Dynamic Causality of Strategic Risk of Indonesia Coal-based Enterprises (Var Model Application)

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Abstract: - Currently, coal is an energy source used as fuel for power plants, which produces 37% of global electricity, and by 2040 it is predicted to produce 22% of the world's electricity. Therefore, the development of a coal company's stock price can reflect companies' management performances in controlling risk which in turn can affect the level of volatility of the company's stock price and become an indicator for investors in making investment decisions in order to get a return. tall one. The formulation of strategic risk of coal subsector companies with the application of the vector autoregressive (VAR) model becomes the basis of this research, where strategic risk is proxied through the growth of stock prices and returns in each coal company that is the sample of the study. The method that will be used in this research is descriptive quantitative through the application of the VAR model to be able to describe the causality relationship between companies. The results obtained are the VAR(2) model of each coal subsector company, which is used as an initial identification of its strategic risk so that the coal subsector company can make mitigation steps in dealing with these strategic risks.

Key-Words: VAR Model, Stock Return, Strategic Risk.

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1 Introduction

Over time, the need for energy, especially coal will increase so that many countries that do not have sufficient natural energy resources to meet their energy needs will import to meet their needs and domestic stability, [1]. In addition, Indonesian coal production is expected to continue to increase, especially to meet domestic needs (power generation and industry) and foreign demand (exports), [2]. The development of coal production for the period 2009-2018 experienced a considerable increase, with production achievements in 2018 of 557 million tons. Of the total production, the export portion of coal reached 357 million tons (63%) and most of them was used to meet the demands of China and India, [3]. Thereby, the high number of Indonesian coal exports makes Indonesia one of the largest coal exporters in the world besides Australia, [4].

On the one hand, domestic coal consumption reached 115 million tons or less than the domestic coal consumption target of 121 million tons, [1]. One of the factors causing the lower realization of coal consumption is the operation of several 35,000 MW Steam Power Plants (PLTU) programs that are not in accordance with the plan and there are several industrial activities that have decreased, [5].

On the other hand, coal companies have a fairly high risk because from the exploration stage to construction they have high uncertainty and very large funds, [6]. Limited company resources and limited access to banks to obtain additional funds are problems faced by many companies, [7]. The capital market provides a solution that can be considered in terms of funding by changing the company's status from a closed company to a public company through an offering of shares to the public (going public). Thus, the company will get funds (capital) to run and develop its business, [8].

Therefore, the development of coal companies' stock prices can reflect the company's management performance in controlling risk which in turn can affect the level of volatility of the company's stock prices and become an indicator for investors in making investment decisions in order to get a high return, [9]. The objective of this study then is to examine the causal relationship of strategic risk of stock returns of coal subsector companies in Indonesia. The novelty of this study is in examining the dynamic relationship of strategic risk caused by the unstable rate of return between coal companies in Indonesia.

2 Literature Review and Hypothesis Development

Corporate risk management has been widely studied, such as research conducted by, [10], which revealed that BASEL III requires banks to mitigate their strategic risks. In this study, two scenarios are offered in terms of strategic risk management control that can be applied in the banking world, which are a comprehensive definition of strategic risk itself, and a framework that uses the cost of equity component to estimate the amount of economic capital needed to mitigate the risk. strategic risk. On the one hand, the framework simulates the bank's net income and uses a Value at Risk (VaR) approach to measure economic capital requirements. The framework can also be used to evaluate the impact of strategic changes in the required economic capital, [11].

On the other hand, [12], in their empirical research found that Vector Autoregressive (VAR) (1) modelling is the best model to be applied in the analysis of the dynamic relationship between Sharia stock prices, sharia stock indexes, and changes in the rupiah exchange rate against foreign currencies. The results of their research also revealed that each variable is only influenced by its respective historical data, and the results of the impulse response function indicated that the response of all variables is difficult to reach the zero point or equilibrium point after a shock to other variables occurs in the short term. The VAR(1) modelling is then used as a model to predict the data for each variable for the next six months which shows the results of the Sharia stock variable data and currency exchange rates moving stable, and the Islamic stock index is predicted to increase significantly.

However, as far as observations, research on strategic risk analyzed using the VAR approach in coal-based companies has not been widely carried out. For this reason, the state-of-the-art research that we are going to do is to provide a causal relationship model of stock returns in the coal subsector in Indonesia in mitigating its strategic risk.

