an increasing and reducing volatility tendency in the first and third waves of IHSG volatility increase. In contrast, ISSI volatility dropped, except for the second wave. When the percentage change was compared, each wave of COVID-19 consistently delivered more extensive volatility changes to the IHSG than the ISSI. The IHSG experienced an increase in volatility of up to 135.91% during the first wave, exceeding the ISSI's growth of 97.54%. Similarly, the IHSG experienced a volatility change of 8.2 % in the second and third waves, while the ISSI experienced a volatility change of less than 5%.

To confirm that the spread of the COVID-19 variant caused the change in value, a different test should be performed, comparing the IHSG and ISSI value groups before the spread of the COVID-19 virus and IHSG and ISSI value groups after the virus variant spread. Before executing the difference test, the data were assessed to determine their normalcy as a determinant of the different test methods used. Since the number of samples from each variable exceeded 50, the Kolmogorov-Smirnov test was performed to determine normality (Cleff, 2014). The following criteria were employed to make decisions in this test:

- The value of sig. >0.05 means the data are normally distributed, and the comparison test is carried out using the paired t-Test method.
- The value of sig. <0.05 indicates that the data are not normally distributed, and the comparison test is conducted using the Wilcoxon Rank Test method.
    - According to Table 2, a significant value of 0.05 was observed in the IHSG and ISSI variables in the first wave. In the Delta and Omicron variant waves, the IHSG and ISSI variables showed a significance value greater than 0.05. As a result, it is possible to conclude that the IHSG and ISSI data in the first wave were normally distributed. In contrast, the IHSG and ISSI data in the Delta and Omicron variant waves were

not. Based on these findings, the Wilcoxon Rank Test was the best alternative test method for the IHSG and ISSI variables in the first wave. Meanwhile, the paired t-test method was employed for the IHSG and ISSI variables on the Delta and Omicron waves.

Table 2. Normality Test Results

	IHSG First Case	ISSI First Case	IHSG Delta	ISSI Delta	IHSG Omicron	ISSI Omicron
N	60	60	60	60	60	60
Mean	5338.0408	155.3993	6011.0562	176.0713	6626.2767	188.1215
Std. Deviation	714.30593	20.05144	120.32383	3.44412	53.83522	1.50301
Test Statistic	.187	.161	.108	.060	.095	.087
Asymp. Sig.	.000	.001	.079	.200	.200	.200

Following that, each data group was assessed using a comparative test based on the method provided by the normality test. Several studies were run to determine the impact of the COVID-19 variant's spread on changes in the IHSG and ISSI values. In this regard, if the various tests reveal a substantial difference, it is determined that changes in the IHSG and ISSI values can occur due to the COVID-19 variant's spread. The following are the decision criteria for the various tests utilizing the paired t-Test or Wilcoxon Rank Test methods:

- The value of sig. >0.05 indicates no significant difference in the stock index value before and after the spread of the COVID-19 variant.
- The value of sig. <0.05 implies a significant difference in the stock index value before and after the spread of the COVID-19 variant.

Table 3. Wilcoxon Rank Test Results

	IHSG Post First Case - IHSG Pre-First Case	ISSI Post First Case – ISSI Pre-First Case
Z	-4.782[b]	-4.782[b]
Asymp. Sig. (2-tailed)	.000	.000

Table 4. Paired T-Test Results

		Difference	t	df	Sig. (2-tailed)
Pair 3	IHSG Pre Delta – IHSG Post Delta	102.29567	3.468	29	.002
Pair 4	ISSI Pre Delta – ISSI Post Delta	4.75933	8.161	29	.000
Pair 5	IHSG Pre Omicron – IHSG Post Omicron	5.35000	.372	29	.713
Pair 6	ISSI Pre Omicron – ISSI Post Omicron	.20767	.718	29	.479

According to Table 3, the value of sig. for IHSG and ISSI in the first wave was 0.05 based on the different test outputs. Similarly, Table 4 revealed the value of sig. for IHSG and ISSI during the Delta variant wave were both 0.05. Meanwhile, when the test period was conducted during the Omicron variant wave, the sig. value of the IHSG and ISSI showed a number greater than 0.05, indicating that it was insignificant. Based on these results, it is possible to conclude that significant changes in the IHSG and ISSI values occurred during the spread of the COVID-19 virus in the first wave and the Delta variant wave.

