VOLATILITY ANALYSIS USING THE EGARCH METHOD: CASE STUDY OF BBCA, BMRI, BRIS

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ABSTRACT

This study aimed to test the volatility model of BBCA and BMRI stocks on the IDX. The research problem is whether there is an influence of BBCA and LQ45 volatility on BMRI and vice versa. The study also tested whether BRIS's volatility was influenced by its majority shareholder, BMRI. The EGARCH model analyzed daily return data for 2015-2022 in bearish/bullish markets. The results showed that the data experienced heteroscedasticity problems, and the EGARCH Student's model was selected. The volatility of BBCA and BMRI returns does not affect each other but is influenced by LQ45 when bearish/bullish. The volatility of BRIS returns is influenced by BMRI only when it is bearish and the LQ45 index when bullish. The implications of the research prove the independence of stock investors (BMRI and BBCA) in making decisions. However, it was indicated that both investors were influenced by the decisions of most investors, which was reflected in the significance of the LQ45 index.

Keywords: EGARCH; Heteroscedasticity; Volatility; Return; Index

ABSTRAK

Tujuan penelitian ini adalah untuk menguji model volatilitas saham BBCA dan BMRI di BEI. Permasalahan penelitiannya adalah apakah terdapat pengaruh volatilitas return saham BBCA dan LQ45 terhadap BMRI dan sebaliknya. Penelitian tersebut juga menguji apakah volatilitas BRIS dipengaruhi oleh return saham pemegang saham mayoritasnya, BMRI. Model EGARCH *digunakan untuk menganalisis data return harian tahun 2015-2022 saat pasar* bearish/bullish. *Hasil penelitian menunjukkan bahwa data mengalami masalah heteroskedastisitas dan model* EGARCH Student's-t *yang dipilih. Volatilitas return BBCA dan BMRI tidak saling mempengaruhi, namun dipengaruhi oleh LQ45 saat* bearish/bullish. *Volatilitas imbal hasil BRIS hanya dipengaruhi oleh BMRI saat* bearish *dan indeks LQ45 saat* bullish. *Implikasi penelitian membuktikan independensi investor saham (BMRI dan BBCA) dalam mengambil keputusan. Namun kedua investor tersebut terindikasi dipengaruhi keputusan mayoritas investor yang tercermin signifikansinya indeks LQ45.*

Kata Kunci : *EGARCH; Heteroskedastisitas; Volatilitas; Return; Indeks*
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INTRODUCTION

Investment decisions in the capital market need to consider market volatility conditions. Volatility refers to price fluctuations as a reflection of investor decisions on information that occurs (Mieg, 2022). Xiao and Aydemir (2007) relate volatility to a measure of risk, where the higher the volatility of financial asset prices, the greater the risk. Factors influencing volatility include investor sentiment on domestic economic news/events and global markets (Baele, 2005) or uncertainty conditions (Su et al., 2019). Therefore, understanding stock market volatility is important in making investment decisions.

Volatility analysis is essential for investors, traders, and fund managers to design trading strategies and minimize the risk of loss (Campasano, 2021). Investing in blue-chip or growth stocks is part of a strategy to avoid the risk of loss due to high market volatility. Leading stocks on the Indonesia Stock Exchange (IDX) in the financial and banking sectors include PT. Bank Central Asia, Tbk. (BBCA) and PT. Bank Mandiri, Tbk.(BMRI), while PT. Bank Syariah Indonesia, Tbk.(BRIS) is a growing stock due to the merger of some of the largest Sharia-based banks in Indonesia.

Table 1. BBCA, BMRI, and BRIS Conditions in 2022

Information	BBCA	BMRI	BRIS
Assets (billion Rp)	1.283	1.570	305
Equity (billion Rp)	212	211	33
Return on Equity (ROE)	21.70	22.62	16.84
Loan/Financing to Deposit Ratio (LDR/FDR in %)	65.23	77.61	79.37
Market capitalization (trillion Rp)	1,078	529	69

Source: https://ojk.go.id/id/kanal/perbankan/data-dan-statistik/laporan-keuangan-perbankan/default.aspx

Three stocks were used in this study for several reasons. BMRI is the largest bank (assets) owned by the Indonesian government (52%), while BBCA is the largest private bank in which PT Dwimuria Investama Andalan is the majority shareholder (54.96%). Although BMRI's assets are more significant than BBCA's (Table 1), the amount of equity and the ratio of ROE are almost the same. Meanwhile, BMRI's credit level compared to deposits (LDR) is more significant than BBCA's. High LDR indicates the size of lending and higher risk. BBCA has the highest market capitalization in the banking sector, reflecting the large amount of investor funds invested in this stock. Both banks show high competition. Meanwhile, BRIS is majority-owned by large state-owned banks (51.47% PT Bank Mandiri, Tbk.; 23.24% PT Bank BNI, Tbk.; 15.38% PT Bank BRI, Tbk. and 9.91% public) (https://ir.bankbsi.co.id/shareholdings.html).

