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PREDICTIVE VOLATILITY MODELS OF JKSE AND FIVE STOCK RETURNS IN DEVELOPED COUNTRIES

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Abstract: This study aims to determine alternative predictive volatility models for the JKSE and five developed country stock price index (Singapore's FTSE, China's SSEC, Japan's Nikkei 225, UK's FTSE, and America's Dow Jones) during a time of slowing world economy (January 2021 – September 2022). The method used to measure the volatility of the stock price index is ARCH (q), GARCH (p,q) and EGARCH (p,q). The results show that JKSE has lower volatility than five other developed countries with a stock price index that tends to increase. The stock price index for the five developed countries have high volatility and tend to decrease for China and Japan, while the stock price index for Singapore, UK and America tend to increase. An alternative predictive volatility model for JKSE stock returns is GARCH (1.1), Singapore's FTSE is ARCH (1), China's SSEC is ARCH (1), Japan's Nikkei 225 is GARCH (1.2) while the UK's FTSE100 and America's Dow Jones are EGARCH (1,1). These results indicate that FTSE and Dow Jones stock returns have a leverage effect where good news causes less volatility than bad news. When there is volatility in stock returns, especially FTSE100 and Dow Jones, business risk increases.

Keywords: *Volatility, ARCH/GARCH/EGARCH, stock price index, stock returns*

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1. Introduction

Over the past three years, the Indonesian economy has tended to slow down due to Covid-19, as well as the global economy. The Covid-19 problem has not been resolved; the Russian invasion of Ukraine began on February 24, 2022. The impact of the war was extraordinary because the war occurred before Covid-19 ended. This means that the economic impact of Covid-19 is still being felt, then weakened again by the emergence of the Russia-Ukraine war. The IMF (International Monetary Fund) has warned that a war between Russia and Ukraine, as well as sanctions imposed on Russia will have a severe impact on the global economy.

Many developed countries (Western World) such as America and most of Europe support Ukraine. The existence of an embargo on Russia caused Russia to choose a policy of only selling oil and gas in rubles. Meanwhile European countries have an energy dependence on Russia of around 40%. If there is no energy supply from Russia, it will have a big impact on the economies of European countries.

The Russia-Ukraine conflict has driven up commodity prices, concerns over inflation, and fears of a global economic recession. Oil prices soared to a high of $130 per barrel and US oil futures closed up 3.6 percent at $123.7 per barrel. The energy sector responded positively to the increase in oil prices. Chevron shares jumped 5.2 percent. Enphase Energy and SunPower increased by 10.8 percent and 18.7 percent, respectively. The United States stock market or Wall Street closed in 'red' on Tuesday, March 8, 2022. According to the CNBC report, the S&P 500 experienced its deepest decline since October 2020 with a decrease of 0.72 percent to 4,170.67. The Dow Jones Industrial Average fell 184.74 points to 32,632.64, while the Nasdaq Composite fell nearly 0.3 percent to 12,795.55. Until now, investors are faced with the sentiment of soaring commodity prices and slowing economic growth. Rising prices for oil, gasoline, natural gas and precious metals such as nickel and palladium sparked fears of a slowdown in global economic growth amid soaring inflation.

Tuesday, February 22, 2022, Asian stock exchanges fell, Nikkei (Japan) opened falling 1.54 percent, Han Seng (Hong Kong) fell 2.28 percent, Shanghai Composite (China fell 0.78 percent, Straits Times (Singapore) corrected 0, 58 percent and Kospi (South Korea) fell 1.7 percent. JCI (Indonesia) moved in the red zone after opening down 0.25 percent (CNBC Indonesia).

Various information related to Covid-19 and the Russia-Ukraine war spread on social media is true, but there is also a hoax. Some believe in information based on data and some believe in hoax news. The results of research from Boni and Ahmad (2021) show that social media has an effect on the level of trust of millennials in Jakarta. This means that what is conveyed by social media, whether it is fact or rumor, can affect millennial society.

The existence of information that is disseminated on various social media will influence people's behavior, including in responding to the stock price index, which is indeed very sensitive to issues. Stock itself is an alternative in investing for the community. Investors, especially retail investors, must be aware that stock prices can fluctuate according to information circulating, both information based on facts and data, as well as information that is not yet clear. The risks faced can be large amidst economic and geopolitical uncertainties.