4.1.2. Analysis

Because the IHSG and ISSI values changed significantly, the two stock indices were assessed to have weak resistance to the COVID-19 crisis during the first and Delta variant waves. The findings of this analysis are proportional to the findings of Hasan et al. (2021) against the Dow Jones and FTSE indexes, showing that both Islamic and conventional stocks are vulnerable to the consequences of the COVID-19 issue. Still, it is necessary since the COVID-19 issue prompted Indonesia to enter an economic slump, resulting in numerous national companies losing income and terminating worker contracts (Febrianto & Rahadi, 2021).

Interestingly, a different stock market reaction occurred during the third wave caused by the Omicron variant. Based on the various tests above, there was no significant difference in the IHSG and ISSI values before and after Indonesia's spread of the Omicron variant. It could happen because of differences in investor behavior in responding to events that occurred (Thampanya et al., 2020). According to the Indonesia Stock Exchange (IDX) monthly report from March 2020, when the COVID-19 virus first invaded Indonesia, net trade by worldwide investors was negative, specifically -3.49 billion share units. When the Delta version began to spread in May 2021, the IDX stated that net trading by worldwide investors was similarly negative at -1.64 billion share units. Meanwhile, worldwide investor mood continued to recover in December 2021, as demonstrated by a positive net trade of 5.69 billion shares.

The restrictive policies enforced by the local government may impact the behavior of stock investors. Of course, it can also affect stock price swings. At first, banning community activities led to panic selling among stock investors. Regarding COVID-19 prevention policies, the Indonesian government imposed Large-Scale Social Restrictions (PSBB) at the outbreak's start in reaction to the virus's increasingly widespread dissemination (Debora, 2020). When the Delta variety became more widespread, the authorities promptly imposed an Emergency Community Activity Restriction (PPKM), followed by PPKM Level 4 in the Java-Bali region, for more than a month (Bardan, 2021). These two policies severely restricted people's activities, causing economic activity to suffer. Meanwhile, as the Omicron form spread, the government merely applied PPKM level 3 with less stringent limitations, which was only valid for one month (Waseso, 2022). The presence of relaxation policies during the wave of the Omicron variant undoubtedly provides an opportunity for the economy's wheels to turn more steadily.

The influence on stock prices can also be attributed to COVID-19 instances. Haryanto (2020) and Khalid et al. (2021) discovered that the number of COVID-19 models substantially impacted stock value and volatility. Based on the Indonesian COVID-19 Handling Task Force report, the number of active COVID-19 cases in March 2020 reached a very high level, accounting for 85.80% of all positive cases recorded. The number of active cases was still at 5.6% as of May 2021, and the positive monthly rate was 10.7 %, which was greater than the WHO (World Health Organization) standard. Meanwhile, active cases declined dramatically to 0.1% in December 2021, with a positive rate of only 0.11 %. Based on these findings, it is highly probable that the occurrence of the Omicron variety in December 2021 did not result in significant changes to the IHSG and ISSI values.

4.2. Volatility Analysis

4.2.1. Results

Most earlier studies employed stock return data as the observed variable in the GARCH model (Azakia et al., 2020; Irfan et al., 2021; Mhd Ruslan & Mokhtar, 2021; Nurdany et al., 2021). To calculate the return value of each stock index, the stock price data must be transformed into a natural logarithm using a first-order differential equation (Aliyev et al., 2020). Adopting this transformation could make it easier for researchers to measure changes in a stock's value and rate of return.

