

## Does COVID-19 Affect The Share Market Volatility In Indonesia?

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**Abstract:** Volatility in financial markets reflects the level of risk that will be faced by investors due to fluctuations in stock price movements and stock returns which indicate the uncertainty of returns that investors will receive. This study uses daily data on JCI returns for the period January 1 2017 to October 30 2021 with the aim of modeling the volatility of JCI returns both before the Covid-19 crisis and during Covid-19. In addition, it is intended to see changes in the volatility of JCI returns due to the Covid-19 crisis. The research findings are that both before the crisis and during Covid-19 the appropriate volatility model is a model that has a leverage effect problem, namely EGARCH (1,1). there is a difference in the stock price index EGARCH return model between before and during Covid-19. Another finding is the influence of the variance in the previous period, the previous model was higher than during Covid-19.

**Keywords:** Volatility; Covid-19; Return; Model EGARCH.

**Abstrak:** Volatilitas di pasar keuangan mencerminkan tingkat risiko yang akan dihadapi oleh investor karena fluktuasi pergerakan harga saham maupun return saham yang memperlihatkan adanya ketidakpastian return akan diperoleh investor. Penelitian ini menggunakan data harian return IHSG periode 1 Januari 2017 sampai dengan 30 Oktober 2021 bertujuan untuk memodelkan volatilitas return IHSG baik sebelum masa krisis Covid-19 dan semasa Covid-19. Selain itu, dimaksudkan untuk melihat adanya perubahan volatilitas return IHSG karena krisis Covid-19. Temuan penelitian adalah baik sebelum krisis maupun semasa Covid-19 model volatilitas yang sesuai adalah model yang memiliki masalah leverage effect yaitu EGARCH (1,1). terdapat perbedaan model EGARCH return indeks harga saham antara sebelum dengan semasa Covid-19. Temuan lain adalah pengaruh variance periode sebelumnya, model sebelum lebih tinggi dibandingkan dengan semasa Covid-19.

**Kata Kunci:** Volatilitas; Covid-19; Return; Model EGARCH.

### INTRODUCTION

According to the LPI (Indonesian Economic Report) published by Bank Indonesia in 2021, the Corona Virus Disease 2019 (Covid-19) pandemic has tremendously impacted the dynamics of the 2020 world economy, including Indonesia. Covid-19 spread to almost 178 countries worldwide and infected more than 85 million people, bringing more than 1.8 million deaths during 2020. This condition caused a health and humanitarian crisis, an economic crisis, and increased poverty in various countries. This unfavourable development to the global economy cannot be avoided due to the implementation of mobility restriction policies to reduce the spread of Covid-19. Multiple indicators show that consumption, investment, and production in many countries fell sharply, resulting in a decline in international trade. There was also heavy pressure on financial markets in line



with the uncertainty of global prospects, which, if continued, would risk having a spillover impact on financial system stability.

Meanwhile, in the capital market, stock trading on the Indonesia Stock Exchange (IDX) has recorded seven trading halts since March 2020. Last year, the first time the JCI collapsed by more than 5 per cent was on March 9, 2020, or a week ago. After announcing the first Covid-19 case in Indonesia (CNBC, 11 November 2021). At that time, the JCI, which started 2020 at the 6,300 level, finally left the 6,000 level at the end of January and finally plunged to 3,937.63 on March 24, 2020. This figure was the lowest since at least June 4, 2012, when the JCI closed at 3,654.58. Despite the high number of investors, transaction volumes in 2019 were still higher than in 2020. It was recorded that in 2019, the transaction volume was 36,534,971,048, while in 2020 it was 27,495,947,445. This reflects that most investors tend to wait and see, waiting for the right time to make transactions (KPKLN, March 31, 2021). In November 2021, the Composite Stock Price Index (JCI) finally broke a 4-year record after jumping to 6,700 in early trading on November 11, 2021. JCI opened up 0.170 per cent to a level of 6,694.580 while surpassing the highest level in history. The last was reached on February 19, 2018, at 6,689.290. Ten minutes after the market opening, the JCI had reached 6,702. The transaction value reached Rp 2.360 trillion with a trading volume of 4.970 billion shares. Foreign investors recorded a net purchase of Rp 196.730 billion in the regular market but a net sale of Rp 159.040 million in the negotiated and cash market.

Capital market conditions have relatively high volatility during Covid-19, which can be seen from daily or weekly transactions (KPKLN, March 31, 2021). Investors who are usually called "traders" take advantage of this condition by making fast transactions, of course, with high risk. Research conducted by Widodo and Suryanto (2021) showed a change in the return volatility of the JCI, LQ45 and JII due to COVID-19. Rahmayani and Oktavilia (2020), based on research conducted, shows that Covid-19 does not establish an effect in the short term on the model market but has a natural impact over a long time.

Volatility is one thing that exists in financial markets. Today, global markets are becoming more volatile, and this phenomenon has become an increasing concern for researchers, academics and portfolio managers in studying market volatility. Volatility indicates the price movement of a stock index, which negatively impacts the income of a particular individual and the overall health of the country's economy. Stock market volatility is primarily expressed in the probability of future price deviations from expected values. Volatility can be defined simply as the frequency and depth of fluctuations in the market price of an asset (Roni et al., 2017).

This study aims to model the return volatility of the JCI before and during the Covid-19 pandemic. It is hoped that with this research, it will be known whether there is a change in the volatility of the capital market due to Covid-19 if it occurs, and whether the volatility of the capital market in Indonesia will be higher during Covid-19 when compared to before Covid-19.

The difference between this study and previous research is that in addition to modelling the return volatility of the JCI index using ARCH-GARCH and testing the asymmetry effect, a large volatility calculation is also carried out. Hence, it will be easier for researchers to compare the volatility of the JCI return before and during Covid-19.



## THEORETICAL REVIEW

Information about stock market performance is summarized in an index called stock market index that reflects the performance of stocks in the market. This index describes the movement of stock prices so it is also called a price index share. If all listed shares are used as a component of the index calculation, it is called the Composite Stock Price Index (JCI). JCI was first introduced on April 1, 1983 as an indicator of the movement of listed stock prices. As for the need to know the stock index, namely as an investment reference for investors; assist investors to determine whether they will sell, hold, or buy one or more shares; and to avoid bias due to corporate action (Saraswati, 2020).

