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Predicting Co-Movement of Banking Stocks Using Orthogonal GARCH

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Abstract: This study investigates the application of orthogonal generalized auto-regressive conditional heteroscedasticity (OGARCH) in predicting the co-movement of banking sector stocks in Indonesia. All state-owned banking sector stocks in Indonesia were studied using daily data from January 2013 to December 2019. The findings indicate that the OGARCH method can simplify the covariance matrix. Most state-owned banking stocks in the banking sector have a similar principal component influencing their conditional variance. Nonetheless, one stock has different principal components. The findings imply that combining the state-owned banking stocks with different principal components effectively reduces the risk of state-owned banking stock portfolios.

Keywords: OGARCH; principal component analysis; state-owned enterprises; banking sector returns

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1. Introduction

Risk minimization is the underlying principle of portfolio construction. The main themes of portfolio construction in investment are asset allocation and portfolio selection. As the portfolio consists of more than one asset, determining the assets included in the portfolio is crucial. To minimize portfolio risk, the assets, such as stocks, should be negatively correlated (Markowitz 1952; Robiyanto 2018). Notwithstanding the importance of correlation in constructing portfolios, most of the time the retail investors in the Indonesia Stock Exchange do not pay attention to the effect of stock correlation when investing in banking stocks. The existing general assumption explains that state-owned enterprise (SOE) stocks in the banking sector have different characteristics and are unrelated to each other.

In practice, each stock will have different characteristics, although they tend to have the same movement (co-movement) that is due to similar factors influencing them. According to Bandyopadhyay and Ganguly (2012), the economic cycle affects the mutual dependence or the same co-movement of firms' stocks. When a country experiences a recession, it will affect many firms simultaneously. Hence, there is a tendency to include stocks with the same driving factors in the same portfolio. In modern portfolio theory, similar factors are called systematic risk.

In contrast to systematic risk, the unsystematic component of portfolio risk is diversifiable. Thus, it raises the importance of correlation consideration (Atahau 2014). This study aims to determine the co-movement in question using the OGARCH method. This method can simplify examining the same risk factors on various financial instruments to produce a covariance matrix. The importance of co-movement of banking stocks for investors allows them to choose stocks in their investment portfolio that cannot be combined in one portfolio based on the more straightforward method of the variance-covariance matrix, which is still considered a challenge for capital market players in Indonesia. In addition, it also facilitates the formulation of better investment strategies since it prevents combining stocks with co-movements in a portfolio. Meanwhile, the importance of co-movement of banking stocks for policymakers (especially the State Ministry of State-Owned Enterprises) also provides inputs in formulating policies related to the potential for banks with a systemic impact on the SOEs in the banking sector, especially those related to the co-movement of SOE stocks. Moreover, it serves as a basis for formulating the policies for establishing SOE banking holding.

There have been several studies that empirically examined co-movement. For example, the studies by Bai (2011); Byström (2004); Muharam et al. (2020); Robiyanto (2017); De la Torre Torres (2013); Robiyanto and Pangestuti (2017) use the dynamic conditional correlation-GARCH (DCC-GARCH) method to form a portfolio of stocks in Indonesia and Malaysia with gold. The DCC-GARCH can overcome the problem of abnormal data distribution commonly found in the distribution pattern of stock returns on the Indonesian stock market. In stock co-movement research, an OGARCH application is required because in the application of the OGARCH model, linearly observed time-series data can be converted into independent time-series data using PCA (Luo et al. 2015). In addition, the OGARCH method is a method that can be used to simplify the process of examining the same risk factor on various financial instruments to produce a covariance matrix. However, this method was still relatively rarely used in previous research.

The banking sector is one of the drivers of the Indonesian capital market. The application of multivariate GARCH in the banking sector has been studied by Elyasiani and Mansur (2004) in measuring bank stock return sensitivities to long-term and short-term interest rates. Bandyopadhyay and Ganguly (2012) reviewed the co-movement study in large corporations and the banking sector and found bank stock portfolio return sensitivities that were due to changes in both long-term and short-term interest rates. Furthermore, Byström (2004) examined the co-movement between the Nordic stock markets during the Asian Financial Crisis using the OGARCH method. The results indicated that the OGARCH produced the right degree of co-movement compared to other methods. It means OGARCH can create a positive definite covariance to overcome the estimation problems using different GARCH models. Meanwhile, Bai (2011) studied the co-movement of the world's leading energy sector stocks—such as BP, Chevron, Conoco Phillips, Exxon Mobil, and Shell—using the OGARCH. The author confirmed that it could simplify highly complex calculations and even calculate the volatility and correlation of the stocks studied. In other fields, such as pension funds, De la Torre Torres (2013) simplified the investment portfolio calculation using the OGARCH. Furthermore, in the studies using the regional-level stock market, Robiyanto (2017) and Muharam et al. (2020) used the method previously used by Byström (2004). They found that their results supported the research conclusions (Byström 2004).