The stock price fluctuations of BMRI and BBCA (Figure 1) have similar trends under the fluctuations of the LQ45 index in the last eight years. However, since 2018, BBCA's stock performance has grown higher than that of BMRI. Meanwhile, BRIS shares (since June 1, 2018) have experienced high fluctuations since rumors of merging BRI Syariah shares with other Islamic banks (BMRI and BBNI). Even the global financial crisis due to the 2020 pandemic made BBCA and BMRI's share prices experience a decline; BRIS shares did not experience this.

Empirical research on stock volatility is generally associated with company performance, including liquidity (Będowska-Sójka &; Kliber, 2019; Mortazian, 2022; Cheriyan & Lazar, 2019), leverage (Rathgeber et al., 2021; Chon & Kim, 2021), profitability (de Silva, 2017; Wijayanti et al., 2023) as well as external factors such as exchange rates (Kennedy &; Nourizad, 2016; Blau, 2018), interest rates (Banerjee &

Kumar, 2009; Eldomiaty et al., 2020), gold price (Kumar &; Robiyanto, 2021). The problem of this study is whether the volatility of individual stocks is influenced by the shares of competitors (BBCA and BMRI) and whether the share price (BRIS) is influenced by the share price of the majority owner of the company (BMRI). This study also examines whether fluctuations influence the volatility of these stocks (BBCA, BMRI, BRIS) in the stock index of the market (LQ45). Volatility modeling due to other stock volatility (contagion) effects in Indonesia is still relatively limited. Therefore, this research is essential to explain stock volatility better.

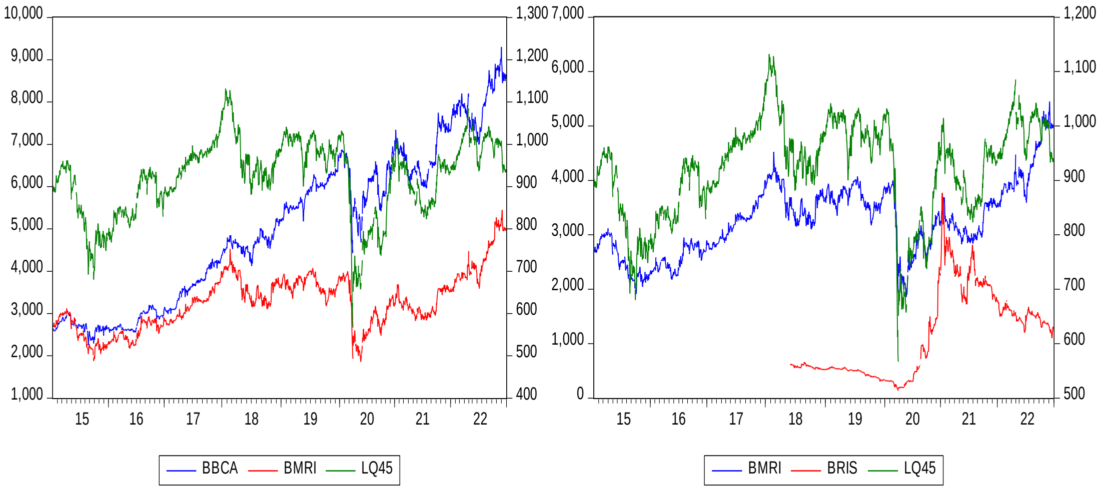

Figure 1. Price Fluctuations of BBCA, BMRI, BRIS, and LQ45 Index 2015-2022

The contagion effect refers to the interdependence between market economies, such as macroeconomic similarities, trade relations, and loans from banks (Dornbusch et al., 2000; Reinhart et al., 2007). The term is often used to describe the adverse effects of certain events, such as financial crises, on other sectors or countries. The impact of the contagion effect is an event when a crisis occurs in one country, can have a negative impact on another country, and will result in a weakening of the economy (González-Hermosillo et al., 2003). Forbes and Rigobon (2002) define the contagion effect as when an affected country triggers market movements in the region and substantially increases connectedness between countries.

Asgharian & Liu (2022), based on text-based network industry classifications (TNIC) data, show that the contagion effect of competing companies dominates, and the impact caused by adverse return shocks is more significant. Li and Luo (2020), based on stock data on A-share Shanghai and Shenzhen in 2009-2017, found that the overall level of industry competition was negatively correlated with the risk of falling stock prices and the company's competitive position. However, the study's results also showed that the correlation was insignificant for companies with high competitiveness. Altintig et al. (2009), based on data on the cement industry in Turkey, show the impact of privatization increases efficiency but is bad news for its competitors.

Studies on volatility prediction models in financial markets are still relatively limited. Volatility (σ) is a dispersion of the return of a particular security or market index that can be measured using the standard deviation or changes between the returns of the same security or its market index (Sahiner, 2022). According to Franses and McAleer (2002), stock market volatility models are needed to forecast stock market movements more accurately, even if there are shocks in the market.

