Indonesian Stock Market Risk Analysis: Implementation of the GARCH Model on the JKSE Index

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Abstract: This study aims to analyze stock market risk in Indonesia using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model on the Composite Stock Price Index (JKSE). The GARCH model is used to estimate stock market volatility, which is an important indicator in market risk assessment. The JKSE daily data used in this research covers a certain period and is analyzed to identify volatility patterns and potential risks that can influence investment decisions. The findings show that the GARCH model can effectively capture the dynamics of volatility in the Indonesian stock market, providing deeper insight into the level of risk faced by investors. These findings have important implications for portfolio management and risk mitigation strategies in the Indonesian stock market.

Keywords: Indonesian Composite Index, GARCH Model, Volatility Risk, Investment Decisions

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1. Introduction

The Indonesian stock market in recent years has experienced significant volatility due to the influence of various global and domestic factors. For example, in 2023, the Composite Stock Price Index (JKSE) experienced a decline of 15% in three months, mainly triggered by global economic uncertainty and tighter monetary policy in developed countries (Marpaung & Pangestuti, 2024). Additionally, geopolitical tensions and rising domestic inflation worsened investor sentiment, causing a spike in volatility in the Indonesian stock market. Data shows that JKSE volatility peaked in May 2023, with Indonesia's volatility index (VIX) rising by 30%, the highest level since the 2008 global financial crisis (Saputra et al., 2023). This condition highlights the vulnerability of the Indonesian stock market to external shocks and underscores the importance of a deeper understanding of market risk for more effective portfolio management (Soedarmono et al., 2022).

This volatility phenomenon has motivated many studies that use econometric models to understand stock market dynamics. One of the most frequently used models is Generalized Autoregressive Conditional Heteroskedasticity (GARCH), which has proven effective in capturing heteroscedasticity in financial data, where the residual variance depends on the prior variance (Bollerslev, 1986; Engle & Bollerslev, 1986). However, previous studies in Indonesia are often limited to narrow analysis periods or does not take dynamic global factors into account. For example, (Azhar et al., 2020) found that the GARCH model was able to provide more accurate estimates of Indonesian stock market volatility, but there was still room to expand the data coverage and analysis period.

Thus, we aim to fill this gap by applying the GARCH model to JKSE daily data which covers a wider period and considers the influence of global factors. Thus, this research is expected to provide more comprehensive insight into the volatility of the Indonesian stock market and the risks faced by investors (Helwege et al., 2014; Tay et al., 2009). This research also aims to identify volatility patterns that can be used as a basis for making investment decisions and more effective risk mitigation strategies in the future. The main contribution of this research is to provide an in-depth analysis of Indonesian stock market volatility by considering the dynamic global context, as well as offering practical implications for investment managers and policy makers (Baillie & DeGennaro, 1990). Thus, this research not only adds to the existing literature but also has direct relevance for risk management practices in capital markets.

2. Literature Reviews

2.1 Stock Market Volatility

Stock market volatility is a very important measure in the world of finance, reflecting the level of risk and uncertainty faced by investors. High volatility can indicate market instability, which is often caused by factors such as global economic changes, government policies and geopolitical events. Poon & Granger (2003) noted that volatility is a key element in asset pricing and risk management models because it provides valuable information about possible future price changes. More recent study by Rodríguez-López et al. (2021) showed that global stock market volatility has increased significantly over the last decade, mainly due to growing global economic and political uncertainty. In Indonesia, stock market volatility is often associated with changes in economic policy and government intervention in an effort to stabilize the economy (Darinda & Permana, 2019). A deep understanding of this volatility is very important, especially for investment managers who must make decisions based on proper risk analysis.

2.2 Model GARCH

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) is an econometric model that is widely used in volatility analysis, mainly because of its ability to capture heteroscedasticity in financial data. The GARCH model, developed by Bollerslev (1986) as an extension of Engle (1982) ARCH model, allows a more dynamic analysis of volatility variability over time. (Engle & Bollerslev, 1986) showed that the GARCH model is able to accommodate non-constant variance distributions, which are a common characteristic of financial data. More recently, research by (Hansen & Lunde, 2020) highlighted that GARCH models, although effective, can experience limitations when used in highly volatile market environments, such as those occurring during the COVID-19 pandemic. Another study by (Ali et al., 2022) also suggested that modifications or extensions of GARCH models, such as GARCH-M or EGARCH, may be needed to more accurately capture volatility dynamics in fast-growing markets such as Indonesia.