By implementing the OGARCH method, this research is expected to produce a more straightforward approach to predicting the SOE stocks' co-movement in Indonesia's banking sector since the capital market players are unfamiliar with this method. Instead, they use the heuristic methods such as correlation coefficient in constructing stock portfolios. The objects studied are the state-owned banks because they are the dominant players in the Indonesian banking industry. According to the industry profile report of December 2019, during the 2018–2019 period, banking SOEs accounted for a 43 to 44% market share in terms of total assets compared to all banking industry players in Indonesia. In addition, the method is expected to facilitate the formulation of investment strategies for stocks in the banking sector in Indonesia. The findings of this study are expected to provide valuable input for investors to select appropriate banking stocks to be included in their investment portfolio. Hence, the objectives of this study are to apply the OGARCH method for calculating the variance–covariance matrix to predict the co-movement of stocks of SOEs engaged in the banking sector in Indonesia and to formulate the right investment strategy for the SOE banks in Indonesia. Understanding the co-movement of these stocks helps to understand the types of banking stocks that cannot be combined in one portfolio. As a result, the investors can improve their stock portfolio formulation since an active investment strategy for the stock portfolio of SOEs in the banking sector can be formulated by avoiding the inclusion of stocks with co-movements. For the state-owned regulators, this research is expected to serve as the basis for formulating the policies regarding the establishment of SOE banking holding. This research also provides a novelty in predicting the co-movement of SOE stocks in the banking sector in Indonesia since most researchers still use heuristic measures such as multivariate GARCH, which possess some estimation problems. This research is arranged into five sections: introduction, literature review, methodology (including materials), results (including discussion), and conclusions.

2. Literature Review

2.1. Co-Movement Analysis

Previous research has studied the co-movement between asset returns: different stock indices (Koulakiotis et al. 2012) and between stock and bond (Lee 2021; Skintzi 2018). Furthermore, other researchers have also studied the co-movement between different markets. Lehkonen and Heimonen (2014) studied the emerging market time-varying stock market co-movement in terms of the U.S. investors, while Ma et al. (2019) focused on the market co-movement in Shanghai and Hong Kong. Different studies applied various methods to measure the co-movement between assets and markets. Lee (2021) used OLS quantile regression to examine the dynamic co-movement between the stocks and treasury bonds in Europe. The findings showed nonlinear effects of co-movement driving factors in the EU asset markets. To account for the nonlinearity, Koulakiotis et al. (2012) applied time-varying copula models in examining a combination of co-movement and integration effects on the volatility of cross-listed equities in Frankfurt, Zurich, and Vienna. The research provided a piece of evidence on the ability of the new model to outperform the linear-based correlation (the constant conditional correlation (CCC)-GARCH and the DCC-GARCH). The superiority of the proposed model was in its ability to account for nonlinear and time-dependent relationships. The DCC model by Engle (2002) is a generalization of Bollerslev (1990)'s CCC model. The DCC is adequate to investigate time variations in the correlations of asset returns and capture the time-varying nature of the correlations, and it can also model large covariance matrices. It examines the heteroskedasticity of the return volatility and can be used to analyze multiple asset returns simultaneously without adding too many parameters. A recent study by Paolella et al. (2021) applied a new OGARCH for a (potentially large) multivariate set of non-Gaussian asset returns to restrict the time variation in conditional covariances. The findings showed that more stable (less volatile) risk minimization strategies and transaction costs were reduced significantly. Lehkonen and Heimonen (2014) used the DCC to measure the stock market co-movement among the BRIC countries, major industrialized economies (UK, Germany, and Japan), and the developed neighboring countries (Canada, Australia, and Hong Kong) by first decomposing the stock return indices to several timescales using wavelet analysis. For the Indonesian market, research focusing on the co-movement of stock markets concerning the asymmetric volatility of stock returns in the Indonesian market has been conducted by Leeves (2007), who investigated the asymmetric volatility of stock returns in Indonesia during the Asian crisis in the late 1990s period.

2.2. Portfolio Analysis

A portfolio analysis was introduced by Markowitz (1952). It serves as the basis for many studies involving investment analysis. If a portfolio consists of assets related to one another, there would be no diversification benefits. Hence, a lower correlation between assets constructing portfolios resulted in a more diversified portfolio with a lower risk (Bandyopadhyay and Ganguly 2012). According to the idiosyncratic risk hypothesis, diversification eliminates the specific (idiosyncratic) risk (Atahau 2014). The remaining risk is the systematic risk measured by beta in a diversified portfolio.