Mandelbrot (1963) revealed that stock market volatility based on time series data shows volatility clustering as a phenomenon that can be modeled with econometric analysis models, including ARCH or GARCH. ARCH or Autoregressive Conditional Heteroscedastic (Engle, 1982), developed into GARCH or Generalized Autoregressive Conditional Heteroscedast*ic* (Bollerslev, 1986), uses heteroscedasticity data to be modeled as a residual variance. ARCH treats the mean and variance models simultaneously. GARCH (1.1) is a commonly used model where residual variance is affected only by one previous period. Suppose the residual variance is affected by fluctuations in the square of the residue from some previous period and the residual variance from some previous period. In that case, the model becomes GARCH (p, q). Research on the use of the GARCH model for volatility analysis in Indonesia and Hungary during the pandemic is done by Setiawan et al., (2021), in the European market by Villar-Rubio et al. (2023), and banking stocks in Pakistan by Mohsin et al. (2020).

This study used the Exponential Generalized Autoregressive Conditional Heteroscedasticity or EGARCH model developed by Nelson (1991) based on the GARCH model (Bollerslev, 1986). Stock volatility analysis uses the beta value to measure a stock's price sensitivity to changes in its market price. Time series data allows analysis of the historical behavior of stock prices or the market as a whole. But. Time-series data has unstable price fluctuation patterns or experiences volatility clustering (Kim & Song, 2020). The EGARCH model does not limit model parameters and adds an element of asymmetry in the volatility response to price changes. EGARCH allows the modeling of asymmetric effects where conditions of equal magnitude increase or decrease in price can have different impacts (Ezzat, 2012). According to Villar-Rubio et al. (2023), EGARCH can be used to forecast future volatility so that better decisions are taken. Therefore, this study was conducted to test whether BBCA's share price volatility is influenced by BMRI's share price and LQ45 Index and vice versa. The study also examines whether the volatility of BRIS share prices is influenced by the share price of its majority owner (BMRI) and the LQ45 Index.

METHOD

The data used in this study were obtained from www.idx.co.id, www.investing.com, and www.yahoofinance.com. The data is returned as income that will be received if a certain amount of money is invested in financial assets. Stock return is the difference in stock price (P_i) in a period (t) with the previous period ($t-1$), which is calculated using the formula: $R_i=[P_i-P_{i(t-1)}]/P_{i(t-1)}$ (Hudson & Gregoriou, 2015). The stocks to be studied are BBCA, BMRI, and BRIS in 2015-2022. The market return is the difference from the price listed on the composite index, which is calculated using the formula: $R_{mt}=[P_{mt}-P_{m(t-1)}]/P_{m(t-1)}$ (Hudson & Gregoriou, 2015) where R_{mt} is the market return of LQ45 index. P_{mt} and $P_{m(t-1)}$ are the closing indices of LQ45 in period (t) with the previous period ($t-1$).

Before the model analysis, a stationary test was carried out with a root test unit. Based on the Augmented Dickey-Fuller (ADF) test value, the criteria used are $\delta=0$, meaning the data is not stationary, and $\delta\neq0$, meaning the data is stationary, where $\delta=0$ is accepted if probability>0.05 and vice versa. Data is not stationary if the variance is not constant. After the stationary data, the return will be described first with the ARMA (Autoregressive-Moving-Average) model to determine the estimated parameters for the EGARCH model. The ARMA model was introduced by Peter Whittle (1951) and published by George EP Box and Gwilym Jenkins in 1970 (Box,

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2013). This ARMA test is carried out to determine the capabilities and feasibility of the model. The GARCH model is used if the data show an effect of heteroscedasticity. The effect of heteroscedasticity can be seen based on the results of the ARCH-LM test. The effect of heteroscedasticity on ARMA is used as a basis for conducting GARCH modeling.

Stock return volatility is measured by the EGARCH model equation with conditional mean and conditional variance. The volatility return model with the EGARCH model equation with the conditional mean is:

$Y_{BBCA}=\beta_0+\beta_1R_{BMRI}+\beta_2R_{LQ45}+e_t$ ....(Equation 1)

$Y_{BMRI}=\beta_0+\beta_1R_{BBCA}+\beta_2R_{LQ45}+e_t$ ....(Equation 2)

$Y_{BRIS}=\beta_0+\beta_1R_{BMRI}+\beta_2R_{LQ45}+e_t$ ....(Equation 3)

Model analysis using the EGARCH model (p,q) with an alpha value of 5%. While the EGARCH model (Nelson, 1991) with conditional variance to show the residual variety (σ_{2t}) is influenced by the residual square of the previous period ($|(\mu_{t-1})/(\sigma_{t-1})|-(\mu_{t-1})/(\sigma_{t-1})$) and residual variance of last periods (σ^2_{t-q}) is:

$\ln(\sigma^2_t)=C_6+C_7|(\mu_{t-1})/(\sigma_{t-1})|-C_8(\mu_{t-1})/(\sigma_{t-1})+C_9\ln(\sigma^2_{t-1})$ ....(Equation 4)

RESULT AND DISCUSSION

The results of the descriptive analysis describe the time-series data characteristics of daily stock returns during the study period. The characteristics of the data described, including mean, median, maximum, minimum, and standard deviation, are presented in Table 1. The data shows average returns on BBCA(R_{BBCA}), BMRI(R_{BMRI}), BRIS (R_{BRIS}) and LQ45(R_{LQ45}) of 0.09 percent, 0.07 percent, and 0.02 percent with standard deviations of 1.62 percent, 2.24 percent, and 1.41 percent. The kurtosis value of the data has a high level of sharpness (>3) or leptokurtic (abnormal curve).