Composite stock price index (JCI) often used as a stock indicator used by investors to sell and buy shares. Changes in the stock price index can occur due to changes in stock prices on the stock exchange or changes in the total base value of shares. Investing in the stock market is often faced with risks because stock prices are volatile and stochastic; stock prices move in seconds and minutes, so the index value also moves up and down quickly; this movement is known as volatility. Volatility occurs because it occurs due to differences in interests between buyers and sellers of shares. The existence of volatility will cause the risk and uncertainty faced by investors to be greater so that investors' interest in investing becomes unstable. A volatile market will make it difficult for companies to raise their capital in the capital market because it has a higher level of uncertainty than the stock returns obtained (Widodo and Suryanto, 2021). Therefore, investors should estimate the volatility of the stocks used as portfolios to immediately adjust if there is a movement in global economic conditions.

Volatility is mainly related to the investment market. Volatility is taken from the physical term where a very unstable substance is right on the surface of the water. If the temperature increases, the substance will become a gas, whereas if the temperature decreases the substance will immediately turn into a liquid. The volatility of stock returns explains the level of tendency of returns to change (Ekananda, 2019).

Volatility it refers to the fluctuation or movement in the price of a particular stock or major index over time. Volatility is the up and down movement of a security's price over a certain period. In higher volatility, dramatic changes occur in the security's cost, which can be turned in the other direction in no time. Volatility will increase as soon as the stock price drops. This will increase significantly, especially during recessions as well as financial crises. This creates an atmosphere of uncertainty and, for this reason, hinders effective investment. Black highlights that while bad news is discovered, market prices immediately shrink, and good news pushes up market prices to increase the index's impact (Santoso et al., 2020).

According to the Efficient Market Hypothesis proposed by (Widodo and Suryanto, 2021) states that a market is said to be efficient if no one, both individual investors and institutional investors, will be able to obtain abnormal returns (abnormal). return), after adjusting for risk, using existing trading strategies. That is, the prices formed in the market are a reflection of existing information or "stock prices reflect all available information".

Another expression states that in an efficient market the prices of assets or securities quickly and completely reflect available information about these assets or securities. The process of changing the price of the security that causes volatility. Economists often interpret that changes in the price of these securities are evidence that the market is



functioning properly and investors are obtaining information efficiently (Widodo and Suryanto, 2021).

Modelling and forecasting stock market volatility has been the subject of vast empirical and theoretical investigation over the past decade or so by academics and practitioners alike. There are a number of motivations for this line of inquiry. Arguably, volatility is one of the most important concepts in the whole of finance. Volatility, as measured by the standard deviation or variance of returns, is often used as a crude measure of the total risk of financial assets. Many value-at-risk models for measuring market risk require the estimation or forecast of a volatility parameter. The volatility of stock market prices also enters directly into the Black–Scholes formula for deriving the prices of traded options (Brooks, 2019).

Experts have carried out research related to volatility modelling. Santoso et al. (2020) uses the closing prices of daily stock price indexes, namely: JCI (Jakarta Composite Index), and INDU (Dow Jones Industrial Average Index), SPX (Standard and Poors 500 Index), CCMP (NASDAQ Index), in Hong Kong HSI (Hang Seng Index), NKY (Nikkei 225 Index) and TPX (Tokyo Price Index), STI Singapore (Strait Times Index), and South Korea, KOSPI (Korea Composite Stock Price Index), SENSEX (India Composite Stock Market Index), FBM KLCI (Malaysia's Kuala Lumpur Composite Index), and Thailand, SET (Thai Composite Stock Market Index) with an observation period of January 2, 2008, to December 31, 2018. The results show that each stock index has a leverage effect, but the corresponding asymmetric volatility model is different. The TGARCH model is the best model for measuring the return volatility of the stock indexes INDU, SPX, CCMP, HSI), and NKY and TPX). Meanwhile, EGARCH is the best model in emerging markets, Indonesia (JCI) and Malaysia (FBMKLCI), as well as Korea (KOSPI). While the GJR-GARCH model is the best model in Singapore (STI) and Thailand (SET).

(Sari et al., 2018) use daily stock data for four countries: Indonesia, Singapore, Japan and Hong Kong. The results show that the volatility estimation model between the four countries is different, but all have an asymmetric effect. (Lin, 2018), in the Chinese capital market, found that the SSE Composite Index has a time-varying and clustering pattern. This result is in line with the findings of Autoregressive Conditional Heteroscedasticity (ARCH) and the effect of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) on the SSE Composite Index (Lin, 2018). Saiti, Bacha and Masih used the Dynamic Multivariate Generalized Autoregressive Conditional Heteroscedasticity method.

(Jebran et al., 2017) research used several methods to test the volatility transmission and the relationship between the sharia index and the conventional index. Using the Vector Error Correction Model (VECM), the researchers found that there was a significant short-term and long-term relationship between the sharia index and conventional indices while using the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) models, we found an asymmetric two-way volatility spillover between the sharia index and the conventional index.

(Bisma, 2020) uses companies that are members of LQ45 for the LQ45 period during the observation period from 2009 to 2019 and have never been excluded from the index, a total of 16 companies. The test results found that all data had volatility; using the GARCH model, it was found that all companies were affected by the error and return volatility of the previous period. Meanwhile, the analysis of leverage or asymmetric effects found as



many as 14 companies tested proved to have an asymmetric effect where negative news had a more significant impact on volatility than positive news. While two companies have a gamma coefficient value below zero, it can be concluded that it does not have an asymmetric value.

(Sudarto et al., 2021) conducted stock return modelling in the banking sector listed on the Indonesia Stock Exchange. The population in this study amounted to 45 banking companies listed on the Indonesia Stock Exchange (IDX) for 2014 to 2018. The results show volatility in the conclusion that our best model between the Threshold Generalized Autoregressive Conditional Heteroscedasticity (T-GARCH) model and the Exponential Generalized Autoregressive Conditional Heteroscedasticity (E-GARCH) model in predicting stock returns of the banking sub-sector listed on the Indonesia Stock Exchange is the EGARCH model.

## METHOD

The object of this research is the return volatility of the JCI daily stock price index. The data is taken from Yahoo Finance from January 1, 2017, to October 30, 2021. Then the time is separated into before the Covid 19 crisis, namely January 1 to December 30, 2018, and during covid 19 from January 1, 2019, to October 30, 2021.