Therefore, it is interesting to know how the volatility of stock prices in Indonesia and five developed countries (Singapore, China, Japan, UK and America) amidst the current world situation. What is the predictive volatility model for stock returns that is appropriate for Indonesia and the five developed countries?

To solve the problem, the first step is to identify the stationarity of the variable, the second is to test the stationarity of the variable, and the third is to determine the appropriate predictive volatility model for the stock return.

Generally, volatility is proxied by the standard deviation of returns, which has important implications for calculating risk (Ariefianto, 2012). So, volatility shows the level of risk of an investment asset. High volatility indicates a risk as well as a high return. Therefore, by knowing the level of volatility of investment assets owned, it is hoped that investors will be more careful in managing their investments.

Apart from measuring risk, volatility can also be used to forecast using time series data, where this sometimes gives rise to heteroscedastic phenomena. This happens because the market movement suddenly drops dramatically if there is bad news, then calms down again, extreme fluctuations or volatility clustering occurs (Ariefianto, 2012).

Many economic time series data show high volatility following relatively fixed time periods (Enders, 2004). Volatility can be interpreted as the variance value of data changes, often expressed by the conditional standard deviation of a time series (Tsay, 2005). To model univariate volatility, conditional heteroscedastic models have been developed, including the autoregressive conditional Heteroscedastic (ARCH) and Generalized Autoregressive Conditional Heteroscedastic (GARCH) models.

Engle (1982) developed the concept of ARCH (Autoregressive Conditional Heterocedasticity) to explain volatility and the phenomenon of heteroscedasticity. ARCH is used to estimate the existence of heteroscedasticity in a time series data so that forecasting results can be more accurate. However, the ARCH model is less efficient when estimating data, because it often requires estimating quite a lot of parameters or requires a long lag. Therefore, the ARCH model was further developed by Bollerslev (1986) and Taylor (1986) with the concept of Generalized ARCH (GARCH). With the GARCH model, capital market researchers can estimate the level of volatility of a capital market.

In the GARCH model, volatility is influenced by data and volatility in several previous periods, so that positive and negative residuals have the same effect on volatility. Therefore, the GARCH model can only explain the symmetrical effect on volatility. If there is an asymmetric effect in volatility, one of the alternatives used is the EGARCH model.

According to Nelson (1991) because the GARCH model apparently cannot explain the influence of negative issues and positive issues, he developed the Exponential GARCH (EGARCH) model to see both positive and negative effects (Yoseva et al., 2015).

The composite index stock price data shows that in the data there is an ARCH effect so that the composite index stock price data can be overcome by using the ARCH model. However, forecasting using ARCH cannot detect the factors that influence significant price changes (Suhartini, 2007).

Maskur & Nusantara (2009) show that there is no difference between the conventional stock price index (IHSG and LQ45) and the Islamic stock price index (JII). Both conventional and sharia stock price indices have high and persistent volatility, only the Kompas 100 has low volatility.

The research results from Nawatmi (2012) show that exchange rates have ARCH and GARCH effects. So, the volatility of the exchange rate is affected by the volatility of the current and previous exchange rates. The sum of the ARCH and GARCH coefficients shows that the exchange rate is persistently volatile. The estimation results show that exchange rate volatility is not significant. Meanwhile, world GDP and Indonesia's GDP have a positive effect on international trade, not only in the short term but also in the long term.

The best model for JKSE is GARCH (1.2), while FTSE100 is GARCH (2.2), Nasdaq produces best model GARCH (1.1) and STI with GARCH (2,1). The results of the comparison of JKSE and FTSE100, Nasdaq and STI show that even though JKSE fluctuates moderately, there is a tendency for its stock index to increase, while other stock indexes fluctuate very high and tend to decrease their stock index (Kharisya, 2015).

The results of research from Nusantara & Nawatmi (2017) show that stock price movements and foreign exchange prices are detected to have volatile movements so that the application of the mean is irrelevant. Capital market volatility tends to be low. Forex market information has an important role in volatility in the capital market. Volatility in the capital market and foreign exchange market tends to be dominated by the role of bad news.