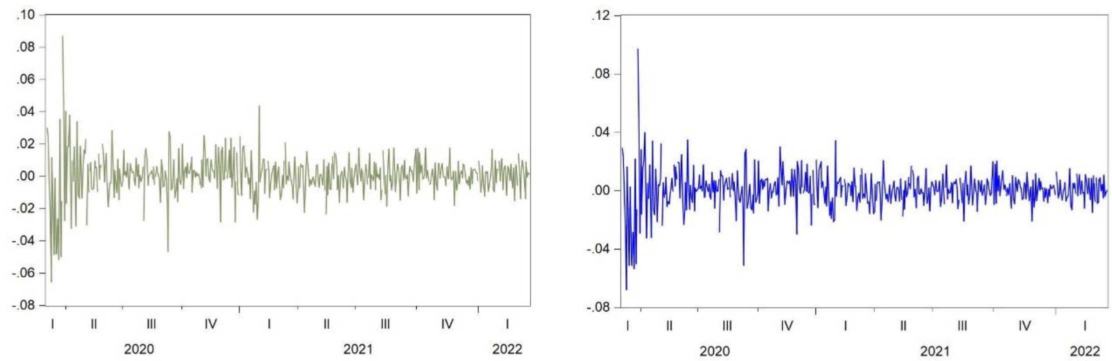

Figure 6. The Volatility of ISSI and IHSG Return

The data transformation results were then exhibited in a graph to show the volatility. The ISSI and IHSG return exhibited identical volatility in the graph above. Significant changes would follow changes in the high rate of return. This condition is referred to as volatility clustering, one of the characteristics of heteroscedastic data that must be examined using the GARCH model (Enders, 2004). As a result, the two stock indexes under consideration, i.e., ISSI and IHSG also displayed volatility clustering.

Besides being heteroscedastic, the GARCH model also requires that the data to be analyzed must be stationary. To ensure this, the stationarity test was carried out using the Augmented Dickey-Fuller (ADF) method to identify the presence of a unit root in the observed data. The basis for decision-making in the stationarity test is as follows:

- A probability value of >0.05 indicates that the data contains a unit root and is not stationary.
- A probability value of <0.05 indicates that the data does not contain a unit root and is stationary.

Table 5. Stationarity Test Results

		ISSI		IHSG	
		t-Statistic	**Prob.***	**t-Statistic**	**Prob.***
Augmented Dickey-Fuller test statistic		-17.56089	0.0000	-17.03850	0.0000
Test critical values:	1% level	-3.976629		-3.976629	
	5% level	-3.418889		-3.418889	
	10% level	-3.131986		-3.131986	

Based on Table 5, the resultant probability value at the level was <0.05. Similarly, the statistical value of the ADF test, -17.56 for ISSI and -17.04 for IHSG, was less than the value of the corresponding critical areas. Therefore, the researchers could conclude that the ISSI and IHSG data were stationary since they lacked a unit root. The ADF test results, which revealed that the data were stationary at the level, were then used to create ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots based on the correlogram graph. Afterward, ACF and PACF charts were used in ARMA modeling to determine the correct order.

The PACF plot was used to determine the AR (Autoregressive) order, while the ACF plot was employed to determine the MA (Moving Average) order. Significant ACF and PACF values were determined based on the lag with a plot exceeding the boundary line. Based on Table 6 and 7, both returns showed ACF and PACF plots exceeding the limit at the lag third. Therefore, the tentative models that could be used were ARMA (3.0), ARMA (0.3), and ARMA (3.3). Each model was then estimated to get the coefficient of determination (R2), AIC, and SIC. The best ARMA model chosen was the one with the largest R2 and the smallest AIC and SIC values.