Research on volatility in emerging markets, including Indonesia, has shown that these markets tend to have higher volatility compared to markets in developed countries. Factors contributing to this include low market liquidity, dependence on foreign capital flows, and domestic political instability. (Bekaerta & Harvey, 1997) in their classic study, emphasized that volatility in emerging markets is often driven by unstable capital inflows and outflows, which can be exacerbated by political uncertainty. More recent research by (Szczygielski et al., 2024) showed that volatility in developing country stock markets is also influenced by global sentiment and changes in monetary policy in developed countries, which often trigger sharp fluctuations in local markets. In Indonesia, research by (Oetomo et al., 2016) found that volatility in the Indonesian stock market was influenced by fiscal and monetary policies, as well as by changes in the global investment climate.

2.3 Volatility

The use of the GARCH model in volatility analysis has become standard in the financial literature, especially in studies involving stock markets in developing countries. The GARCH model is often used to predict stock market volatility and identify risk patterns that can influence investment decisions. For example, research by (Abdullah et al., 2017) showed that the GARCH model provides more accurate volatility predictions in the Bangladesh stock market, a market that has similar characteristics to Indonesia. (Azhar et al., 2020) in his study of the Indonesian stock market found that the GARCH model can provide more accurate estimates of volatility compared to other traditional models, especially in the face of unstable market conditions. Furthermore, research by (Alotaibi & Mishra, 2015) examined that the application of a GARCH model adapted to local market conditions can provide more relevant and reliable results for risk prediction in developing stock markets.

3. Research methods

3.1 Research Design

This research uses quantitative methods to evaluate the volatility of the Composite Stock Price Index (JKSE) by applying the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Data analysis was performed using SAS software, which facilitated the statistical calculations required for this study. The data used in this research is daily data from the Composite Stock Price Index (JKSE) which includes 1826 observations. This data is taken from credible sources and further processed using SAS to produce detailed analysis output. The average of the analyzed data is 6315.711 with a standard deviation of 681.4323, indicating significant fluctuations in the index during the period studied.

3.2 Analysis Procedure

Data analysis was carried out using several statistical procedures available in SAS, such as ARIMA and AUTOREG, which was then continued with the application of the GARCH model to model JKSE volatility.

3.3 ARIMA procedure

The ARIMA procedure is used to identify patterns in the JKSE time series. The results will show significant autocorrelation, in a strong series in the residuals. This autocorrelation is analyzed further to ensure that the selected model is able to accurately capture volatility patterns.

3.4 AUTOREG procedure

The AUTOREG procedure is used to estimate the autoregressive model before proceeding to the GARCH model. This estimation result includes Sum of Squared Errors (SSE) and Root Mean Square Error (RMSE). Furthermore, the Augmented Dickey-Fuller Test was also applied to detect the presence of a unit root in the data, and the results showed that the data had stationarity characteristics that needed to be taken into account in further analysis.

3.5 Model GARCH

After the results from ARIMA and AUTOREG are analyzed, the GARCH(1,1) model is applied to model conditional volatility in JKSE data. This model was chosen because of its ability to capture heteroscedasticity that changes over time, which is common in financial data. Parameter estimation was carried out using the Maximum Likelihood Estimation (MLE) method via SAS. This GARCH model provides deeper insight into the volatility of the Indonesian stock market during the study period.

3.6 Diagnostic Test

After the GARCH model is estimated, diagnostic tests are carried out to ensure the accuracy and reliability of the model. The ARCH-LM test is used to check for the presence of remaining heteroscedasticity in the model residuals, ensuring that the GARCH model has successfully captured the volatility pattern in the data. The Ljung-Box test is applied to detect autocorrelation that may still exist in the model residuals. The results confirm that the model has overcome the autocorrelation problem well.

4. Results and Discussion

To understand the basic patterns and characteristics of the volatility of the Composite Stock Price Index (JKSE) over the last five to six years, the first step is to plot the JKSE daily price data. Visualization of this data is important to provide an overview of stock price trends and fluctuations in the period studied.

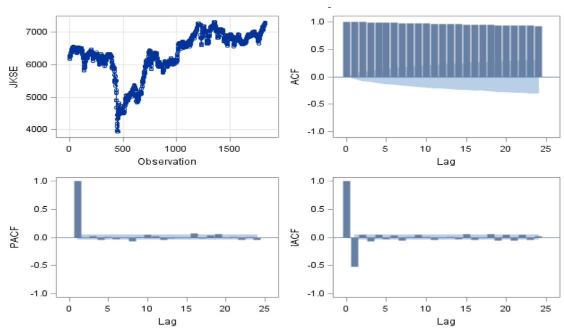

Figure 1. JKSE Daily Price Movement Plot (2018-2023)

From trend analysis, we can see that the JKSE experienced significant fluctuations, with several periods of sharp declines followed by strong recoveries. The ACF graph shows a significant short-term correlation, while PACF confirms that most of the influence comes from the first lag. This indicates that models that include a simple autoregressive component may be effective in capturing these patterns. IACF provides further confirmation of the appropriate model selection, indicating that this data is suitable for processing using ARIMA or GARCH models with autoregressive components.