Risk and volatility are two things that are related, especially in research on capital markets. The movement of stocks and indices is influenced by many factors so that volatility is common, and this certainly affects risk assessment. This research is descriptive in nature. The method used is the GARCH symmetric model and the TARCH and EGARCH asymmetric models. The results show that the Indonesian capital market has symptoms of volatility clustering. The Indonesian Capital Market is more sensitive to negative news than positive. The GARCH models that can be implemented are GARCH (1,1); TARCH (1,1) and EGARCH (1,1) with the EGARCH (1,1) have slightly better prediction results than the other two models (Agung & Fida, 2018).

Akpan & Moffat (2017) trace discrete time series patterns over time related to the GARCH effect and asymmetric GARCH effects. There are weaknesses in the GARCH model in modeling the asymmetry of the GARCH effect. The existence of the GARCH effect is sufficiently captured by the GARCH model (0,1). The GARCH model (0.1) adequately predicts the GARCH effect but fails to capture the asymmetric effect in discrete series stock price returns. The EGARCH (0.1) and TGARCH (0.1) models with positive and negative effect sizes considered.

Thalassinos et al. (2015) tested the GARCH model to compare the forecasting power of stock return volatility in the Czech stock market. The models used are GARCH, GJR-GARCH and EGARCH. The results show that stock return volatility shows significant persistence and asymmetric effects and shows that the EGARCH model has the best forecasting performance compared to other models.

2. Research Method

2.1. Data and Data Source

The data used in this research is weekly secondary data from 1 January 2021 – 11 September 2022. There are six stock price indices used, namely JKSE Indonesia, FTSE Singapore, Nikkei225 Japan, SSEC China, FTSE100 UK and Dow Jones USA. Data source from yahoofinance.com and investing.com.

2.2. Variable Stationarity Testing

The main problem faced by time series data is its ability to fulfill the assumption of stationarity. The term stationarity refers to the stationary point process or more popularly the stochastic process. Based on the definition from The Cambridge Dictionary of Statistics Everit and Skrondal (2011), the stationary point process is:

The distribution of the number of events in a fixed interval (t_1, t_2) is invariant under translation, i.e. is the same for (t_1+h, t_2+h) for all h.
The joint distribution of the number of events in fixed interval (t_1,t_2), (t_3,t_4) is invariant under translation, i.e. is the same for all pairs of intervals (t_1+h, t_2+h), (t_3+h, t_4+h) for all h.
Stationary process on time series data is known as weak stationary, has three features, namely:

Mean : $E(Y_t) = \mu$ ………………………….(1a)
Variance : $\text{var}(Y_t) = E(Y_t - \mu)^2 = \sigma^2$ ………………………….(1b)
Covariance : $\gamma_k = E[(Y_t - \mu)(Y_{t+k} - \mu)]$ ………………………….(1c)

If the data is stationary, the mean, variance and covariance will be the same regardless of the size of the data, this is called time invariant.

Stationary nature has an important meaning in maintaining the generalization of the results of the analysis. Conversely, if the stationary nature is not met, the resulting analysis will be casuistic. In other words, non-stationary time series data have different mean values or different variations, or both are different all the time.

Time series data is said to be stationary at degree one or I (1), meaning that the data has a unit root at degree one (1) or integrated at degree one. In general, symbolized by I (d). Mathematically it can be formulated as follows:

$$Y_t - Y_{t-1} = (1-L)Y_t = \epsilon_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2)}$$

This study will use the Kwiatkowski, Phillips, Schmidt, and Shin Test (KPSS) stationary testing technique which is a further development of the Dickey-Fuller model. So understanding the KPSS testing technique will be easier if you understand the Dickey-Fuller concept first.

Starting from the Dickey-Fuller stationarity testing model which is based on the equation:

$$\Delta y_t = \alpha y_{t-1} + \varepsilon_t \;\; ; \alpha = \rho - 1 \; ; \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

The hypothesis applied to the equation is:

H0: α = 0
Ha: α < 1

The value of α is evaluated using:

$$t_\alpha = \frac{\hat{\alpha}}{se\,(\hat{\alpha})} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3a)}$$

However, testing using the t-distribution does not show consistent results. Therefore MacKinnon (1996) modified the standard Dickey-Fuller test.