In its development, the portfolio analysis can be done using various methods, such as the Markowitz method (Markowitz 1959), single index model (Ali and Mehrotra 2008), and DCC-GARCH (Hedi Arouri et al. 2015; Robiyanto and Pangestuti 2017). The portfolio analysis requires a calculation of the correlation matrix and covariance between assets. A portfolio consisting of an extensive asset collection implies a more complex calculation. Therefore, a method that can simplify the calculation is crucial. One of the methods considered to simplify the calculation is the OGARCH method. Thus, a hypothesis that can be proposed is as follows:

Hypothesis. *OGARCH can predict the co-movement of state-owned banking sector stock returns.*

3. Research Methodology

The data used in this study was the daily closing price data of SOE stocks in the banking sector listed on the Indonesia Stock Exchange before the COVID-19 pandemic from 2 January 2013 to 30 December 2019 with 1699 observations. This particular period shows no changes in the number of banking state-owned enterprises. Besides, none of these SOEs held a seasonal equity offering through the right issue, which could affect the theoretical price of the stock to avoid the confounding effect. There are four SOE stocks in the banking sector whose stocks were owned directly by the Government of the Republic of Indonesia. They are BBNI (PT. Bank Negara Indonesia (Persero) Tbk), BBRI (PT. Bank Rakyat Indonesia (Persero) Tbk), BBTN (PT. Bank Tabungan Negara (Persero) Tbk), and BMRI (PT. Bank Mandiri (Persero) Tbk). The data was obtained from both Bloomberg and the Indonesia Stock Exchange.

Before analyzing the data using the OGARCH, the return on the SOE stocks were calculated. The authors refer to Gitman and Zutter (2015) in calculating the stock price return. The formula used is as follows:

$$Return_{i,t} = (Stock\ Price_{i,t} - Stock\ Price_{i,t-1}) / Stock\ Price_{i,t-1} \tag{1}$$

Most financial modeling researchers agree that the GARCH method is the most widely used and accepted model for time-varying volatility models in finance. The following is a typical GARCH (1,1) model (Duncan and Liu 2009):

$$R_t = \mu + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = \gamma + v\varepsilon_{t-1}^2 + \delta\sigma_{t-1}^2 \tag{3}$$

where: $\varepsilon_t | \Omega_{t-1} \sim \mathcal{N}(0,\ \sigma_t^2)$.

Returns are assumed to be dependent on their (zero) mean observation. The ε_t (error term) is assumed to be conditioned on previous information (Ω_{t-1}) and normally distributed with a zero expected value and conditional variance (σ_t^2).

Apart from GARCH, the OGARCH method would be best applied in a highly correlated series (Bai 2011). Therefore, a correlation analysis of the SOE stock price return of the banking sector was examined. The OGARCH analysis was done using the Eviews 12 program. The authors employed the OGARCH method since a portfolio analysis requires a calculation of the correlation matrix and covariance between assets involving a more complex calculation as the number of assets increases. In other words, a method can be used to simplify examining the same risk factors on various financial instruments to produce a covariance matrix. It combines principal component analysis (PCA) with the GARCH technique. The PCA is often described as a set of procedures that uses changes in orthogonal variables to simplify important information from a series of highly correlated variables into variables that are not/poorly correlated (Robiyanto 2017). Luo et al. (2015) explained that using the PCA in an OGARCH model, the observed time-series data are linearly transformed into independent time-series data. These new orthogonal variables are then referred to as principal components (PC), and the number of PCs will be less than the number of initial variables (Bai 2011). Several studies highlighting the superiority of the OGARCH method in comparison to other available methods include (Alexander 2000, 2001; Klemm 2013; Robiyanto 2017; Bai 2011).

In conducting the estimation using the OGARCH, several steps are conducted. First, a correlation analysis of the SOE stock price return of the banking sector was examined since the OGARCH method would be best applied in a highly correlated series (Bai 2011). Thus, the data should be standardized into matrix $XTX_{k,}$ formerly YTX_k (TX_k: daily return k of SOE banking stocks at T day) by estimating the variance averaged for each y_i to obtain matrix XX′. Then, the PCA analysis is conducted based on matrix XX′ to obtain the eigenvalue vector and eigenvalue.

The resulted eigenvalue matrix (denoted by L with m_{th} refer to its column $1_m = (m_{1,m},\ldots, l_{k,m})$, 1 KX eigenvector associated eigenvalue λ_m) is transformed into columns $\lambda_1 > \lambda_2 > \ldots > \lambda_k$. The following step is to determine the number of principal components. When the first principal component has been selected, the resulting m_{th} principal component is as follows:

$$P_m = x_1 1_{1,m} + x_2 1_{2,m} + \ldots + x_k 1_{k,m} \tag{4}$$

From the equation, $x_i = i_{th}$ column of X_n column; TX_n matrix is taken out from X and represents the principal component matrix $P = X_n W_n$. After employing the PCA, the next step is conducting the GARCH estimation: measuring the conditional variance of the principal components i_{th} p_i, i = 1, N is estimated by GARCH(1,1), and conditional variance matrix of X_n with the following formulas:

$$p_{i,t} = \varepsilon_{,t} \tag{5}$$

$$\sigma_{i,t}^2 = \omega_{i,t} + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \tag{6}$$