After analyzing the basic patterns of daily price data for the Composite Stock Price Index (JKSE), the next step is to carry out correlation analysis to understand the relationship between key variables that influence market volatility, as well as checking for the presence of noise in the data.

Table 1. Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	9999.99	6	<.0001	0.997	0.994	0.991	0.988	0.985	0.982
12	9999.99	12	<.0001	0.979	0.975	0.971	0.968	0.965	0.962
18	9999.99	18	<.0001	0.958	0.954	0.951	0.948	0.944	0.941
24	9999.99	24	<.0001	0.938	0.936	0.933	0.930	0.927	0.924

From Table 1, it can be seen that the Chi-Square values for all lags are very high, and the p-value (Pr > ChiSq) is very small (<.0001), indicating that we can reject the null hypothesis that this data is white noise. This means that the JKSE data has a significant autocorrelation structure, and this pattern is not random. A commonly used technique in time series analysis to overcome problems such as non-stationarity and white noise in data is to differencing.

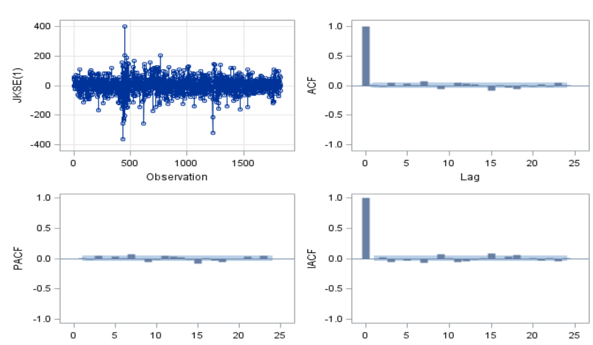

Figure 2. Trend and Correlation Analysis for JKSE

The first differentiation on JKSE data has succeeded in eliminating trends and reducing significant autocorrelation in the original data. The JKSE(1) data now exhibits more stationary characteristics, which is an important prerequisite for more advanced time series analysis, such as the use of ARIMA or GARCH models. Nevertheless, there is still some autocorrelation remaining in the first lag, which needs to be taken into account when building the model.

4.1 ARIMA procedure

After carrying out the first differencing on the JKSE data and ensuring that the data is more stationary, the next step is to estimate the model parameters using Conditional Least Squares Estimation. This estimation is important to determine the ARIMA model that best fits the differencing data.

Tabel 2. Conditional Least Squares Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
IN	0.59767	1.11530	0.54	0.5921	0
MA1,1	-0.85808	0.12951	-6.63	<.0001	1
AR1,1	-0.83010	0.14014	-5.92	<.0001	1

The estimation results show that the ARIMA model with AR(1) and MA(1) components is the right model for JKSE data after the first differencing. Both components are significant at a very high level of significance, indicating that both the autoregressive and moving average components should be considered in further modeling. This model will be used as a basis for further volatility modeling, such as the application of the GARCH model, to capture more complex volatility dynamics in JKSE data.

4.2 ARCH Interference Test

After estimating the ARIMA model, the next step is to check the presence of ARCH (Autoregressive Conditional Heteroskedasticity) effects in the model residuals. The ARCH test is performed to determine whether there is time-dependent heteroscedasticity in the residuals, which, if present, would indicate that a GARCH model needs to be applied to capture these volatility dynamics.

Tabel 3. Tests for ARCH Disturbances Based on OLS Residuals

Order	Q	Pr > Q	LM	Pr > Lm
1	1817.4112	<.0001	1784.9812	<.0001
2	3586.4407	<.0001	1785.4456	<.0001
3	5309.6319	<.0001	1785.4729	<.0001
4	6995.5003	<.0001	1785.7753	<.0001
5	8648.2099	<.0001	1785.8007	<.0001
6	10257.3093	<.0001	1786.7001	<.0001
7	11814.9500	<.0001	1786.9631	<.0001
8	13318.1184	<.0001	1787.0192	<.0001
9	14768.3649	<.0001	1787.0332	<.0001
10	16176.8203	<.0001	1787.4694	<.0001
11	17550.5051	<.0001	1787.6458	<.0001
12	18880.9503	<.0001	1788.2960	<.0001

The ARCH test results above show that both the Q and LM statistics for all orders have very small p-values (<.0001), which means we reject the null hypothesis that there is no ARCH effect in the residuals. In other words, there is strong evidence that the residuals from the estimated ARIMA model exhibit conditional heteroscedasticity, where the residual variance is not constant but changes over time. The presence of this ARCH effect shows that the ARIMA model alone is not enough to capture all volatility dynamics in the JKSE data. Therefore, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model should be used to better model the existing volatility.