Table 1. Descriptive Statistics

	N	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
R_{BBCA}	1590	0.0009	0.0012	0.1733	(0.0791)	0.0162	0.7477	13.24
R_{BMRI}	1590	0.0007	0.0021	0.1580	(0.1299)	0.0224	0.2062	6.83
R_{BRIS}	877	0.0016	(0.0065)	0.2500	(0.1440)	0.0423	2.5983	15.19
R_{LQ45}	1590	0.0002	0.0003	0.1492	(0.0826)	0.0141	0.4464	14.14

Source: Data processed

The results of the unit root test (Table 2) show that all data used to measure the research variable had significant p-values (<0.05) at the level, and BBCA shares were differentiated one (1st difference). Based on the test, it produces all stationary data and has no root unit.

Table 2. Stationarity Test

	ADF Test	*p*-values
R_{BBCA}	(18.0623)	0.0000
R_{BMRI}	(30.4254)	0.0000
R_{BRIS}	(26.3574)	0.0000
R_{LQ45}	(29.8242)	0.0000

Source: Data processed

Note: This unit root test examines whether these variables have unit roots using *Augmented Dickey-Fuller (ADF).* The test for each variable contains t-statistics, according to MacKinnon (1996). All variables are significant at 1%, 5%, and 10% and indicate stationary processes.

ARMA Model

Furthermore, parameter estimation is determined based on the ARMA, and the best model is selected based on the smallest *Akaike Information Criteria* (AIC) (Gujarati & Porter, 2009). Parameters are diagnosed based on probability values that are more excellent than the significant level (0.05). In addition, heteroscedasticity's problem is identifying residual test results with probability values ($\alpha<0.05$). The autoregressive model (AR) specifies that the output variable depends linearly on its previous value. At the same time, the moving average (MA) indicates that the estimated residual is a linear combination of the respective residues of the past. Estimation of EGARCH parameters in the overall data shows that ARMA (1,1) has significant AR (1) and MA (1) with the smallest AIC in the equation.

Table 3. Stationarity Test

Model	AR	MA	SIC	AIC	R^2_{Adj}	ARCH
ARMA (1,1)	0.0000	0.0000	-6.204340	-6.224548	0.559504	0.0000
ARMA (12)	0.0000	0.0012	-6.194858	-6.215066	0.555280	0.0000
ARMA (22)	0.1410	0.0000	-6.194552	-6.214759	0.555143	0.0000
ARMA (21)	0.0000	0.0000	-6.167602	-6.187810	0.542988	0.0000
ARMA (31)	0.0000	0.1045	-6.191737	-6.211945	0.553888	0.0000

Source: Data processed

Table 4 illustrates R_{BBCA} values as dependent variables and R_{BMRI} and R_{LQ45} as independent variables measured using EGARCH (1,1), with data distribution variations as Normal, Student' s-t, and Generalized Error Distribution/GED at various Log-likelihood, AIC, and ARC values.

Table 4. BBCA Return Volatility Model Using EGARCH (1.1)

	EGARCH					
	Normal	ρ-value	Student's-t	ρ-value	GED	ρ-value
C	(0.0001)	0.4197	(0.0001)	0.0379	(0.0001)	0.0457
R_{BMRI}	(0.0032)	0.1290	(0.0008)	0.7143	(0.0025)	0.2290
R_{LQ45}	0.0100	0.0590	0.0075	0.1541	0.0094	0.2290
Log-likelihood	4,482.91		4,548.88		4,541.33	
AIC	(5.6134)		(5.6950)		(5.6855)	
ARCH		0.0337		0.4608		0.1728
C_6	(0.7003)	0.0000	(0.7504)	0.0000	0.6773)	0.0000
C_7	0.2241	0.0000	0.3053	0.0000	0.2525	0.0000
C_8	(0.0844)	0.0000	(0.0746)	0.0046	(0.0730)	0.0022
C_9	0.9366	0.0000	0.9368	0.0000	0.9419	0.0000
$T_{Dist/GED}$		0.0000	4.5208	0.0000	1.2371	0.0000

Source: Data processed

The best model has the smallest AIC value (-5.6950), is free of symptoms of heteroscedasticity (ARCH>0.05), and has a significant variance equation ($C_6<0.05$) in Students. The parameter estimation results of the EGARCH parameter (1.1) with Student show that the volatility of the BMRI stock or the LQ45 index does not significantly influence the volatility of BBCA shares. The best model is EGARCH (1,1) where the Student's-t distribution (Equations 1 and 4) is:

$R_{BBCA}=-0.0001-0.0008\ R_{BMRI}+0.0075\ R_{LQ45}+e$ ……………………………………(Equation 5)

$\ln(\sigma^2_t)=-0.7504+0.3053\,|(\mu_{t-1})/(\sigma_{t-1})|\,-0.0746(\mu_{t-1})/(\sigma_{t-1})+0.9368\ln(\sigma^2_{t-1})$ ....(Equation 6)

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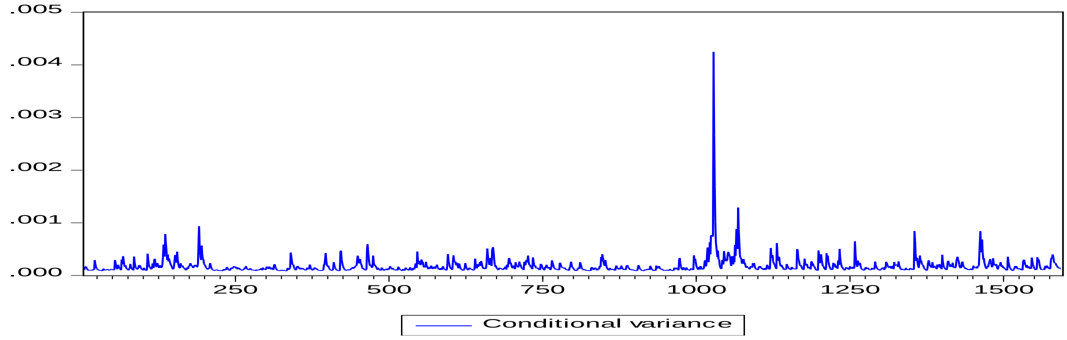

Figure 2. BBCA Conditional Variance
Source: Data processed.
Note: Figure 2 shows the conditional variance of R_{BBCA} affected by the previous day's return at a significance level of 5%.

Table 5 illustrates R_{BMRI} values as dependent variables, R_{BBCA} and R_{LQ45} as independent variable measurements using EGARCH (1,1) with variations in data distribution are Normal, Student's-t, and Generalized Error Distribution/GED at various Log-likelihood, AIC, and ARCH values.

Table 5. BMRI Return Volatility Model Using EGARCH (1.1)

	EGARCH					
	Normal	ρ-value	Student's-t	ρ-value	GED	ρ-value
C	0.0006	0.0410	0.0004	0.1148	0.0003	0.1519
R_{BBCA}	(0.0078)	0.6082	(0.0057)	0.7218	(0.0035)	0.8217
R_{LQ45}	1.2357	0.0000	1.1988	0.0000	1.2069	0.0000
Log-likelihood	4,543.44		4,613.38		4,594.74	
AIC	(5.6894)		(5.7759)		(5.7525)	
ARCH		0.3903		0.2750		0.2848
C_6	(0.7822)	0.0000	(0.3504)	0.0120	(0.4692)	0.0068
C_7	0.1122	0.0000	0.0679	0.0053	0.0790	0.0005
C_8	(0.0351)	0.0126	(0.0317)	0.0398	(0.0318)	0.0662
C_9	0.9182	0.0000	0.9650	0.0000	0.9520	0.0000
$T_{Dist/GED}$			5.9018	0.0000	1.3206	0.0000

Source: Data processed

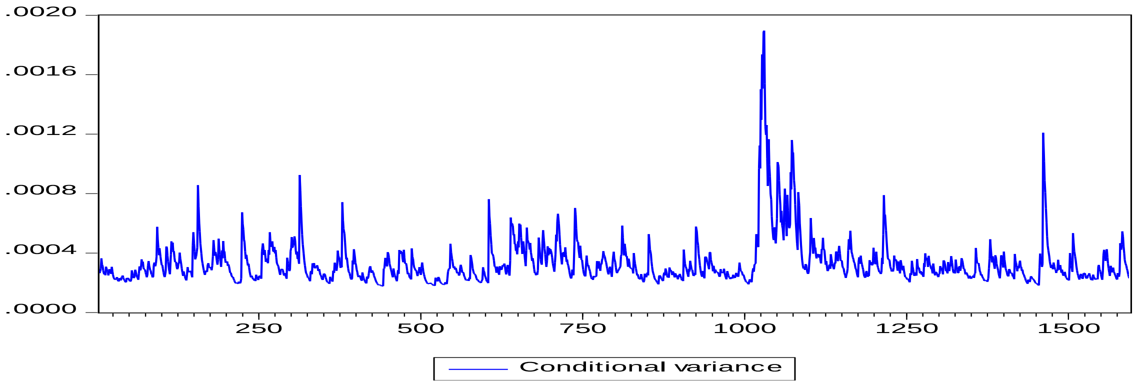

Figure 3. BMRI Conditional Variance
Source: Data processed.
Note: Figure 3 shows the R_{BMRI} conditional variance for 2015-2022 affected by the previous day's return at a significance level of 5%.