While the variable in this study is the volatility of the stock obtained from the adjusted closed price of the JCI, an adjusted closed price is used because it has been changed to the share price if the company takes corporate action. A stock return is an expected return on investments made in stocks or several groups of stocks through a portfolio. Most financial data tends to move quickly and fluctuate, so it is not stationary at high-level stochastic variations to overcome this; the logarithm difference is used. The use of logarithm difference will reduce fluctuations in the data, so it is expected that the results of the calculation of returns will be stationary. Therefore, the JCI return calculation is used the following formula: (Singh and Teena, 2019), (Marobhe and Pastory, 2020):

$$RIHSG_t = \ln \left( \frac{IHSG_t}{IHSG_{t-1}} \right) \times 100 \text{ per cent} \dots \dots \dots (1)$$

Here  $RIHSG_t$  refers to the daily returns of the JCI,  $IHSG_t$  is daily closing price during “t” period, and  $IHSG_{t-1}$  is daily closing price during “t-1” period.

**Tools and Techniques used. Descriptive Statistics.** To know the distributional properties of the daily return series under consideration descriptive statistics like skewness, kurtosis and normality distribution.

**Stationarity Tests.** Stationarity test is the first step in estimating the model for time series data. Data that is not stationary will cause the model estimation results to be spurious. In other words, the estimation results are inaccurate, so the data stationarity test needs to be carried out to ensure that the data used in estimating the model is stationary. The data is said to be stationary if the observed data condition does not have a certain movement pattern, in other words the data used does not contain a trend pattern. A series is said to be stationary if it has a constant mean, constant variance, and constant covariance for each different lag.

The data stationarity test used the Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) test (Brooks, 2019).



The ADF Test Formulation is:

$$\Delta Y_t = a_0 + a_1 t + \gamma Y_{t-1} + \sum_{i=2}^p \beta_i \Delta Y_{t-i+1} + \varepsilon_t \dots \dots \dots (2)$$

Where  $\Delta$  is first difference operator,  $Y_t$  is Time series value at time  $t$ ;  $Y_{t-1}$  is time series value lagged by one periods is time index,  $a_0$  is a intercept/constant,  $\gamma$  is the coefficient presenting process root,  $p$  is the lag order of the first-difference process and  $\varepsilon_t$  is error term

The procedure for determining whether the data is stationary or not by comparing the ADF statistical value is coefficient  $\gamma$  in  $Y_{t-1}$  with the critical value of the Mackinnon statistical distribution. The ADF statistical value is a comparison between the standard error of. If the absolute value of the ADF statistical value is greater than the absolute value of the critical value of the Mackinnon statistical distribution, it is concluded that the data is stationary.

**Phillips–Perron (PP) Tests.** The unit root test using the Augmented Dickey-Fuller (ADF) assumes that the error term ( $\varepsilon_t$ ) is independent with an average of zero, and is not interconnected (non-autocorrelation). The Philip Perron unit root test (PP test) includes the element of autocorrelation in the error term by including the element of difference lag. The unit test Root PP test uses a non-parametric method to control the high order serial correlation in a series. (Ekananda, 2019).

The PP statistical value does not follow the normal distribution but follows the PP statistical distribution, with a critical value from the Mackinnon statistical distribution. Suppose the absolute value of the PP statistic is greater than the absolute value of the essential value of the Mackinnon statistical distribution. In that case, it is concluded that the data is stationary (Brooks, 2019)

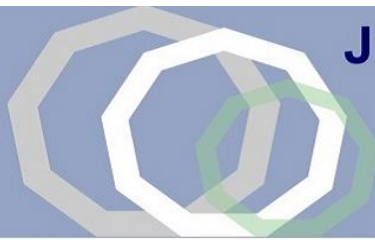
**Heteroscedasticity Tests.** The purpose of the present analysis is to study the volatility aspect of the series under consideration that requires testing for existence of the Auto Regressive Conditional Heteroscedasticity (ARCH effect) in residuals of the daily returns series using Lagrange Multiplier (LM) test. The residuals required for this testing can be calculated by running the any of the mean equations AR (1), MA (1) or ARMA (1,1) depending on the suitability (Savadatti, 2018).

**ARCH Model.** Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by (Brooks, 2019) to model time varying volatility or forecast conditional variance. ARCH models assume the variance of the current error term or innovation to be a function of the previous time periods' error terms. Another important feature of many series of financial asset returns that provides a motivation for the ARCH class of models, is known as 'volatility clustering' or 'volatility pooling'. Volatility clustering describes the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign) to follow small changes. In other words, the current level of volatility tends to be positively correlated with its level during the immediately preceding periods (Brooks, 2019). This model captures the volatility clustering observed in series returns.

ARCH model specifications:

$$y_t = \mu_t + \varepsilon_t, \text{ where } e_t = z_t \sigma_t \dots \dots \dots (3)$$





$\mu_t$  is  $E_{t-1}(y_t)$  is conditional mean information set at time t-1 or non-stochastic component that is predictable and  $\varepsilon_t$  is error term or shock or stochastic component that is unpredictable,  $z_t$  is iid (independent and identical distributed) random variables with zero mean and unit variance means iid (0.100).

$y_t$  has a conditional variance:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 \dots\dots\dots (4)$$

ARCH effect means heteroskedasticity is modelled as conditional variance of squared residuals obtained from mean equation as from AR (1) model. ARCH (q) specification for conditional variance  $\sigma_t^2$  is follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_q \varepsilon_{t-q}^2 \dots\dots\dots (5)$$

The null hypothesis is No ARCH effect. If value of test statistic is greater than critical value from chi square distribution or coefficient of  $\alpha$  is statistically significant or p value less than 0.05 then null hypothesis is rejected (Singh and Teena, 2019).

**GARCH Models.** The stationer data at the level then uses the ARMA (Autoregressive Moving Average) model. At the same time, the non-stationary data at the station and stationary at the first difference use the ARIMA (Autoregressive Integrated Moving Average) model.

**White Noise Test.** Verify the ARMA or ARIMA model with the white noise error term. A time series data is white noise if it has an average error term of 0 and a constant variance. White noise test, using Box Ljung-Box test (LB Test) (Brooks, 2019).

LB Test :

$$LB = n(n + 2) \sum_{i=1}^m \left( \frac{\hat{\rho}_k^2}{k-1} \right) \approx \chi_{\alpha}^2(df=k) \dots\dots\dots (6)$$

Where n is the number of samples, k maximum lag,  $\hat{\rho}_k^2$  is ACF or autocorrelation function. LB approaches the Chi Square distribution with a degree of freedom k. Time series data is said to be white noise if the LB value is greater than Chi Square with a degree of freedom k.