The standard Dickey-Fuller unit-root turns out to only have validity if the data is in an AR (1) process. If the data is in a higher order, then the white-noise assumption for the confounding error will be violated. Therefore, the standard Dickey-Fuller test process is improved to become Augmented Dickey-Fuller (ADF). The construction of the ADF test uses a parametric correction factor for high order by applying the assumption that the data in question follows the AR (p) pattern and adds a lag operator to data changes. Mathematically it is formulated as follows:

$$\Delta y_t = \alpha y_{t-1} + \beta_1 \Delta y_{t-1} + \cdots + \beta_p \Delta y_{t-p} + v_t \quad \ldots\ldots\ldots\ldots\ldots \text{(4)}$$

Besides the advantage of the operator lag for a looser autoregressive, it turns out that ADF is also asymptotic to the existence of the moving average process (Said & Dickey, 1984).

2.3. The Kwiatkowski, Phillips, Schmidt, and Shin Test

The Kwiatkowski, Phillips, Schmidt and Shin test (KPSS) performs a stationarity test using the assumption that the data tested has a stationary trend (null hypothesis). The KPSS calculation is based on the OLS residual value from the regression on yt on the exogenous variable xt.

$$y_t = \delta x_t + u_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5a)}$$

The evaluation of δ is based on the LM statistic:

$$LM = \sum_t \frac{S(t)^2}{T^2 f_0} \quad \text{..} (5b)$$

Where: f_0 is the residual spectrum estimator at zero frequency and S(t) is the residual cumulative function which is formulated:

$$S(t) = \sum_{r=1}^{t} \hat{u}_r \quad \text{..} (5c)$$

The value of $\hat{u}_t$ is based on:

$$\hat{u}_t = y_t - \hat{\delta}(0)x_t \quad \text{..} (5d)$$

2.4. ARCH(q), GARCH (p,q) and EGARCH (p,q) methods

The process of Autoregressive Conditional Heteroschedastity (ARCH) is often used to model time varying risk. The modeling can identify time-related risk factors that generally occur in the money market and capital market. The ARCH process is not only an approach that identifies volatility but is also capable of identifying macro market spillover effects as well as identifying the impact of information or innovation on market volatility.

The basic ARCH model basically has two forms, namely the conditional mean equation and the conditional variance equation. The two models must be estimated simultaneously. In general, the ARCH process (q) can be formulated:

Yt = E{yt|It} + εt ; mean process where: εt ~ D(0, ht)

and $h_t = \omega + \sum_{i=1}^{q} \alpha i \epsilon_{t-i}^2$ ARCH variance process (q)

The ARCH model involves autoregressive (AR) and moving average (MA) processes that are unified into ARMA. This process has the consequence of requiring a long process of time. Because of these problems, a more concise model was developed in terms of time use, namely Generalized ARCH (GARCH).

The GARCH model is a development of the ARCH model. In the GARCH Model, volatility is influenced by data and volatility in several previous periods, so that positive and negative residuals have the same effect on volatility. Therefore, the GARCH model can only explain symmetrical effects in volatility (Ika, 2007).

The GARCH model (p,q) can be formulated as follows:

$$h_t = \omega + \sum_{i=1}^{q} \alpha i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-1}$$

If there is no ARCH or GARCH effect, then αi; βi = 0; sum $[\sum_{i=1}^{q} \alpha i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-1}]$ describes the long-term GARCH solution and if the sum is equal to 1 then it is included in the category integrated GARCH (IGARCH).