Table 5 shows that EGARCH(1.1) Student's-t is the best model (AIC-5.7759) and free of heteroscedasticity (ARCH>0.05). The BMRI stock volatility model shows that the effect of BBCA share price volatility is insignificant, but the LQ45 stock index is significant. The model variance value shows a significant value (<0.05). It means residual variance is affected by residual square fluctuations from some previous periods and residual variance from some previous periods. The formulation of the EGARCH variance model is $\ln(\sigma^2_t)$, with the expected result as a_1<0 and significant. The calculation of the table shows that the EGARCH coefficient is C_6 with a negative value with a significant p-value = 0.0000. The best model is EGARCH (1,1) where the Student's-t distribution (Equations 2 and 4) is:

R_{BMRI}=0.0004-0.0057 R_{BBCA}+1.1988 R_{LQ45}+e ....(Equation 7)

$\ln(\sigma^2_t)$=-0.3504+0.0679|$(\mu_{t-1})/(\sigma_{t-1})$|-0.0317$(\mu_{t-1})/(\sigma_{t-1})$+0.9650$\ln(\sigma^2_{t-1})$ ....(Equation 8)

Table 6. BRIS Return Volatility Model Using EGARCH (1.1)

	EGARCH					
	Normal	ρ-value	Student's-t	ρ-value	GED	ρ-value
C	(0.0116)	0.3243	(0.0039)	0.0000	(0.0048)	0.0000
R_{BMRI}	(0.0659)	0.1105	0.0073	0.8524	0.0360	0.2301
R_{LQ45}	0.8684	0.0000	0.7803	0.0000	0.8521	0.0000
Log-likelihood	1,723.70		1,978.81		1,947.35	
AIC	(3.9238)		(4.5053)		(4.4333)	
ARCH		0.9542		0.6249		0.8256
C_6	(1.3486)	0.0000	(1.0325)	0.0000	(1.3512)	0.0000
C_7	0.6644	0.0000	0.7659	0.0011	0.5193	0.0000
C_8	(0.1136)	0.0003	(0.2762)	0.0304	(0.1360)	0.0782
C_9	0.8610	0.0000	0.8874	0.0000	0.8512	0.0000
$T_{Dist/GED}$			2.3113	0.0000	0.7690	0.0000

Source: Data processed

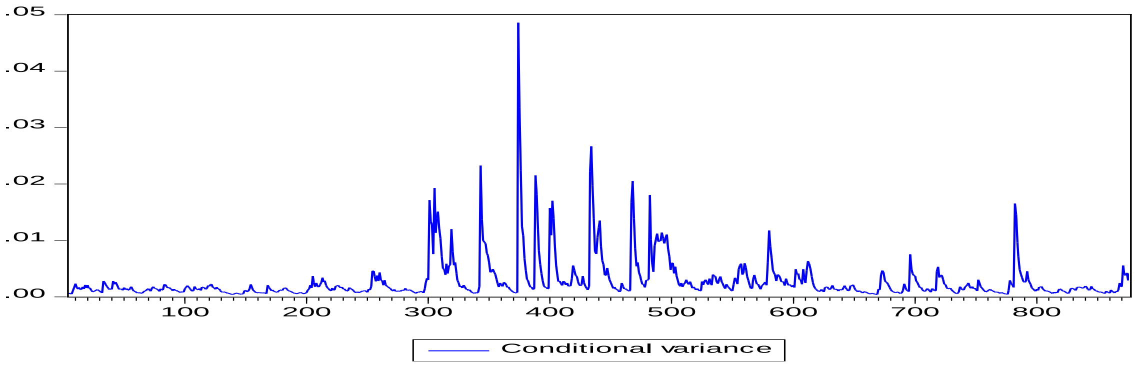

Figure 4. BRIS Conditional Variance

Source: Data processed.

Note: Figure 4 shows the R_{BRIS} conditional variance for 2015-2022 affected by the previous day's return at a significance level of 5%.

Table 6 shows that EGARCH (1.1) Student's-t is the best model (AIC-4.5053) and free of heteroscedasticity (ARCH>0.05). The BRIS stock volatility model shows that the effect of the volatility of the majority owner's share price (BMRI) is not significant, but the LQ45 stock index is significant. The model variance value shows a significant value (<0.05). It means residual variance is affected by residual square fluctuations from some previous periods and residual variance from some previous periods. The

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formulation of the EGARCH variance model is ln(σ2t), with the expected result being a1<0 and significant. The calculation of the table shows that the EGARCH coefficient is C6 with a negative value with a significant p-value = 0.0000. The best model is EGARCH (1,1) where the Student's-t distribution (Equations 3 and 4) is:

R_{BRIS}=-0.0039+0.0073R_{BMRI}+0.7803R_{LQ45}+e ....(Equation 9)

ln(σ^2_t)=-1.0325+0.7659|(μ_{t-1})/(σ_{t-1})|-0.2762(μ_{t-1})/(σ_{t-1})+0.8874ln(σ^2_{t-1}) ....(Equation 10)

The volatility model shows that the EGARCH with the Student' s-t distribution type is the best model for future testing in bearish and bullish market conditions.