**ARCH Model.** ARCH (Autoregressive Conditional Heteroscedasticity) modelling is a model (1986) in (Brooks, 2019) developed to overcome heteroscedasticity problems in time series data. The ARCH (p) model is:

$$Y_t = \beta_0 + \beta_1 X_t + \varepsilon_t \dots\dots\dots (7)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_p \varepsilon_{t-p}^2 \dots\dots\dots (8)$$

$\alpha_0, \alpha_1, \dots, \alpha_p$  greater than 0

Equation (7) is called the conditional mean, while equation (8) is conditional variance, which captures the heteroscedasticity of the error term. In this case, Engle (1982) in (Brooks, 2019) proxies the error variance with the error term squared. However, in its implementation, the ARCH model requires a long p-value, causing problems in interpretation. Therefore, Bolerslev (1986) in (Brooks, 2019) improved the ARCH model



by adding the previous time error term variance to the conditional variance; the model is called GARCH (General Autoregressive Conditional Heteroscedasticity). Model).

**GARCH Model.** The GARCH model represents that current conditional variance also depends on previous conditional variances and the lag of the square of the remainder. The GARCH conditional variance (p,q) model is:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_{i-1} \varepsilon_{i-1}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \dots\dots\dots (9)$$

$\alpha_0, \alpha_1, \dots, \alpha_p, \beta_1, \beta_2 \dots \beta_q$  greater than 0

$\alpha_i + \beta_j$  expected to be close to 1 for a valid model. Financial data, which is time series data, generally have a high coefficient  $\alpha_i$ , which indicates the magnitude of the reaction to changes in volatility due to shocks in the model market. The high value of the coefficient  $\beta_j$  indicates the high persistence of the capital market due to shocks.

The GARCH model can be used to predict the variance error term. The main characteristic of the GARCH model is that the conditional variance forms the ARMA process. In the general GARCH model, there is a conditional variance element consisting of three elements, namely:  $\alpha_0$  is the average conditional variance, the GARCH element is  $\sum_{j=1}^p \beta_j \sigma_{t-j}^2$  is the process of MA (Moving Average) with order p. This element provides information to traders to estimate the future trend variance. The intuition of the equation, if the volatility is higher, it will cause the conditional variance equation to provide larger forecast variance information. Traders will increase the forecast for future variances. While the ARCH elements are  $\sum_{i=1}^q \alpha_{i-1} \varepsilon_{i-1}^2$  shows information about the volatility of the previous period. This volatility is calculated based on the square of the error term of the previous period from the error term of the conditional mean equation. The ARCH element is in the form of an AR process with order q. This element provides information about the volatility of the conditional mean equation used by traders to estimate the forecasted variance (Ekananda, 2019).

The ARCH/GARCH model that is formed is then verified for the following problems: error term normality, white noise and the presence of the ARCH effect. (Brooks, 2019) suggest that the GARCH (1,1) model is sufficient to model clustering volatility in financial data. Therefore, the researcher followed (Brooks, 2019) suggestion using GARCH (1,1).

Model GARCH(1,1) is:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \dots\dots\dots (10)$$

$\alpha_0, \alpha_1, \beta_1$  greater than 0

Where  $\sigma_{t-1}^2$  is variance of the previous period's error term or (t -1),  $\alpha_0$  constant component,  $\alpha_1$  parameters of ARCH,  $\beta_1$  parameters of GARCH,  $\varepsilon_{t-1}^2$  the previous period's squared error term or (t -1). Expected  $\alpha_1 + \beta_1$  less than and closer to 1.

**Asymmetrics test.** The classic ARCH and GARCH models have the assumption that all the effects of shocks on volatility have a symmetrical distribution. However, the asset returns do not always have a symmetrical distribution, but also an asymmetric distribution, thus the GARCH asymmetric model represents that (Santoso et al., 2020).

After being verified, the ARCH/GARCH model was tested for the presence of asymmetry. The researcher uses the formula from Engle-Ng test (Brooks., 2019) to test





whether there is a problem with the asymmetric model have proposed a set of tests for asymmetry in volatility, known as sign and size bias tests. The Engle and Ng tests should thus be used to determine whether an asymmetric model is required for a given series, or whether the symmetric GARCH model can be deemed adequate. In practice, the Engle–Ng tests are usually applied to the residuals of a GARCH fit to the returns data. Asymmetric testing, using the following model:

$$\mu_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- \mu_{t-1} + \phi_3 S_{t-1}^+ \mu_{t-1} + v_t \dots \dots \dots (11)$$

Where  $S_{t-1}^-$  as an indicator dummy that takes the value 1 if and zero otherwise,  $S_{t-1}^+$  is  $1 - S_{t-1}^-$ , so that picks out the observations with positive innovations. Significance of  $\phi_1$  indicates the presence of sign bias, where positive and negative shock have differing impacts upon future volatility. On the other hand, the significance of  $\phi_2$  or  $\phi_3$  would suggest the presence of size bias, where not only the sign but the magnitude of the shock is important. A joint test statistics for formulated in the standard fashion by calculating  $nR^2$  from equation (11) which will asymptotically follow a Chi Square distribution with three degrees of freedom under the null hypothesis of no asymmetries effects (Brooks, 2019).

Brooks further stated that the curve between the value of lagged shock and the value of conditional variance will be symmetrical, if there is no asymmetric effect, otherwise it will not be symmetric if there is an asymmetric effect. If there is an asymmetric effect, then the next model is the EGARCH and GJR-GARCH model (Alijev et al., 2020). The research of (Santoso et al., 2020) shows that the EGARCH model (1.1) is suitable for the developing countries that are used as research samples, namely: Indonesia and Malaysia.

**The EGARCH model.** The exponential GARCH model was proposed by Nelson (1991) in (Brooks, 2019). There are various ways to express the conditional variance equation, but one possible specification is given by:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[ \frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \dots \dots \dots (12)$$

Where  $\sigma_{t-1}^2$  is variance of the previous period's error term or (t -1),  $\omega$  constant component,  $\beta$  parameters of ARCH,  $\beta_1$  parameters of GARCH,  $\varepsilon_{t-1}^2$  the previous period's squared error term or (t -1).The model has several advantages over the pure GARCH specification. First, since the is modelled, then even if the parameters are negative, will be positive. There is thus no need to artificially impose nonnegativity constraints on the model parameters. Second, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative,  $\gamma$ , will be negative. Note that in the original formulation, Nelson assumed a generalised error distribution (GED) structure for the errors. GED is a very broad family of distributions that can be used for many types of series (Brooks, 2019). To find out whether there is a leverage problem or asymmetric response, judging from the  $\gamma$  sign, if the negative value is significant, there is a leverage problem.