Table 6. Correlogram of ISSI Return

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.000	0.000	6.E-07	0.999
		2	-0.096	-0.096	4.6031	0.100
		3	0.192	0.194	23.171	0.000
		4	0.024	0.012	23.472	0.000
		5	0.042	0.082	24.349	0.000
		6	0.007	-0.030	24.374	0.000
		7	-0.049	-0.046	25.592	0.001
		8	0.017	-0.009	25.736	0.001
		9	-0.154	-0.172	37.806	0.000
		10	-0.082	-0.065	41.228	0.000

Table 7. Correlogram of IHSG Return

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.018	0.018	0.1613	0.688
		2	-0.075	-0.076	3.0124	0.222
		3	0.183	0.187	19.899	0.000
		4	-0.004	-0.020	19.907	0.001
		5	0.068	0.102	22.245	0.000
		6	0.034	-0.009	22.827	0.001
		7	-0.055	-0.039	24.383	0.001
		8	0.034	0.009	24.972	0.002
		9	-0.140	-0.163	35.035	0.000
		10	-0.093	-0.071	39.462	0.000

Table 8. Summary of ARMA Modelling for ISSI and IHSG Returns

Stock	Model	R^2	AIC	SIC
	ARMA (3, 0)	0.0336	-5.8771	-5.8517
ISSI	ARMA (0, 3)	0.0329	-5.8764	-5.8510
	ARMA (3, 3)	0.0322	-5.8737	-5.8398
	ARMA (3, 0)	0.0301	-5.8469	-5.8216
IHSG	ARMA (0, 3)	0.0279	-5.8446	-5.8193
	ARMA (3, 3)	0.0282	-5.8429	-5.8091

Based on Table 8, it can be seen that the best model for returns was ARMA (3,0). This model demonstrated that the return value heavily influenced the return on ISSI and IHSG in the most recent period over the preceding three periods. The chosen ARMA model was used as the mean equation in the GARCH model analysis. To identify the presence of the GARCH effect as an element of volatility in the model, a heteroscedasticity test using the ARCH-LM (Lagrange Multiplier) method was performed on the mean equation formed from the ARMA model. The basis for decision-making in the heteroscedasticity test is as follows:

- A probability value of >0.05 implies that the data does not contain intense volatility and is homoscedastic, so it does not need to be estimated using the GARCH model.
- A probability value of <0.05 implies that the data contains intense volatility and is heteroscedastic, so it needs to be estimated using the GARCH model.

Table 9. Heteroskedasticity Test Results

Indicator	ISSI	IHSG
F-statistic	57.42780	43.70854
Obs*R-squared	51.67620	40.33075
Prob. F	0.0000	0.0000
Prob. Chi-Square	0.0000	0.0000

Table 9 shows the results in the form of a probability value lower than 0.05 for both ISSI and IHSG data. Based on this parameter, the ISSI and IHSG return data were both heteroscedastic and volatile. Thus, the next step was to estimate how much volatility happened based on the observed data using the GARCH model. The GARCH model estimation generally yields two types of equations: the mean and the variance equations. According to the ARMA model, the mean equation signifies how much stock returns from the prior period influence the current average stock return.

Table 10. GARCH Model Estimation

Indicator	ISSI		IHSG	
	Coefficient	Probability	Coefficient	Probability
		Mean Equation		
C	0.000717	0.1135	0.000860	0.0608
AR(3)	0.101435	0.0368	0.118476	0.0123
		Variance Equation		
C	4.80E-06	0.0228	5.05E-06	0.0133
RESID(-1)^2	0.059841	0.0219	0.064508	0.0239
GARCH(-1)	0.884831	0.0000	0.877207	0.0000

Meanwhile, the variance equation explains how much the volatility persistence of the stock index is determined by the volatility and the squared error in the previous period. The estimation in Table 10 was carried out using the GARCH (1.1) model. All independent variables in the predicted output had a significant effect since their probability values were less than 0.05. The constant value was also greater than zero, and the outcome of the sum of the coefficients of the independent variable was one. In other words, this model is thought to help evaluate the volatility of the ISSI and IHSG.

4.2.2. Robustness Test

However, before assessing the model, the ARCH-LM test was performed to guarantee that the GARCH model was free of heteroscedastic features. According to Table 11, the heteroscedasticity test using the ARCH-LM approach yielded a probability value greater than 0.05. This value suggests that the ISSI and IHSG return data processed using the GARCH model had been free from heteroscedasticity. These results strengthened the feasibility of the model to be used in analyzing ISSI and IHSG returns.