$$\Sigma_t = g\left(\sigma_{1,t}^2, \ldots, \sigma_{n,t}^2\right) \tag{7}$$

The conditional covariance matrix of X_n is $D_t = W_n \Sigma_t W_t^n$ and the conditional variance matrix of Y is $H_t = \sqrt{VD_t}\ \sqrt{V}$, where $W_n = L_n\ diag(\sqrt{\lambda_t}, \ldots, \sqrt{\lambda_n})$. The amount of components of n chosen to reflect the current system determines the precision of the conditional covariance matrix V_t from the initial return (Robiyanto 2017). Based on the previous narration regarding steps to estimate co-movement using OGARCH, the research flow diagram below is depicted in Figure 1. To verify the findings, the authors ran vector autoregression (VAR) on the sample of state-owned banks' returns. The co-movement exists if the time series involved is bi-directional.

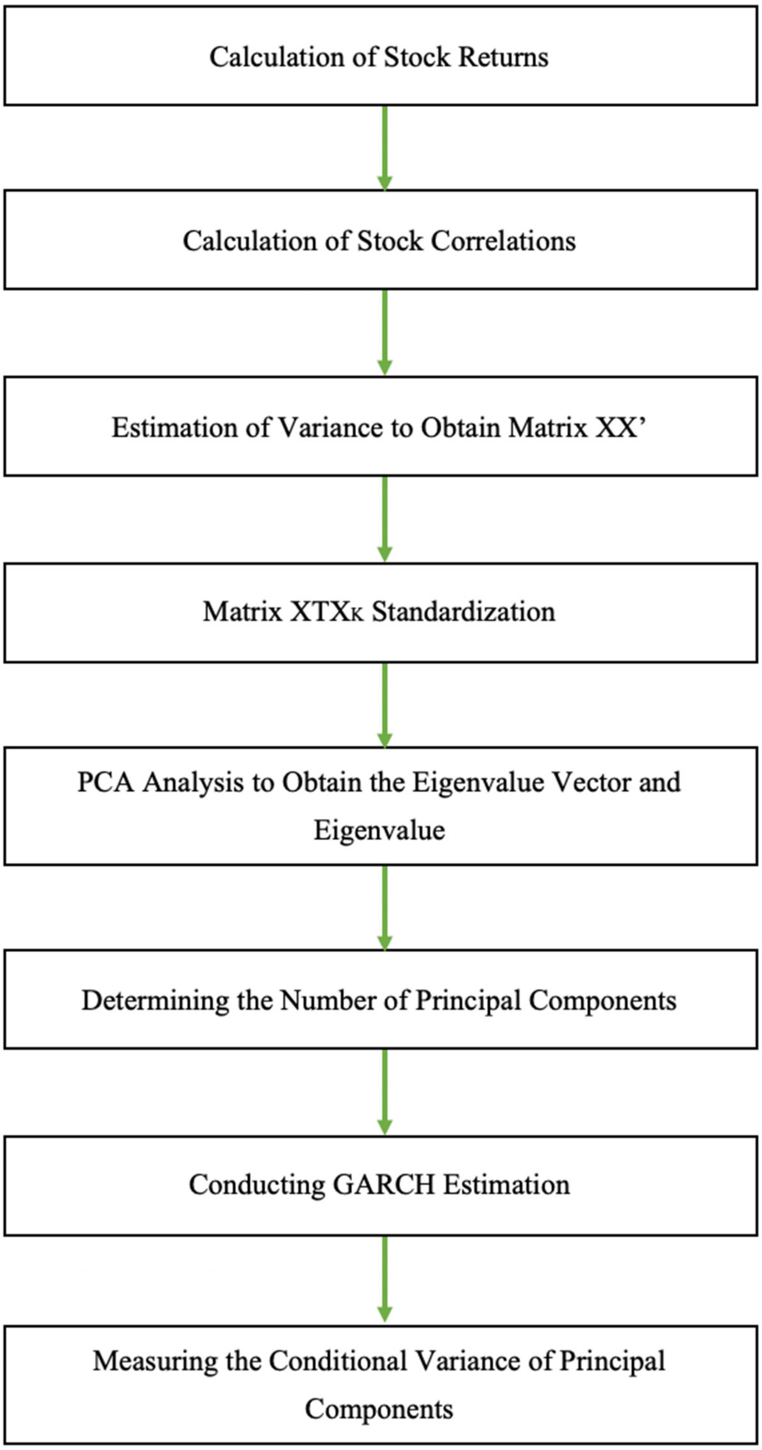

Figure 1. Research flow diagram.

4. Results and Discussion

Table 1 presents the statistic descriptive of all SOE banking stocks in this study: BBNI, BBRI, BBTN, and BMRI.

Table 1. Statistic descriptive.

Statistics	BBNI	BBRI	BBTN	BMRI
Mean	0.000647	0.000877	0.000499	0.000570
Median	0.000000	0.000000	0.000000	0.000000
Maximum	0.123288	0.118149	0.111111	0.136691
Minimum	−0.079787	−0.083443	−0.103933	−0.078313
Std. Dev.	0.020242	0.019926	0.023521	0.019714
Observations	1699	1699	1699	1699

Source: Bloomberg, processed.