The parameter value of equation (12) consists of 2 parts, namely the sign effect  $\frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}}$  and magnitude effect  $\frac{|\mu_{t-1}|}{\sqrt{\sigma_{t-1}^2}}$ . The sign effect shows that there is a difference in the effect between positive and negative shocks in period t on the current variance. The magnitude effect shows the magnitude of the effect of volatility in the t - p period on the current variance.

## RESULTS

**Table 1** shows the descriptive statistics of the JCI Returns before and during the crisis. Observations of 479 RIHSG (Return JCI) series before the crisis had an average value of 0.036 with a standard deviation of 0.810, while during the crisis. In comparison, during the crisis, there were 690 RIHSG with an average of 0.016 and a standard deviation of 1.192. The average return on the IHSG during the crisis was lower than before. Still, the standard deviation was higher, indicating that the JCI return movement during the crisis was higher than before. Furthermore, the distribution of JCI returns shows that it does not follow the normal distribution because the kurtosis value is high and the skewness is low. This result is consistent with (Brooks, 2019) which states that the tendency for financial asset returns to have distributions that exhibit fat tails and excess peakedness at the mean.

**Table 1.** Descriptive Statistics of JCI Returns Before and During the Covid-19 Crisis

	Before Crisis	During Crisis
Mean	0.036	0.0161
Median	0.057	0.0402
Maximum	2.668	10.1907
Minimum	-3.756	-6.5787
Std. Dev.	0.8097	1.1922
Skewness	-0.4994	0.2784
Kurtosis	5.4219	14.112
Jarque-Bera	136.9811	3558.851
Probability	0.000	0.000
Observations	479	690

**Stationerity Test.** Stationarity testing using Augmented Dickey-Fuller (Brooks, 2019) and Phillips-Perron (Brooks, 2019), the results of the unit root analysis are shown in **Table 2**.

**Table 2.** RIHSG Root Unit Tests Before and During the Covid-19 Crisis

	t-Statistic		Critical value	
	Before crisis	During crisis	at 5 per cent	Probability.*
ADF test statistic	-21.726	-13.424	-2.867	0.000
PP test statistic	-22.338	-25.092	-2.867	0.000

Source: Analysis results



**Table 2** shows that the ADF test statistic and PP test statistics from the IHSG both before the crisis and during the Covid-19 crisis were greater than the critical value of 5 per cent so it can be concluded that the IHSG before the crisis and during the crisis was stationary at the level.

**ARMA/ARIMA Modeling.** The results of the ARMA/ARIMA, RIHSG modelling before the Covid-19 crisis were:

**Table 3.** RIHSG ARMA/ARIMA Modeling Before the Covid-19 Crisis

Variabel	Coefficient	Std. Error	t-Statistic	Probability	Description
AR(7)	0.125	0.038	3.271	0.001	***
AR(2)	-0.082	0.042	-1.973	0.049	**
R-squared		0.022			
Adjusted R-squared		0.018			
Akaike info criterion		2.404			
Schwarz criterion		2.430			

Note : \*\*\*) significant at level 1 per cent  
 \*\*) significant at level 5 per cent

Source: Analysis results

**Table 3** shows that the JCI return in the pre-crisis period was influenced by return 2 and return 7 of the previous period. Testing the validity of the ARMA/ARIMA model shows that the model has white noise because the value of Ljung-Box (LB) Test is Q 45,928 of the Correlogram of Standardized Residuals is less than Chi square table at level 5 per cent is 50,998, so it can be concluded that the ARMA model from IHSG has white noise.

Then it is tested to find out whether there is a heteroscedasticity problem, namely by looking at the Q value of Correlogram of Residuals Squared, Q value is 359.000 is greater than Chi square table at level 5 per cent is 50,998, so it is concluded that the ARMA results from the IHSG have heteroscedasticity problems or there is an ARCH effect. Because it has an ARCH effect, then modelled with ARCH/GARCH.

The results of the ARMA, IHSG modelling during the Covid-19 crisis are:

**Table 4.** IHSG ARMA/ARIMA Modeling During the Covid-19 Crisis

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Description
AR(1)	0.083	0.021	3.966	0.000	***
AR(2)	-0.099	0.024	-4.153	0.000	***
AR(3)	0.170	0.021	8.184	0.000	***
AR(9)	-0.116	0.024	-4.856	0.000	***
AR(5)	0.116	0.028	4.125	0.000	***
AR(13)	-0.080	0.027	-2.960	0.003	***
AR(15)	0.103	0.030	3.480	0.001	***
AR(19)	-0.082	0.030	-2.739	0.006	***



R-squared	0.081
Adjusted R-squared	0.070
Akaike info criterion	3.130
Schwarz criterion	3.190

Note : \*\*\*) significant at level 1 per cent

\*\*) significant at level 5 per cent

Source: Analysis results

**Table 4** shows that the JCI return during the crisis period was influenced by return 1 and return 2, return 3, return 9, return 5, return 13, return 15 and return 19 of the previous period. Testing the validity of the ARMA/ARIMA model shows that the model has white noise because the value of Q of the Correlogram of Standardized Residuals is smaller than Chi Square table, so it can be concluded that the ARMA model from IHSG has white noise.

Then it is tested to find out whether there is a heteroscedasticity problem, namely by looking at the Q value of Correlogram of Residuals Squared, Q value is 549.020 is greater than Chi Square table, so it is concluded that the ARMA results from the RIHSG have heteroscedasticity problems or there is an ARCH effect. Because it has an ARCH effect, then modelled with ARCH/GARCH.

To find out whether there is a difference in responses, if there is good news and bad news or whether there is a leverage effect, the Engle-Ng Sign-Bias Test is carried out. The results of the Engle-Ng Sign-Bias Test Return of JCI before the Covid-19 crisis.

**Table 5.** Results of the Engle-Ng Sign-Bias Test Return of JCI before the Covid-19 crisis

	t-Statistic	Probability	Discription
Sign-Bias	-1.136	0.257	
Negative-Bias	-4.423	0.000	***
Positive-Bias	-0.274	0.785	
Joint-Bias	22.915	0.000	***

Note : \*\*\*) significant at level 1 per cent

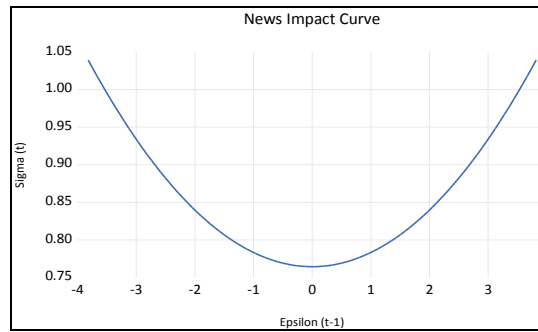
\*\*) significant at level 5 per cent

Source: Analysis results

**Table 5** show of results of the Ng Sign-Bias Test show that the probability of  $\phi_2$  RIHSG is not significant, while of  $\phi_1$ , and  $\phi_3$  is significant. While the Joint-Bias RIHSG, the value of  $n \cdot R^2$  is equal to 22.9148, which is significant because probability value 0.0001 less than 1 per cent. Thus, it is concluded that there is an asymmetry problem, meaning that the above model will give an unequal response when there is good or bad news.