If there is an asymmetric effect on volatility, then one of the alternatives used to analyze is the EGARCH model. EGARCH (Exponential GARCH) is a logarithmic transport model, has a reaction, namely: the difference in the volatility reaction between negative shocks and positive shocks. Attempts to compare individual residuals with the average can indicate signs of shocks, both negative and positive. The implication of the EGARCH process that applies logarithmic form is that the parameter has a positive sign. This means that this model applies the basic variance information so that the positive sign of the parameter is fulfilled. The

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second implication is that EGARCH has a different reaction (asymmetric effect) in responding to negative and positive shocks. EGARCH (p,q) can be formulated in the following form:

$$\text{Log } h_t = \omega + \sum_{i=1}^{q} [\theta_1 \varepsilon_{t-1} + \theta_2(|\varepsilon_{t-1}| - E\{|\varepsilon_{t-1}|\})] + \sum_{q=1}^{p} \beta \log h_{t-i}$$

The resulting output is two parameters for the impact of the residual (ε). In the EGARCH (1,1) model the first parameter (θ1 - θ2) indicates a positive response to shocks in εt-1. The second parameter (θ1 - θ2) is related to the absolute value indicating negative shocks εt-1.

An asymmetric effect occurs when two residuals are the same but have different signs, resulting in different volatility. According to Black (1976) in Karanasos and Kim (2000), the asymmetric volatility response to positive (good news) and negative (bad news) residual values is known as the leverage effect. Good news conditions occur if the observed value is greater than the estimated value, otherwise bad news occurs if the observed value is less than the estimated value. The leverage effect is an example of an asymmetric effect in volatility. In bad news, the volatility value will increase faster than in good news. This situation is known as the leverage effect.

3. Results and Discussion

Before analyzing stock price volatility, a stationarity test is performed. The main purpose of the stationarity test is to prevent spurious regression and identify short-term phenomena that may occur. Identification of variable stationarity through unit roots and KPSS is based on the distribution of data from the variables used, namely JKSE, FTSE Singapore, FTSE 100, SSEC, Nikkei 225 and Dow Jones. Initial data distribution:

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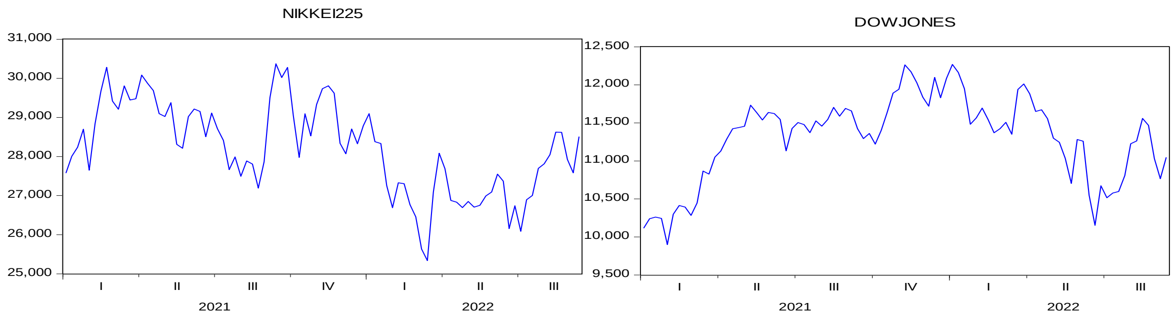
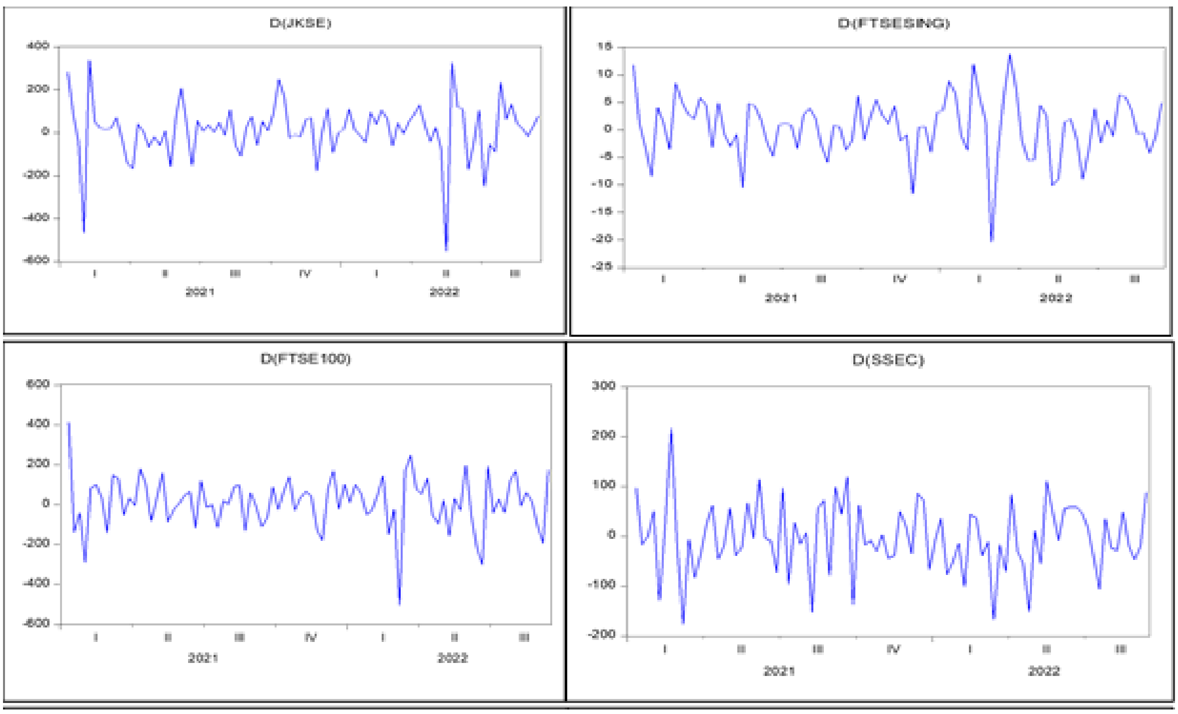