Table 7. BBCA, BMRI, and BRIS Stock Return Volatility Model During a Bearish Market

	EGARCH					
	BBCA	ρ-value	BMRI	ρ-value	BRIS	ρ-value
C	0.0005	0.2892	0.0011	0.0673	(0.0094)	0.0000
R_{BMRI}	(0.0305)	0.2260			0.1653	0.0002
R_{BBCA}			(0.0402)	0.1023		
R_{LQ45}	0.8352	0.0000	1.2826	0.0000	(0.0045)	0.9261
Log-likelihood	2,449.82		2,275.36		1,013.73	
AIC	(6.3126)		(5.8688)		(4.4910)	
ARCH		0.8041		0.8650		0.7703
C_6	(0.7307)	0.0428	(1.5322)	0.1116	(0.6699)	0.0045
C_7	0.0996	0.0402	0.1682	0.0205	2.1018	0.4442
C_8	(0.0201)	0.5128	(0.0026)	0.9465	(0.7858)	0.4718
C_9	0.9281	0.0000	0.8389	0.0000	0.9046	0.0000
$T_{Dist/GED}$	1.3874	0.0000	9.7431	0.0001	2.0249	0.0000

Source: Data processed with EViews 12. The BBCA volatility test uses the EGARCH (1.1) GED model because it has the smallest AIC, while BMRI and BRIS have the EGARCH (1.1) Student's model.

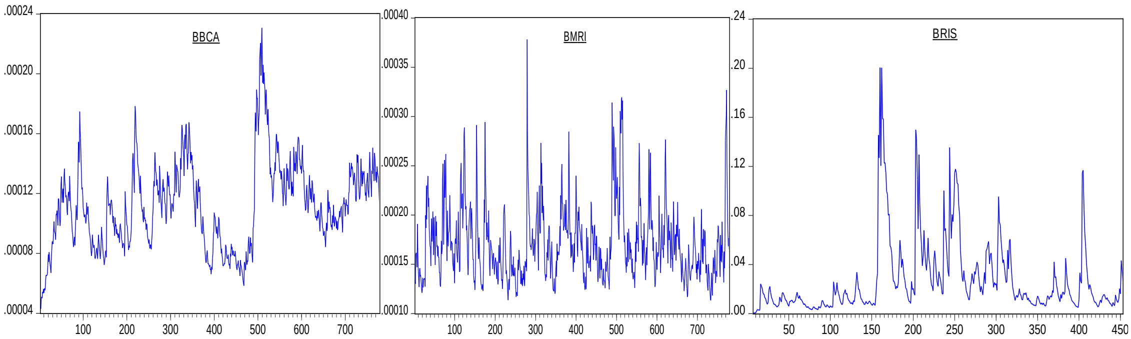

Figure 5. Bearish Conditional Variance

Source: Data processed using EViews 12.

Table 7 illustrates the value of the research variable when the market is down (bearish, R_{LQ45}<0) to test BBCA, BMRI, and BRIS return volatility models. The model showed data accessible of heteroscedasticity (ARCH>0.05) and had a significant variance equation (C_6<0.05). The model variance value shows a significant value (<0.05). It means residual variance is affected by residual square fluctuations from some previous periods and residual variance from some previous periods. Based on the parameter estimates, BMRI shares do not significantly influence the volatility of BBCA stock returns. However, the LQ45 index is significant when it is bearish. The volatility of BMRI shares is not significantly affected by BBCA shares, but the LQ 45 index is significant when it is bearish. While BMRI shares significantly influence the volatility of BRIS stocks, the LQ45 index is not significant when bearish.

Table 8. BBCA, BMRI, BRIS Stock Return Volatility Model During a Bullish Market

	EGARCH					
	BBCA	ρ-value	BMRI	ρ-value	BRIS	ρ-value
C	(0.0037)	0.0000	0.0001	0.8370	(0.0037)	0.0000
R_{BMRI}	0.0240	0.3789			(0.0070)	0.8612
R_{BBCA}			0.0020	0.9347		
R_{LQ45}	0.4807	0.0000	1.1880	0.0000	0.8211	0.0000
Log-likelihood	2,141.05		2,290.38		1,972.58	
AIC	(5.2749)		(5.6445)		(4.5065)	
ARCH		0.5062		0.8065		0.6188
C_6	(5.9823)	0.0000	(0.2394)	0.2091	(1.0311)	0.0000
C_7	0.8763	0.0000	0.0636	0.0597	0.7062	0.0001
C_8	0.0834	0.2611	(0.0435)	0.0411	(0.2615)	0.0146
C_9	0.3452	0.0006	0.9770	0.0000	0.8900	0.0000
$T_{Dist/GED}$	8.0449	0.0003	5.0908	0.0000	2.3781	0.0000

Source: Data processed with EViews 12. Test the volatility of all three stocks using the EGARCH (1.1)