More details, can be seen in the image below:





**Figure 1.** The Curve of the Influence of New Information on the IHSG Before Covid-19

**Figure 1** shows that good news, namely the positive curve, is not the same as bad news (negative curve). In other words, good news and bad news do not have the same impact on stock return volatility. The effect that occurs on volatility originating from bad news in future periods is greater than the effect caused by good news in future periods. Because the IHSG before the Covid-19 crisis had an asymmetry problem, it was modelled with an asymmetry model; the result was EGARCH (1,1).

**Table 6.** JCI EGARCH Return Model Before the Covid-19 Crisis

Variable	Coefficient	Std. Error	z-Statistic	Probability	Description
AR(7)	0.1376	0.0479	2.8728	0.0041	***
Variance Equation					
C(2)	-0.039	0.014	-2.729	0.006	***
C(3)	0.047	0.019	2.486	0.013	**
C(4)	-0.060	0.016	-3.677	0.000	***
C(5)	0.984	0.003	298.518	0.000	***
R-squared		0.016			
Adjusted R-squared		0.016			
Akaike info criterion		2.236			
Schwarz criterion		2.280			

Note : \*\*\*) significant at level 1 per cent  
 \*\*) significant at level 5 per cent

Source: Analysis results

The conditional equation of mean shows that the influential variable is AR (7) significant at the level of 1 per cent. This shows that JCI returns are influenced by JCI returns in the previous 7 periods. While the variance equation, it can be seen that  $\phi$  is -0.039 and significant at level 1 per cent. ARCH effect is 0.047 and GARCH effect -0.060 and Leverage effect is 0.984. Value of  $\alpha + \beta$  is -0.012 is less than 1. Leverage effect (C (4)) is negative and significant because p value is 0.000 less than 0.050 so it can be concluded that there is a problem with the leverage effect.

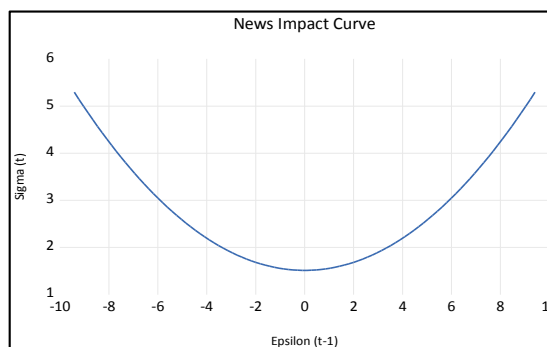
**Table 7.** The results of the Engle-Ng Sign-Bias Test Return of JCI during the Covid-19 crisis

	<b>t-Statistic</b>	<b>Probability</b>	<b>Discription</b>
Sign-Bias	-1.136	0.257	
Negative-Bias	-4.423	0.000	***
Positive-Bias	-0.274	0.785	
Joint-Bias	22.915	0.000	***

Note : \*\*\*) significant at level 1 per cent  
 \*\*) significant at level 5 per cent

Source: Analysis results

The results of the Ng Sign-Bias Test show that the probability of  $\phi_2$  RIHSG is not significant, while of  $\phi_1$ , and  $\phi_3$  is significant. Meanwhile, in the Joint-Bias IHSG, the value of  $n \cdot R^2$  is equal to 27.5357, which is greater than  $\chi^2_{0.05(df=3)}$  is 7.8147. Thus, it is concluded that there is an asymmetry problem, meaning that the above model will give an unequal response when there is good or bad news.



**Figure 2.** The Curve of the Influence of New Information During Covid-19

**Figure 2** shows that good news, namely the positive curve, is not the same as bad news (negative curve). In other words, good news and bad news do not have the same impact on stock return volatility. The effect that occurs on volatility originating from bad news in future periods is greater than the effect caused by good news in future periods. Because the IHSG before the Covid-19 crisis had an asymmetry problem, it was modelled with an asymmetry model, the result was EGARCH (1,1)

**Table 8.** JCI EGARCH Return Model During the Covid-19 Crisis

<b>Variable</b>	<b>Coefficient</b>	<b>Std. Error</b>	<b>z-Statistic</b>	<b>Prob.</b>	<b>Description</b>
AR(2)	-0.087	0.037	-2.315	0.021	**
AR(5)	0.086	0.038	2.261	0.024	**
AR(15)	0.069	0.030	2.347	0.019	**
AR(19)	-0.035	0.035	-0.990	0.322	
AR(3)	0.059	0.043	1.386	0.166	
Variance Equation					
C(6)	-0.193	0.036	-5.350	0.000	***



C(7)	0.250	0.045	5.506	0.000	***
C(8)	-0.099	0.019	-5.300	0.000	***
C(9)	0.947	0.014	65.628	0.000	***
R-squared		0.042			
Adjusted R-squared		0.036			
Akaike info criterion		2.784			
Schwarz criterion		2.845			

Note : \*\*\*) significant at level 1 per cent

\*\*) significant at level 5 per cent

Source: Analysis results

The asymmetric effect on JCI returns before the crisis shows that bad news that occurred in the previous period ( $t-1$ ) will increase return volatility in the current period ( $t$ ) compared to when there was good news in the previous period ( $t-1$ ). Meanwhile, the coefficient is negative and significant at the 5 per cent real level, meaning that the effect of bad news at this time ( $t$ ) on return volatility will be corrected for its effect two days later ( $t + 2$ ). In other words, at  $t + 2$  the volatility will start to decrease.

This decrease in volatility occurred as a result of correction of overreaction or mispriced errors on bad news in the previous period. Overreaction occurs because they are too pessimistic in responding to bad news in the previous period. This attitude accelerates the increase in volatility, so there is an element of mispriced. As a result, there will be a backflow to correct the mispriced.