Figure 1: Stock Price Index Dynamics

Figure 1 shows the volatility of Indonesia's JKSE share price is lower than that of developed countries such as Singapore's FTSE, UK's FTSE, China's SSEC, Japan's Nikkei and America's Dow Jones. Even though the observation period was a period when the global economy tended to weaken, the stock price indices for Indonesia, Singapore, the UK and America tended to increase, while the stock price indices for China (SSEC) and Japan (Nikkei 225) showed a downward trend. Thus, investing in stocks in Indonesia is safer than investing in stocks in Singapore, England or America, moreover in China and Japan it is riskier because in addition to high volatility, stock prices also tend to fall.

The figure also shows that all observed stock prices have distributions showing autoregressive and heteroskedastic characteristics. This is because the ups and downs of the data are relatively wide. If the stock price is changed to the first-degree form or the term is a change in stock price, then the pattern will look like in Figure 2 below:



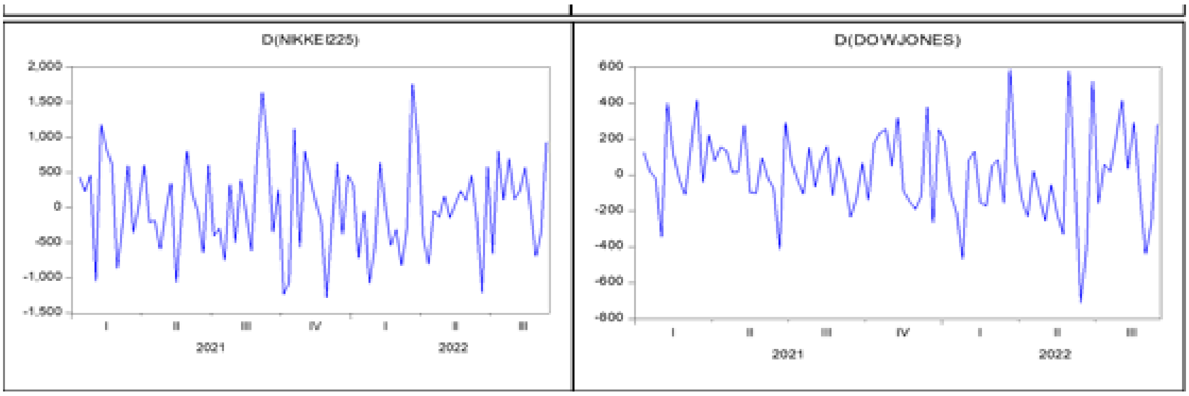


Figure 2: Dynamics of Stock Returns

Figure 2 shows that the autoregressive phenomenon has disappeared, but still shows the heteroscedastic phenomenon. This phenomenon is commonly found in financial sector time series data. To make the identification more certain, a unit root test was carried out.