Table 11. Heteroskedasticity Test Result for GARCH Model

Indicator	ISSI	IHSG
F-statistic	2.071596	1.782812
Obs*R-squared	2.071297	1.783595
Prob. F	0.1507	0.1824
Prob. Chi-Square	0.1501	0.1817

4.2.3. Analysis

Table 10 show the estimated output of the GARCH model formed in analyzing the volatility of the ISSI and IHSG, the resulting equation for the volatility of the ISSI is as follows:

$$\sigma_t^2 = 4{,}80 \times 10^{-6} + 0{,}0598\varepsilon_{t-1}^2 + 0{,}8848\sigma_{t-1}^2$$

Meanwhile, the equation formed for the volatility of the IHSG is as follows:

$$\sigma_t^2 = 5{,}05 \times 10^{-6} + 0{,}0645\varepsilon_{t-1}^2 + 0{,}8772\sigma_{t-1}^2$$

The above equation is a form of the variance equation that describes the factors determining how much stock volatility occurs.

The sum of the coefficients α+β becomes a measure of the volatility persistence in each stock index investigated (Campbell et al., 2012). The greater the sum, the more volatility, and the longer it can last. According to the equation, the volatility persistence of the ISSI stock index was in the region of 0.94. The volatility equation for the IHSG stock index also yielded the same result. Since the resulting value was so close to one, the researchers could conclude that ISSI and IHSG were both highly volatile during the COVID-19 pandemic in Indonesia.

Furthermore, the probability value of each independent variable was less than 0.05, indicating the strength of high volatility. This value suggests that the previous period's volatility (σ2) and squared error (ε2) considerably affected the next period's volatility. The coefficient value on variable ε2 also describes the impact of occurrences outside the model. In this study, variable ε2 in the IHSG equation had a coefficient of 0.0645, more significant than the coefficient ε2 of 0.0598 in the ISSI equation. It demonstrates that external factors outside the model had a more significant impact on IHSG return volatility. In this case, domestic macroeconomic factors or global stock index movements are examples of the events under consideration.

The estimated output of the GARCH model also yielded the same results as the output of the comparative tests, indicating that the COVID-19 problem had a proportional effect on ISSI and IHSG during the pandemic period, which encompasses three waves. These findings are consistent with Hasan et al. (2021), who discovered that Islamic and conventional equities exhibited identical volatility and a strong association during the COVID-19 crisis. This type of effect is typical because the COVID-19 pandemic is not just a financial sector crisis but a multifaceted catastrophe that shocks different social areas of people's lives (Saputra & Ariutama, 2021). Therefore, while ISSI and IHSG have distinct personalities, their impact is not much different.

Fundamental reasons, such as volatility in macroeconomic variables, can also contribute to the persistence of volatility in Indonesian stocks (Thampanya et al., 2020). Based on Nugroho & Robiyanto's (2021) research, the fundamental factors that also experienced volatility during the COVID-19 pandemic included the rupiah exchange rate and world gold price. The volatility in both variables significantly influenced Indonesia's stock exchange market. Another variable that also became the attention was world oil volatility, which increased in the middle of the COVID-19 crisis (Bourghelle et al., 2021). Syebastian et al. (2021) also mentioned a significant correlation between the world oil price and stock volatility in Indonesia. The COVID-19 crisis caused volatility in various domestic and global economic indicators. As a high-risk return investment asset, the stock is undoubtedly easily influenced by volatility, which occurs in other instruments.

Macro-economy variables cause it, but stock market volatility in a country is also caused by volatility in other countries' stock markets. This influence is called a contagion effect, a theory explaining that a crisis occurring in a region or country can spread its effect to another country on a domestic or international scale (Dornbusch et al., 2000). During the crisis of COVID-19, the systemic risk resulting from the contagion effect experienced an increase in the financial sector (Louati et al., 2022). Based on the research by Kamaludin et al. (2021), the capital market condition in ASEAN-5 countries had a solid correlation to the Dow Jones index movement in the middle of the pandemic era. Referring to contagion theory, it is widespread if stocks in Indonesia experienced intense volatility because of Dow Jones index volatility.