In Table 1, BBRI shows the highest average daily stock return (0.0877%) compared to other banking stocks. It might relate to its strong fundamental conditions, as indicated by BBRI being the most SOE banking stocks held by foreign investors. BBRI has the widest outreach, with its coverage scattered all over Indonesia. It focuses on SME lending compared to other SOE banking stocks. In contrast, BBTN has the lowest average daily return (0.0499%) over the research period. It also has the highest deviation (2.35%) compared to other SOE banking stocks. Focusing on mortgage loans differentiates BBTN substantially from other SOE banks. The focus strategy might contribute to its low return and high daily stock fluctuation.

Prior to OGARCH analysis, correlation analysis should be done to measure the correlation between stocks (Robiyanto 2018) stated that OGARCH will be working appropriately if the data set correlates. Table 2 presents the correlation analysis of the SOE stock returns of the banking sector listed on the Indonesia Stock Exchange. Overall, the results show a significant correlation. Thus, OGARCH analysis is suitable for the dataset used in this study.

Table 2. Correlation of SOE stock returns in banking sector listed on the Indonesia Stock Exchange.

	BBNI	BBRI	BBTN	BMRI
BBNI	1			
BMRI	0.629 **	1		
BBTN	0.481 **	0.462 **	1	
BBRI	0.646 **	0.667 **	0.462 **	1

Source: Bloomberg, processed. ** Correlation is significant at 0.01 level (2-tailed).

OGARCH analysis combines GARCH and PCA. It also uses the conditional variances of stocks that are then formed into several main principal components (PC). The analysis results using the OGARCH method involving GARCH and PCA analysis for returns of SOE stock in the banking sector indicate that two principal components explain the variance. The details can be seen in the following Tables 3 and 4.

Table 3. PCA analysis of SOE stock returns in the banking sector.

PC	Eigenvalue	Cumulative Value	Proportion	Cumulative Proportion
1	2.684400	2.072976	0.6711	2.684400
2	0.611424	0.238023	0.1529	3.295823

Source: Bloomberg, processed.

Table 4. PCA analysis for individual banks.

Variable	PC1	PC2
RESID_1_01 (BBNI)	0.518284	−0.180319
RESID_2_01 (BMRI)	0.523108	−0.289585
RESID_3_01 (BBTN)	0.433722	0.897883
RESID_4_01 (BBRI)	0.519255	−0.278265

Source: Bloomberg, processed.

The scree plot in Figure 2 shows that the first and the second components have eigenvalues of more than one, while the eigenvalues of the third and the fourth components are less than one. Based on the eigenvalue results, only two components are appropriate to be formed. These components are named PC1 and PC2. Table 4 and Figure 2 show that the three SOE stocks in the banking sector consisting of BBNI, BBRI, and BMRI can form PC1. The PC1 has an eigenvalue of 2.68 with a proportion of 0.6711, which means that the returns of the three SOE stocks in the banking sector have a co-movement. This first factor can explain 67.11% of the three stocks' returns variance. The eigenvalue cumulative proportion shown in Figure 2 depicts this proportion, along with other PCs with a low proportion. It indicates that the three stocks had the same main risk factor and contributed 67.11% to the conditional variance of each stock. Meanwhile, the BBTN stock forms PC2 with a proportion of 15.29%. It indicates that the BBTN stock did not have the same movements and variances as the others.