When bad news occurs, it will result in a large decline in stock prices. This decrease in turn will increase the debt equity to ratio (ie the ratio that measures the extent to which the company is financed by debt). An increase in debt equity to ratio causes an increase in asset ownership risk, thus indicating an increase in asset volatility. Therefore, the existence of an asymmetric effect appears when the stock market is experiencing a crash. Thus, when there is bad news at this time, it will increase the return volatility on the next day ( $t + 1$ ) compared to when there is good news at this time (Sari et al., 2017)

**Model validation.** Validation of the EGARCH model, including a. White noise test and b. Heteroscedasticity test.

**White Noise Test.** The white noise test shows that the Q value of the Correlogram of Standardized Residuals IHSG before the Covid-19 crisis was equal to 25,984. This value is smaller than the Chi square table is 50,998, so it can be concluded that the EGARCH model from the IHSG before the Covid-19 crisis was white noise.

The white noise test shows that the Q value of Correlogram of Standardized Residuals RIHSG during the Covid-19 crisis was equal to 44,796, this value is smaller than Chi Square table, so it can be concluded that the EGARCH model from the IHSG during the Covid-19 crisis was white noise.

**Heteroscedasticity test.** Heteroscedasticity testing was carried out in 2 ways. The first way to compare the Q value of Correlogram of Residuals Squared with Chi-square table with a 5 per cent significance level. The second way uses the Heteroskedasticity Test: ARCH. If the probability of Obs\*R-squared is greater than 5 per cent, it indicates no heteroscedasticity problem.

The value of Q Correlogram of Residuals Squared before the crisis is equal to 29,002, while Chi Square Table is 50,998; because the value of Q is smaller than the table, it is concluded that the EGARCH model of the IHSG before the crisis does not have

heteroscedasticity problems. This is reinforced by the results Heteroskedasticity Test: ARCH, where the probability of Obs\*R-squared is equal to 0.981, greater than 5 per cent.

The value of Q Correlogram of Residuals Squared during the crisis is equal to 32,676, while Chi Square Table is 50,998; because the value of Q is smaller than the table, it is concluded that the EGARCH model of the IHSG during the crisis does not have heteroscedasticity problems. This is reinforced by the results Heteroscedasticity Test: ARCH, where the probability of Obs\*R-squared is equal to 0.592, greater than 5 per cent.

It can be concluded that the EGARCH RIHSG model before the crisis and the EGARCH RIHSG during the crisis are econometrically valid.

**The RIHSG EGARCH model before Covid-19.** Return IHSG before the crisis was influenced by the return of the previous 7 periods, while the conditional variance equation was:

Conditional Variance RIHSG Model before Covid-19:

$$\ln(\sigma_t^2) = -0,0394 + 0.0474 * \left( \left[ \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right] + E \left( \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) \right) - 0.0597 * \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} + 0.9842 * \ln(\sigma_{t-1}^2) \dots \dots \dots (12)$$

The influence of the previous variance factor was 0.984, the result of volatility when conditions were good was 0.047, the effect of leverage was 0.060, and the effect of bad conditions was 0.012 on changes in the volatility of JCI returns before the Covid 19 crisis. Coefficient  $\square$  negative and significant, indicating an asymmetry (asymmetric response) where there is a difference in response between negative and positive news (Brooks, 2019).

Return IHSG during the crisis is influenced by return 2, return 3, return 5 and return 15 of the previous period, while the conditional variance equation is:

Conditional Variance RIHSG Model during Covid-19:

$$\ln(\sigma_t^2) = -0,1964 + 0.2541 * \left( \left[ \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right] + E \left( \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} \right) \right) - 0.0990 * \frac{e_{t-1}}{\sqrt{\sigma_{t-1}^2}} + 0.9454 * \ln(\sigma_{t-1}^2) \dots \dots \dots (13)$$

The influence of the previous variance factor was 0.945, the large effect of volatility when conditions were good was 0.254, the effect of leverage was 0.099, and the impact of bad conditions was 0.254 on changes in the volatility of JCI returns before the Covid 19 crisis. Coefficient  $\square$  negative and significant, indicating an asymmetry (asymmetric response) where there is a difference in response when it occurs.

## DISCUSSION

The results of this study indicate that the kurtosis value is positive and far above 3. This indicates that the distribution of returns has a leptokurtic form (Sari et al., 2018). Leptokurtic is a form of part Leptokurtic is a form of the middle part of the data distribution that has a more pointed peak. The skewness value shows the skewness of the data. If the skewness value is positive, it means that the series tends to have a long right tail.





Conversely, if the skewness value is negative, it means that the series tends to have a long left tail tendency. **Table 1** shows that the skewness of JCI returns before the crisis was negative, meaning that stock returns tended to have a long left tail, while the skewness of JCI returns during the crisis was positive, meaning that stock returns tended to have a long right tail. the existence of asymmetry from the normal distribution. This result is supported by the results of the Jarque-Bera test, which is used to detect the normality of the data distribution. The test results, for JCI returns both before and during the crisis, show a p-value of less than 5 per cent, meaning the null hypothesis In other words, stock return data are not normally distributed at the 5 per cent level of significance.

**Table 1** shows that the sample standard deviation of both JCI returns before and during the crisis is much larger than the average return. If the value of the standard deviation is more than the average value of the market standard deviation, then the market is categorized as a market with relatively high fluctuations. Meanwhile, if the return of a stock with a deviation value is less than the average value of the market standard deviation, then the market is categorized as a market with relatively low fluctuations (Sari et al., 2018). Thus, JCI returns both before the crisis and during the crisis have high fluctuations.

Based on the conditional variance, it can be seen that the influence of the previous variance, return IHSG, before the crisis was significant compared to the Covid-19 crisis. This is likely due to the micro restrictions implemented by the government to prevent the spread of Covid-19. The Covid-19 Delta variant in July 2021 prompted the government to implement the strengthening of the micro restrictions policy based on the level of strictness applied throughout Indonesia. The intensity of the restrictions on community activities is adjusted according to the level of assessment of the pandemic situation in each Regency/City. The determination of the level of restriction is based on the World Health Organization (WHO) standard, which measures the rate of virus transmission compared to the capacity of testing, tracing and treatment (3T) (LPI, 2021). The economic performance continued to grow positively in the third quarter of 2021 at 3.510 per cent, higher than the 3.49 per cent contraction in the same quarter last year but lower than 7.070 per cent in the second quarter of 2021. The mobility restriction policy that must be adopted by the government's response to the surge in cases of the Delta variant of Covid-19 in July-August 2021 had an impact on the economy, particularly domestic demand. Household consumption only grew by 1.030 per cent in the third quarter of 2021, in line with the limited consumption of the upper middle class. Mobility restrictions also resulted in a lower increase in investment, which was 3.740 per cent in the third quarter of 2021. Government consumption recorded growth of 0.660 per cent (YoY) in line with the reallocation of spending to accelerate the national economic recovery program, including handling the Covid-19 variant. Delta. The positive contribution restrained the deeper slowdown in economic growth from the persistently high export performance. Export growth in the third quarter of 2021 was maintained at 29.160 per cent (YoY), in line with the strong demand from major trading partners.