3.1. Unit Roots Test

The stock price data is tested for stationarity by conducting a unit roots test using the ADF (Augmented Dickey Fuller) and KPSS (The Kwiatkowski, Phillips, Schmidt, and Shin test). The stationarity of the data can be seen in table 1:

Table 1: ADF and KPSS Root Unit Test Results

Indeks harga saham	ADF			KPSS	
	Constant	Constant, linier trend	None	Constant	Linier trend
D(JKSE)	-10.32424	-10.30151	-10.30038	0.113872*	0.103405*
D(FTSESING)	-7.836613	-7.803497	-7.823210	0.149503*	0.086616*
D(FTSE100)	-10.45787	-10.36535	-10.49456	0.333752*	0.196434*
D(SSEC)	-10.46153	-10.39016	-10.49396	0.071392*	0.050943*
D(NIKKEI225)	-9.119141	-9.057336	-9.172242	0.104201*	0.102452*
D(DOWJONES)	-9.225594	-9.294962	-9.265398	0.225409*	0.051109*

Note: Statistical test without a sign is significant, if it is marked *) it is not significant

The results of the unit root test using ADF and KPSS show that there is a tendency for data distribution for all stationary stock price variables at degree one – I(1), namely the differential form. Thus, it can be concluded that the variable to be applied in the model is a differential variable (degree one).

3.2. Stock Return Volatility Predictive Model

The next step determines the ARCH/GARCH/EGARCH predictive model. To determine the predictive model is done by comparing the significance of ARCH/GARCH/EGARCH. ARCH (1) describes a process in which the current volatility is a direct function of the shock of the previous period. If the error range is slower, you can use ARCH (q) at a higher order. However, ARCH at a higher order has the disadvantage of losing more degrees of freedom. To overcome these weaknesses, GARCH is used as an alternative model.

In the GARCH (p,q) model, the variance is modeled not only from the MA (Moving Average) element but also from the autoregressive element. Variation depends on the shock of the previous period and the variance of the previous period. A model with a higher ARCH order is a better model (large log likelihood, small AIC) (Wei, 1990), more detailed predictions.

Table 2:
ARCH, GARCH and EGARCH Calculations in the JKSE and FTSE Stock Markets

Coefficient	D(JKSE)			D(FTSE)	
	ARCH (1)	GARCH (1,1)	EGARCH (1,1)	ARCH (1)	EGARCH (1,1)
C	1295693*	2860.383*		24.65406*	
Resid(-1)^2	0.238584	0.029050		-0.055201*	
GARCH(-1)		0.757832*			
C(4)			-0,.60448		-0.029564
DWR		2.061365*		1.894344*	
ARCH Test		1.030572		0.093484	

Note: *) Significant

Table 2 shows that the appropriate predictive model for Indonesia's JKSE stock returns is GARCH (1.1), while for Singapore, the appropriate model is ARCH (1).

Table 3:
ARCH, GARCH and EGARCH Calculations on the FTSE100 and SSEC Stock Market

Coefficient	D(FTSE100)				D(SSEC)	
	ARCH (1)	GARCH (1,1)	GARCH (1,2)	EGARCH (1,1)	ARCH (1)	EGARCH (1,1)
C	0.004998	5105.543	3584.219*		3750.513*	
Resid(-1)^2	0.171468	0.074054	0.084140		-0.67697*	
GARCH(-1)		0.574935	1.306514*			
GARCH(-2)			-0.614641*			
C(4)				-0.484200*		0.146530
DWR			1.987348*	1.987348*	2.113924*	
ARCH Test			0.194745	0.194745	0.418954	

Note: *) Significant

The appropriate predictive model for UK FTSE100 stock returns is EGARCH (1.1) because the GARCH (1.2) model, although significant, cannot explain the asymmetry effect. While the estimation results show that for British stocks, the coefficient of C (4) shows a negative sign and is significant. This means that in the model there is an asymmetry effect or there is a leverage effect which can only be captured by using the EGARCH model and the results of the diagnostic tests also show no autocorrelation and heteroscedasticity. Meanwhile, the predictive volatility model for SSEC China stock returns shows that the appropriate model is ARCH (1) (Table 3).