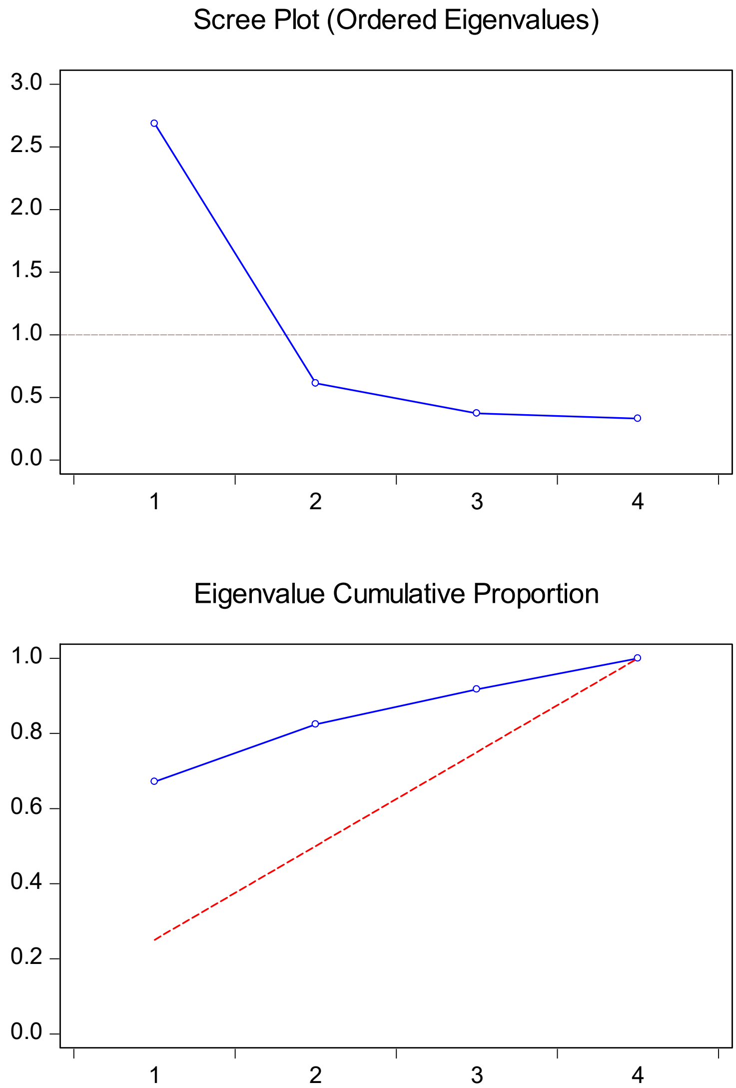

Figure 2. Scree plot and eigenvalue cumulative proportion.

In addition, the authors verified the findings by conducting robustness testing using vector autoregression (VAR) to reinforce the main estimation of this study. Since the OGARCH model is a member of the multivariate GARCH family, it can handle large covariance matrices and ease the computational burden on the volatility estimates and VAR-type calculations. The results of VAR testing with optimal lag can be seen in Table 5 below.

Table 5. Vector autoregression test.

Variable	BBNI	BBRI	BBTN	BMRI
BBNI(−1)	−0.023341	0.062611	0.053417	0.056803
	(0.03464)	(0.03406)	(0.04048)	(0.03373)
	[−0.67377]	[1.83819] *	[1.31960]	[1.68388] *
BBNI(−2)	−0.030026	0.029711	0.015127	−0.058479
	(0.03454)	(0.03396)	(0.04036)	(0.03363)
	[−0.86933]	[0.87492]	[0.37482]	[1.73877]*
BBRI(−1)	0.096446	0.037529	0.029663	0.075826
	(0.03616)	(0.03555)	(0.04225)	(0.03521)
	[2.66755] ***	[1.05572]	[0.70214]	[2.15379] **
BBRI(−2)	0.003060	−0.092323	0.004626	−0.026075
	(0.03615)	(0.03554)	(0.04224)	(0.03520)
	[0.08465]	[−2.59740] ***	[0.10950]	[−0.74071]
BBTN(−1)	−0.060228	−0.047674	−0.034289	−0.050469
	(0.02460)	(0.02419)	(0.02874)	(0.02395)
	[−2.44835] **	[−1.97114] **	[−1.19293]	[−2.10693] **
BBTN(−2)	−0.011554	−0.012258	−0.053730	−0.120284
	(0.02463)	(0.02422)	(0.02878)	(0.02399)
	[−0.46901]	[−0.50612]	[−1.86668] *	[0.20723]
BMRI(−1)	0.088460	0.056856	0.028671	−0.029390
	(0.03596)	(0.03535)	(0.04202)	(0.03501)
	[2.46001] **	[1.60815] *	[0.68236]	[−0.83935]
BMRI(−2)	−0.016109	−0.013436	0.014026	−0.126021
	(0.03601)	(0.03541)	(0.04208)	(0.03507)
	[−0.44730]	[−0.37947]	[0.33332]	[−3.59368] ***

Source: Authors' compilation. * $p < 10\%$ level, ** $p < 5\%$ level, and *** $p < 1\%$ level.

When the BBNI(−1) stock return increases on a previous day, the BBRI and BMRI stock returns also rise significantly. Nevertheless, when the BBNI(−2) stock return increased in the last two days, it significantly impacted the BMRI. A similar trend was also found for BBRI and BMRI. When the BBRI(−1) stock return increases on a previous day, it has a positive and significant impact on BMRI. Conversely, when the BBRI(−2) stock return rises in the last two days, it negatively and significantly impacts the BBNI and BMRI. Analogous to the other two banks, when the BMRI(−1) stock return rises on a previous day, it has a positive and significant impact on the BBNI and itself (BMRI). However, when the BMRI(−2) stock return rises in the last two days, it negatively and significantly impacts itself (BMRI). A different effect is found for BBTN. When the BBTN(−1) stock return rises on a previous day, the BBNI, BBTN (itself), and BMRI all suffer. In contrast, when the BBTN(−2) stock return rises in the last two days, it negatively and significantly impacts itself (BBTN).