Volatility before the Covid-19 crisis was 0.9842 higher than during the crisis, which was 0.9454, this shows that Indonesia's economic activity during the Covid-19 crisis was lower than before the Covid crisis. This can be seen, among other things, from the work from home policy that was implemented by the government in March 2020. This policy has an impact on most of the people who work in offices being forced to work from home, although not all employees, but only involve employees who work in certain fields, some still do activity as usual. Many companies are forced to lay off or lay off and even lay off



employees. This condition causes the company to reduce the amount of production or temporarily stop production and ultimately affect sales. This also applies to the opposite, the purchasing power of people affected by Covid-19 has decreased so that demand has also decreased, causing companies to reduce the amount of production. In the end, this will reduce turnover and ultimately affect the company's finances and performance. The Financial Services Authority said that of the 475 issuers that submitted financial reports in the first quarter of 2020, 58.730 per cent of issuers experienced a decline in profits. The decline in the company's performance can lower the stock price on the stock exchange. On the other hand, the reduction in the number of employees by companies causes an increase in the number of unemployed and affects macroeconomic conditions (Saraswati, 2020).

Research conducted by (Rahmayani and Oktavilia, 2020) the Covid-19 pandemic would cause economic weakness in the long-term, especially in the stock market sector. However, the short-term model has a different result from a long-term model for the pandemic variable. The total cases accumulated of Covid-19 in Indonesia have no significant effect on Indonesia's stock market in the shortterm. In other words, the economy has not been paralyzed by the pandemic in the short-term, but it affects the long-term. The other difference from the long-term model was that both the foreign interest rate and domestic inflation has no significant effect on Indonesia's stock market. While there was a new variable that has a significant negative impact on the stock market in Indonesia, i.e., the exchange rate (USD/IDR), then, both the foreign stock (DJI) and commodity price (Brent oil) were the same in the long-term model that has a significant positive effect on Indonesia's stock market.

These results are in line with the research of (Widodo and Suryanto, 2021), (Santoso et al., 2020), (Sudarto et al., 2021), (Jebran et al., 2017), where the model The appropriate volatility for JCI returns both before the crisis and during the crisis is the EGARCH asymmetric model.

The IHS volatility model, both before the crisis and during the Covid-19 crisis, which is GARCH (1.1), shows that the volatility of the return of a stock market is not only influenced by current shocks and volatility but is also influenced by previous shocks and volatility.

The GARCH model represents that the current conditional variance also depends on the previous conditional variances and the lag squared error term. The GARCH model indicates that the volatility of asset returns describes clustering volatility as seen from lagged variances.

The classic ARCH and GARCH models assume that all shock effects on volatility have a symmetric distribution. But in fact, asset returns do not always have a symmetrical distribution but also an asymmetric distribution which the asymmetrical GARCH model represents. The characteristic that often appears in the observation of data volatility in the financial sector is the existence of asymmetric volatility. The classic GARCH model ignores the asymmetric volatility phenomenon which is more suitable for stock return volatility modelling, because it captures the leverage effect, namely the negative correlation between volatility and past returns. This asymmetrical condition generally arises when the stock market is in a crash situation, namely during a significant decline in stock prices, which will have a continuing effect on a significant increase in stock volatility. As a result, it causes the impact of negative events (bad news) to be more significant than positive events (good news) on asset volatility. Engle and Ng (Brooks, 2019) also explain that positive and negative information have different impacts on



volatility, so bad news tends to have a higher volatility impact than good news (Sari et al., 2018).

The EGARCH (1.1) model shows that the effect of bad news on return volatility is greater than good news because of the leverage effect. This phenomenon, in fact, does occur in financial markets. When bad news happens, it will result in a large decline in stock prices. This decrease, in turn, will increase the debt-equity to ratio. An increase in debt-equity to ratio causes an increase in asset ownership risk, thus indicating an increase in asset volatility. Therefore, an asymmetric effect appears when the stock market is experiencing a crash. Therefore, when there is bad news, it will increase the return volatility on the next day ( $t + 1$ ) compared to when there is good news.

These results are consistent with the research by (Awartani and Corradi, 2005), which states that the GARCH asymmetric model plays an essential role in predicting volatility. (Liu and Hung, 2010) also noted that the GARCH asymmetric model improved prediction and forecasting results. The GARCH model is weak compared to the asymmetric GARCH model in describing the volatility of stock market returns. Thus, the estimation results of the GARCH asymmetric model become more precise in determining risk management strategies for a stock market.

## CONCLUSION

This study shows that the JCI return, both before the Covid-19 crisis and during the Covid-19 crisis, is stationary at the level, so it can be modelled with ARMA. The results of the ARMA modelling have been validated so that white noise is then tested with the LM Test. The results of the LM Test indicate that there is a heteroscedasticity problem. Then proceed with the ARCH-GARCH volatility model. The use of the ARCH-GARCH volatility model shows a problem of asymmetry or leverage effects. Therefore, an asymmetry model is used, and the appropriate model is the EGARCH model.

The EGARCH model shows that JCI returns have high volatility both before the Covid-19 crisis and during the Covid-19 crisis. There is a leverage effect, where the volatility will increase if it is against something considered bad news by investors.

The findings of this study are: there are differences in the volatility of stock price index returns between before and during Covid-19. Another finding is that the effect of variance in the previous period, before Covid-19, was higher when compared to during Covid-19. This possibility is due to the micro restriction implemented by the government, resulting in a decrease in trading activity in Indonesia.

The findings of this paper implied some recommendations to stock stakeholders, including investors as well as the stock market authority. First, the continuous effort to enhance domestic retail investor participation in emerging stock market, including in Indonesia is a must. Next, diversification of the foreign investors in the Indonesia stock market could be an additional alternative, especially foreign investors. (Santoso et al., 2020). Finally, for the reason that on daily stock return volatility, this paper does not use domestic macroeconomic indicators, Bank Indonesia policy rate, inflation, and GDP growth announcements impact on stock market volatility around announcement date, stock market stakeholders need to pay extra attention to information irregularities that have the potential to bring negative sentiment to the market. Therefore, in further research, it is necessary to think about including these variables.



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