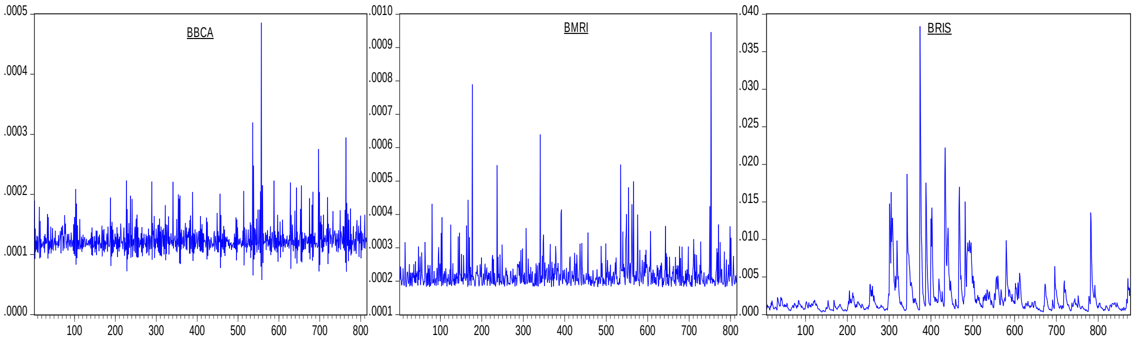

Figure 6. Bullish Conditional Variance
Source: Data processed.

Table 8 illustrates the value of the research variable when the market is bullish (R_{LQ45}>0) to test the return volatility models of the third stocks. The best model is shown by the smallest AIC value, free of heteroscedasticity (ARCH>0.05) and having a significant variance equation (C_6<0.05). It means residual variance is affected by residual square fluctuations from some previous periods and residual variance from some previous periods. Based on the results of parameter estimates, BMRI shares do not significantly influence the volatility of BBCA stock returns. However, the LQ45 index is significant when bullish. The volatility of BMRI shares is not significantly affected by BBCA shares, but the LQ 45 index is significant when bullish. While BMRI shares do not significantly influence the volatility of BRIS stocks, the effect of the LQ 45 index is significant.

Volatility clustering on the three stocks and large kurtosis values indicates the heteroscedasticity problem (abnormally distributed data) that occurs in BBCA, BMRI, and BRIS. Heteroscedasticity in time series financial data results is under the assumption of constant error variants not being met (Ogata, 2012; Stojanovski, 2015; Rice et al., 2020). It impacts false analysis results in parameter estimation in statistical models (spurious regression) and results in biased conclusions (Gujarati & Porter, 2009;

Lauridsena & Kosfeld, 2011; Farbmacher & Kögel, 2017). Tanjung (2015) also shows that stock return data in the Jakarta Islamic Index (JII) is not normally distributed or experiencing heteroscedasticity. The results of the study by Novanti et al. (2020) prove that the return on banking stocks, including BMRI and BBCA, is heteroscedasticity. Therefore, volatility modeling using the EGARCH(1.1) model with the Student's distribution shows a better ability to describe stock volatility. It aligns with the research of Mohsin et al. (2022) and Villar-Rubio et al. (2023).

The returns volatility of BBCA and BMRI does not significantly affect each other, but both indices are significantly affected by the market return (LQ45 index), both bearish and bullish. Meanwhile, the volatility of BRIS stock returns is significantly influenced by BMRI shares only when bearish and the LQ45 index when bullish. Rumors of the merger of BRI Syariah, Bank Syariah Mandiri, and BNI Syariah in 2018 could ignore the influence of market volatility. BBCA and BMRI represent the most prominent banks with solid fundamentals and good performance, so they are routinely included in LQ45. As part of blue-chip stocks, they are generally owned by institutional and long-term investors who trade information-based (informed trading). Investors tend to be rational with enough time to gather information and move independently of each other. In behavioral finance, investors of both stocks (BMRI and BBCA) do not imitate each other in making investment decisions, unaffected by the increase/decrease in the share price of both. However, both stock investors (BMRI and BBCA) are indicated to follow market volatility, which is reflected in the significance of the influence of market returns (LQ45) both when investors are pessimistic (bearish) and optimistic (bullish). Investors of both stocks tend to adjust their behavior to the majority sentiment. Therefore, further research is possible to test the individual herding behavior of these banking stocks.

CONCLUSION

The EGARCH(1.1) model with a type distribution model can be used in forecasting stock volatility. The results of comparing the three models show almost the same ability in modeling to find the effect of index volatility. Based on the assessment of residual error or variance and AIC, it was found that the EGARCH(1,1) Student gave better results than the normal distribution or GED. Analysis of the EGARCH model is needed to overcome the abnormalities in the distribution of time series financial data. The theoretical implication of this study is that a stock's price volatility is influenced by investor sentiment in general, which is reflected in market volatility (stock index) during bullish and bearish markets. The practical implication of this research is that the importance of market volatility analysis can be used to determine the suitable investment (portfolio) strategy for investors and to reduce volatility risk.

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