Table 4:
ARCH, GARCH and EGARCH Calculations on the Nikkei Stock Market

Coeffisient	D(Nikkei225)			
	ARCH (1)	GARCH (1,1)	GARCH (1,2)	EGARCH (1,1)
C	379535.8*	271956.9	299972.6	
Resid(-1)^2	0.079982	0.081647	0.046292	
GARCH(-1)		0.261002	1.193925*	
GARCH(-2)			-1.023772*	
C(4)				-0.0962257
DWR			2.003052*	
ARCH Test			0.003048	

Note: *) Significant

For Nikkei Japanese stock returns, the appropriate predictive volatility model is GARCH (1,2). Diagnostic test results showed no autocorrelation or heteroscedasticity (Table 4).

Table 5:
ARCH, GARCH, and EGARCH Calculations in the Dow Jones Stock Market

Coefficient	D(Dow Jones)		
	ARCH(1)	GARCH (1,1)	EGARCH(1,1)
C	49911.56*	-644.5257*	
Resid(-1)^2	0.090559	-0.076005*	
GARCH(-1)		1.109829*	
C(4)			-0.642637
DWR		1.859750*	1.995553*
ARCH Test		0.270185	0.000676

Note: *) Significant

Table 5 shows that the results of the C (4) coefficient test are negative and significant. If the asymmetric effect is significant, then the appropriate model is the EGARCH model. While the GARCH model, although significant, the GARCH model can only explain the symmetry effect in volatility. If there is an asymmetric effect in volatility, one of the alternative predictive models that can be used is the EGARCH model.

The presence of asymmetric volatility is most apparent during stock market crashes when large stock price declines are associated with a significant increase in market volatility. A formal econometric model has been developed by researchers to capture asymmetric volatility (Wu, 2001)

An asymmetric effect occurs when two residuals that are the same size but have different signs produce different volatility. According to Black (1976) in Karanasos and Kim (2000), the asymmetric volatility response to positive (good news) and negative (bad news) residual values is known as the leverage effect. The leverage effect is an example of an asymmetry effect in volatility. If the asymmetric effect is significant, the appropriate model is EGARCH, but if it is not significant, the appropriate model is ARCH/GARCH.

Table 2-5 shows that those with an asymmetry or leverage effect are those with a negative and significant C (4) coefficient. This means that stocks from UK (FTSE100) and America (Dow Jones) have a leverage effect.

The leverage effect is a negative relationship between past returns and the volatility of future returns. The leverage effect is the ratio between debt and equity. The higher the leverage effect, the greater the risk or volatility or variance of a company. The existence of a leverage effect means that debt is higher than equity where a positive shock has a small effect on the conditional variance (log GARCH) compared to a negative shock (negative news). This means that good news generates smaller volatility or variance than bad news for stock returns in UK and America. When there is volatility in stock returns, especially in the UK and America, business risk increases and investors will move their funds to countries with less investment risk.

This is supported by the fact that there was a Russian invasion of Ukraine, the condition of the countries that were members of NATO (became enemies of Russia), their economy was weakening, inflation was high, as well as unemployment.

4. Conclusion

Based on the results of the analysis, it shows that the JKSE stock price index (Indonesia), has lower volatility than the volatility of developed countries (Singapore, UK, China, Japan and America). Indonesian stock price indices also tend to increase as well as Singapore, British and American stock price indices, while Chinese and Japanese stock price indices tend to decrease. Thus, stock investment in Indonesia is relatively safer because the volatility is lower than in developed countries and the stock price index also tends to increase.

The appropriate predictive volatility model for the Indonesian stock index is GARCH (1.1); Singapore: ARCH (1); China is ARCH (1); for Nikkei Japan is GARCH (1.2), while the UK: EGARCH (1,1); as well as America: EGARCH (1,1). That is, only UK and American stocks have a leverage effect. This means that good news generates lower volatility than bad news, so that business risks in the UK and America increase.

Stocks belonging to the FTSE100 and DowJones are riskier. Therefore, for investors who want to be safe, be careful investing in shares of companies in UK and America. While the JKSE stock index is relatively safe, buying these shares will benefit investors.

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