The identical volatility between IHSG and ISSI clarified that Islamic rules application in ISSI stocks does not ensure stronger endurance during the crisis. It was caused by the substantial impact of COVID-19 in many aspects, affecting either the real or financial sector. IHSG and ISSI values also reached their lowest and highest values in a decade because of this pandemic. It confirms the presence of great volatility in Indonesian stocks during COVID-19. The great volatility also indices that Indonesian investors are sensitive to financial news, especially during the crisis. Based on supply and demand law, investors' preference as customers is strongly correlated with the stock price.

V. Conclusion and Recommendation

5.1. Conclusion

The stock market experienced high volatility and uncertainty due to the pandemic. In less than a month, the COVID-19 crisis resulted in the drop of IHSG value to its lowest point in the last decade. Both Islamic and conventional stocks experienced similar volatility during the COVID-19 pandemic. Based on the different test results using the paired t-test and Wilcoxon rank test methods, it was concluded that the ISSI and IHSG experienced significant changes before and after discovering the first case of COVID-19. Significant changes in both values were also found when the Delta variance spread. In contrast, when the third wave occurred due to the presence of the Omicron variant, ISSI and IHSG did not experience significant shocks.

This condition might happen because the community's immunity has been developed, and the government has been able to implement adaptive policies to prevent virus transmission. The policy was then relaxed during the spread of the Omicron variant, where the government allowed various community activities in public spaces. During the first wave of cases and the Delta variant wave, the number of active cases and the positivity rate were still above the WHO standard. Meanwhile, when the Omicron variant was found, the active cases and the positivity rate approached 0, below the WHO standard.

The volatility in ISSI and IHSG is also proven by detecting heteroscedasticity elements in stock return data. Based on the heteroscedasticity test results, it was found that both stock indices had a heteroscedastic return value and experienced high volatility. By applying the GARCH model in the analysis, the strength of stock volatility could be measured along with the factors influencing it. The estimation results of the GARCH model conclude that both Islamic and conventional stocks had an immense volatility power with an identical value of 0.94 or close to 1. The current volatility is also significantly influenced by the previous volatility and the squared error representing other previous events outside the model.

Moreover, the volatility in Islamic and conventional stocks was not much different, even though both stocks had different characters in the debt and income ratio. Fundamental factors also caused this high volatility in the form of shocks in several macroeconomic variables, including the rupiah exchange rate, gold prices, and world oil prices. In addition, the contagion effect that occurred during the COVID-19 crisis also contributed to the spread of systemic risk in global stock indexes on stock volatility in Indonesia.

Furthermore, the identical result between IHSG and ISSI estimation was caused by the pandemic's significant effect on either the real or financial sector. It implies that ISSI is not more stable than IHSG to face the crisis, and vice versa. Besides, Islamic rules application in ISSI stocks does not ensure more vital endurance during the crisis. The effect of the crisis also cannot be denied by Indonesian stocks, so it influences the investors' preference, which is sensitive to financial news.

5.2. Recommendation

This study indicates that the volatility in the stock market may last as long as the crisis is not over. Therefore, investors are suggested to pay attention to the volatility that occurred in the previous days to predict stock prices in the future. Since the stocks have experienced high volatility throughout the pandemic, stock issuing companies should adapt quickly and prepare alternative strategies to maintain stock price stability amid a crisis. Likewise, government agencies are highly encouraged to maintain macroeconomic stability, including exchange rates, inflation, and interest rates.

This research, nonetheless, has several limitations on the information presented. The use of ISSI and IHSG as variables representing sharia and conventional stocks was not enough to reveal the differences in character between the two stocks, considering that the IHSG includes all issuers listed on the Indonesia Stock Exchange, both sharia and conventional stocks. So far, no index has included conventional stocks only. Therefore, it is recommended for further researchers who want to compare the performance of Islamic and conventional stocks to classify between the sharia and conventional stocks specifically.

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