After carrying out the ARCH test and finding that there is conditional heteroscedasticity in the ARIMA model residuals, the next step is to estimate the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to model volatility in the JKSE data. The GARCH model is used to capture volatility dynamics that change over time.

Table 4. Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Intercept	1	6191	179.4182	34.51	<.0001
AR1	1	-0.9971	0.001451	-687.32	<.0001
ARCH0	1	120.2319	20.8905	5.76	<.0001
ARCH1	1	0.0592	0.006855	8.64	<.0001
GARCH1	1	0.8798	0.0168	52.50	<.0001

The results of the GARCH model parameter estimation show that all model parameters are significant at a very high level. This confirms that the GARCH(1,1) model is a suitable model for modeling volatility in JKSE data. The significant ARCH1 and GARCH1 parameters indicate that current volatility is influenced by past shocks and volatility, which supports the use of the GARCH model for further analysis. After estimating the GARCH model, the next step is to visualize the estimation and prediction results from this model. The following graph shows a comparison between the estimation and prediction results of the GARCH model against actual data.

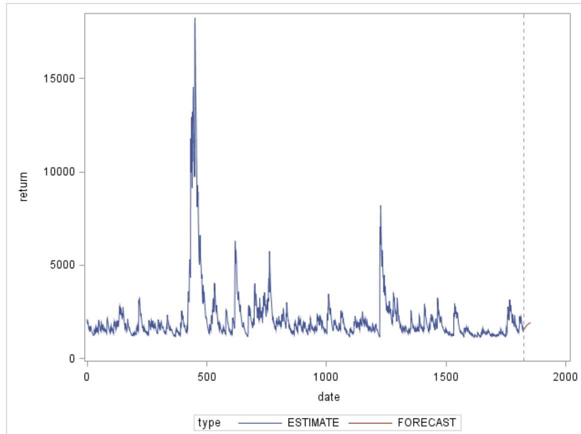

Figure 3. Plot of Estimation and Prediction Results of the GARCH Model

From the graph above, we can observe several important things. *First*, there are several very high peaks in volatility, indicating periods of extreme volatility. This may occur during periods of economic uncertainty or significant global events. *Second*, model fit the blue line (ESTIMATE) generally fits the volatility pattern seen in the actual data, indicating that the GARCH model is able to capture volatility dynamics quite well. *Third*, volatility prediction: The red line (FORECAST) shows that the model expects an increase in volatility in the future, albeit at a lower level compared to some historical peaks. Fourth, decreasing volatility: At the end of the graph, we see that volatility is trending downward, except for a few small spikes predicted by the model. This could reflect more stable market conditions after a period of high uncertainty. This graph provides visual insight into the GARCH model's ability to predict volatility in the Indonesian stock market. With relatively accurate predictions, this model can be used by investors and policy makers to make better decisions in dealing with market volatility.

5. Conclusion

This research has succeeded in applying the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to analyze stock market volatility in Indonesia, especially the Composite Stock Price Index (JKSE). The research results show that the GARCH model is able to capture the dynamics of volatility in the Indonesian stock market, which is characterized by the significance of the model parameters at a very high level. The GARCH(1,1) model used in this research shows that current volatility is significantly influenced by past volatility and shocks that occurred in the market, which is reflected in the significance of the ARCH and GARCH parameters. These results confirm that volatility in the Indonesian stock market is not random but has a pattern that can be predicted using appropriate models.

These findings have important practical implications for investment managers and policy makers, as a better understanding of market volatility can assist in more effective portfolio risk management and investment strategies. In addition, this research makes a significant contribution to the existing literature by providing an in-depth analysis of Indonesian stock market volatility in a dynamic global context. In order to expand future research, it is recommended to consider modifying or extending GARCH models such as GARCH-M or EGARCH to capture more complex volatility dynamics in fast-growing markets such as Indonesia. In addition, further research involving data from a longer period and considering various global factors could provide more comprehensive insight into the volatility of the Indonesian stock market.

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