The authors also ran impulse response functions (IRF) to highlight the VAR test results. In general, the IRF's results support the main findings. There is a large deviation of stock movement between BBTN and the rest of the state-owned banking stocks. In contrast, only a small deviation pattern of stocks' movement among the rest of state-owned banking was found during the observation period. It implies that the co-movement of stocks persisted between the BBRI, BMRI, and BBNI, which contradicted the BBTN stock movement during the observation period. The so-called impulse response function (IRF) is one way to investigate a model's dynamics.

$$IRF(h,\ \delta) = \frac{\partial \mathrm{y}_{t+h}}{\partial \epsilon_t} \tag{8}$$

Equation (8) shows how a shock $\epsilon_t = \delta$ at time t impacts a system at time $t + h$, assuming no further shocks, $\epsilon_{t\,+\,h} = 0\ \forall\ h$. IRF is considered a practical way of representing the behavior of economic variables (stock returns) in response to shocks to the vector (δ_t). An IRF represents the effect of an unanticipated one-unit change in the impulse variable on the response variable over several subsequent periods (typically 10). In the IRFs graph, one impulse is located in each row, and one response variable is positioned in each column. Each graph's horizontal axis is in the unit of time (daily). In contrast, the vertical axis represents the variable units in the VAR (percentage points). It can be displayed in Figures 3 and 4 below.

Figure 3. Multiple graphs for IRFs.

Figure 3 illustrates the impact of a one-standard-deviation impulse on the BBNI, BBRI, BBTN, and BMRI equation in IRF. Almost one standard deviation shock to BBNI, BBRI, BBTN, and BMRI causes a significant increase and decrease on BBNI, BBRI, BBTN, and BMRI stock return on the 2nd and 3rd day. Unlike the three banking sectors (BBNI, BBRI, and BMRI), one standard deviation shock to BBNI, BBRI, and BMRI resulted in a stable BBTN stock return. Except for one standard deviation shock to BBTN that causes significant decreases on BBTN (itself) on the 2nd and 3rd day. Figure 4 shows that the shock of BBTN stock has a greater influence than other state-owned banking (BBNI, BBRI, and BMRI) shocks. Overall, Figures 3 and 4 (multiple and combined) supported the main findings that BBTN movement patterns and volatility are different from the rest of state-owned banking stocks' movement and volatility. BBTN focused on mortgage loans, evident from its type composition, where mortgage loans dominate other loans. Thus, the property market and economic cycle mainly affect the pricing of loans and their return. It becomes concentrated and no longer diversified when focused primarily on mortgage loans. Pricing and return are lower than other diversified banks, but it is backed by definite collateral, provided that the property market is in a stable condition (does not collapse).

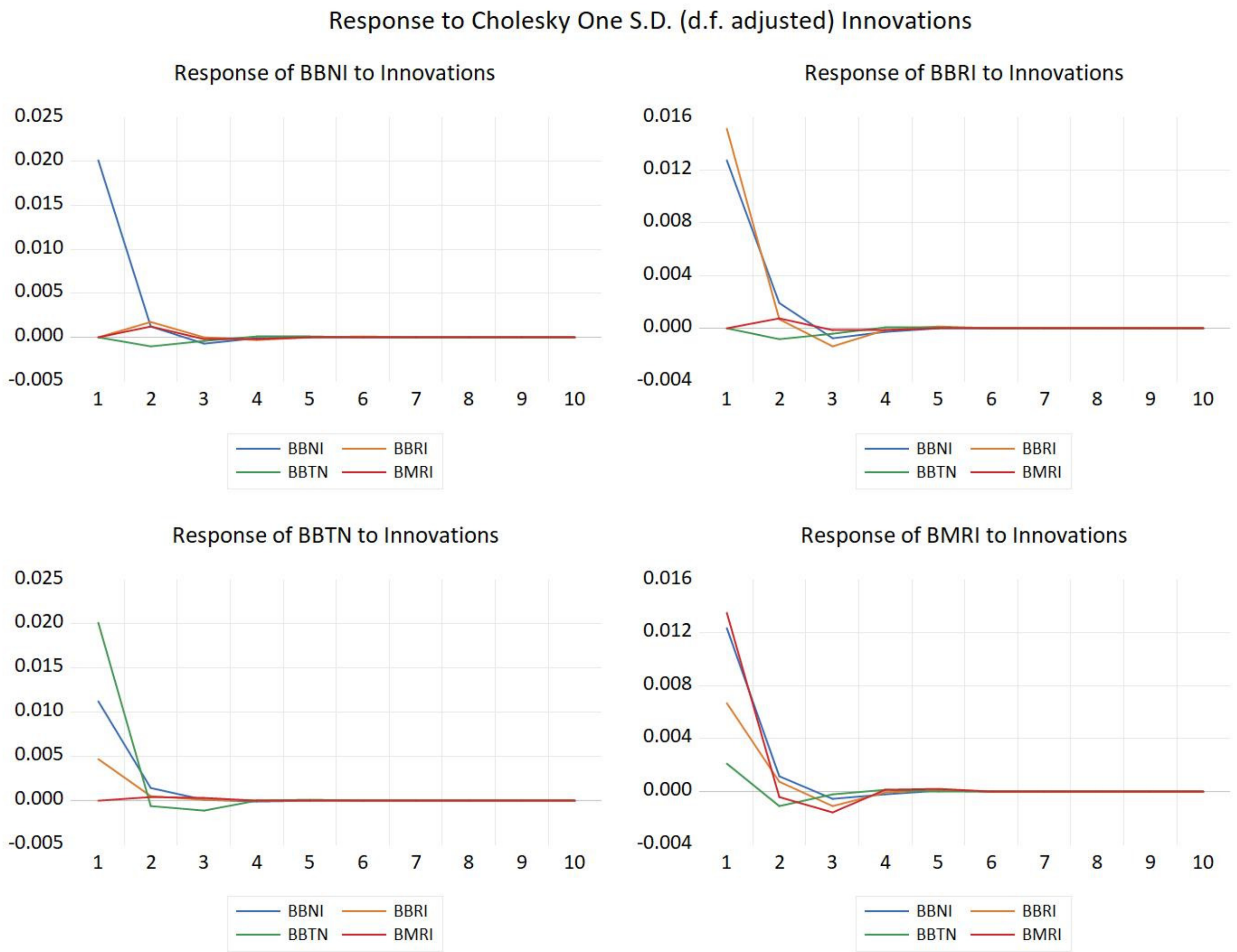

Figure 4. Combined graphs for IRFs.

The three state-owned stocks in the banking sector (BBNI, BBRI, and BMRI) have a similar principal component influencing their conditional variance. On the contrary, the BBTN stock has different principal components. The different principal components of BBTN might be related to its focus on mortgage loans, which were the opposite of the other three state-owned banks in this research. Its stock return sensitivity to common factors such as inflation, interest rate, and economic cycle (systematic risk) was mainly caused by those factors' impact on the property and real estate sector. In addition, the BBTN also has the smallest capital compared to the other sample banks (evidenced by its relative portion in a different capital category), which might implicate its operation and returns. The findings are also supported by the VAR analysis, where the returns of the three SOE stocks in the banking sector move together but not with the returns of BBTN stock.

Furthermore, the IRFs' graphs show that the BBTN tends to move differently from the rest of the state-owned banking stocks. In addition, its volatility is also different from the BBNI, BBRI, and BMRI. Besides, both principal components in this study contribute 84.61% toward explaining the conditional variance return of the four SOE stocks studied in the banking sector.

Based on the findings of this study, it can be concluded that the hypothesis is supported empirically. The OGARCH method can predict the co-movement of Indonesia's state-owned banking sector stocks before the COVID-19 pandemic. It summarizes the covariance matrix to be simplified so that further application could facilitate the portfolio calculation. As stated by Paolella et al. (2021), the OGARCH model was suitable for a specified number of leading principal components of the covariance matrix. The results of this study are consistent with the findings by (Bai 2011; Muharam et al. 2020; Robiyanto 2017).

In addition, it is also quite interesting that the remaining 17.6% of the conditional variance return of the four stocks studied could be explained by other components not formed in this study. It implies that undetectable and random factors could affect the conditional variance return of the four stocks studied. Within the capital asset pricing model (CAPM) framework, this finding proves that 82.4% of the risk in the four stocks is systematic risk, while the remaining 17.6% of the total risk is a non-systematic risk.

5. Conclusions

This study finds that the OGARCH method can simplify the covariance matrix of the examined four SOE stocks in the banking sector. Three stocks (BBNI, BBRI, and BMRI) with the same principal component influence their conditional variance. However, the BBTN stock has different principal components. Meanwhile, it is found that 82.4% of the risk of the four stocks is systematic risk, and the remaining 17.6% is a non-systematic risk.

The theoretical implication of this research is providing empirical evidence from the Indonesian banking sector in the ability of OGARCH to remedy the inherent estimation problems found in multivariate ARCH modeling. The findings also imply that investment managers or investors should not put the BBNI, BBRI, and BMRI stocks in the same portfolio as they have the same risk factors. Furthermore, the BBTN stock can be combined with other SOE stocks in other banking sectors. Hence, considering the co-movement of SOE banking stocks in constructing the stock portfolio is crucial for reducing the portfolio risk. In the context of ASEAN countries, this research contributes to the knowledge related to portfolio construction involving SOE banking stocks since there is a similarity in banking industry structure in some ASEAN countries where a few SOE banks dominate the banking industry.

The regulators formulating the policy on holding banks may use the results of this study by considering the potential merging of the SOE banks with similar stock returns co-movement. The policy implication of this research is related to the importance of addressing the specific characteristics of each SOE bank under consideration when aiming to form a bank holding company. It is advisable to place banks with similar characteristics in terms of co-movement into one holding company instead of placing banks with different co-movement into one holding company. Future researchers are suggested to conduct studies on other SOE stocks so that the results can be used to form optimal portfolios, considering that the SOE stocks are often regarded as attractive to be included in a portfolio.

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