3 Research Methods

The variables analyzed in this study are the daily stock return values of the selected sample of coal subsector companies for the last 5 years from 2017 to 2021. The research sample was taken by purposive sampling method, which was coal subsector companies that have been listed on the Indonesian stock exchange (IDX) during the research period, and from the coal subsector companies listed on the IDX. Samples were from 5 (five) coal subsector companies that have the largest captive market shares. Then stock returns from each research sample were used as input in the analysis of causality between each variable by applying the Vector Autoregressive (VAR) application.

VAR modelling can be done in several stages, as follows:

a) Testing Stationary Data

In analysing time series data, the first thing to check is whether the data is stationary or not. There are two ways of testing stationary data, first visually by looking at the graph of the time series data, and second statistically by testing the Augmented Dickey-Fuller Test (ADF Test) method, [13], with the following equation.

$$DF_{\tau} = \frac{\partial_i}{\widehat{Se}_{\partial_1}}$$

and the hypothesis:

H_0: = 0 (not stationary)

H_1: > 0 (stationary)

The null hypothesis is rejected if it is less than -2.57 or the probability value is less than 5%, [14].

b) Estimation of VAR Modelling

The process of VAR modelling on order p (VAR(p)), can be written mathematically as follows, [15]:

$$\theta_j = \beta + \sum_{k=0}^{p} \gamma_k \theta_{j-k} + \varepsilon_j$$

Where k is 1,2, 3…, p; is the k x k matrix; and can be described as follows, [16].

$$\begin{pmatrix} \theta_{1j} \\ \theta_{2j} \\ \theta_{3j} \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} + \begin{bmatrix} \gamma_{11}^k & \gamma_{12}^k & \gamma_{13}^k \\ \gamma_{21}^k & \gamma_{22}^k & \gamma_{23}^k \\ \gamma_{31}^k & \gamma_{32}^k & \gamma_{33}^k \end{bmatrix} \begin{pmatrix} \theta_{1j-k} \\ \theta_{2j-k} \\ \theta_3 j-k \end{pmatrix} + \varepsilon_j$$

c) Granger Causality Test (GCT)

The following is a bivariate of two variables as an example (Ax and Bx), [17].

$$A_x = C_0 + \sum_{k=1}^{p} C_k A_{j-k} + \sum_{k=1}^{p} D_k B_{j-k} + \varepsilon_{1j}$$

$$B_x = N_0 + \sum_{k=1}^{p} N_k A_{j-k} + \sum_{k=1}^{p} M_k B_{j-k} + \varepsilon_{2j}$$

[18], [19], described a linear model of Granger causality, where if Granger Ax causes Bx, then historical data Ax can predict Bx better than historical data Bx alone.

d) Impulse Response Function (IRF)

Research conducted by [20], [21], measuring unexpected events (shocks) or the effect of non-zero residuals can be studied to see the relationship between variables. This is because the VAR model can translate shocks into variables using a non-zero residual value if only if some structural restrictions have been considered previously. [22], stated that IRF is a function of understanding more deeply the impact of changes in each variable in analysing multivariate time series.

e) Forecasting Stock Return Value Data

The last stage in the VAR(p) model method is to predict stock return value data from each variable over a certain period, where the stock return value of a company is influenced not only by the historical data of the company itself but also can be influenced by the historical data of other companies, taking into account unexpected events during the period of the study, [16].

4 Results and Discussion

The analysis in this study begins with a description. Based on the formulation of the problem in this study, the research sample was determined, namely the state-owned coal subsector company, PT Bukit Asam, Tbk and from a private company, PT Adaro Energy, Tbk. The stock price data of the two companies were obtained from the www.yahoo.finance.com from 2017 to 2021 and from the published annual reports of each company. From the data collection, the return values of each company were calculated which were used as the basis for calculating and analyzing the causal relationship on the strategic risk of stock returns in coal subsector companies in Indonesia.

4.1 Stationary Conditions

Before estimating VAR modelling for PTBA and ADRO stock returns, each observed data series needs to be tested for stationary first. To run this test, we checked visual and statistical tests to get more valid results. Figure 1 shows a graph plotting the data series of each variable. The graph visually explains that the two data series are stationary because the mean and variance are around zero, respectively.

Furthermore, based on the baseline statistical test, we apply the ADF unit-root test whereas, as shown in Figure 2, both data series have a probability value of less than 5% indicating they have a unit-root which is measured as a stationary data set.

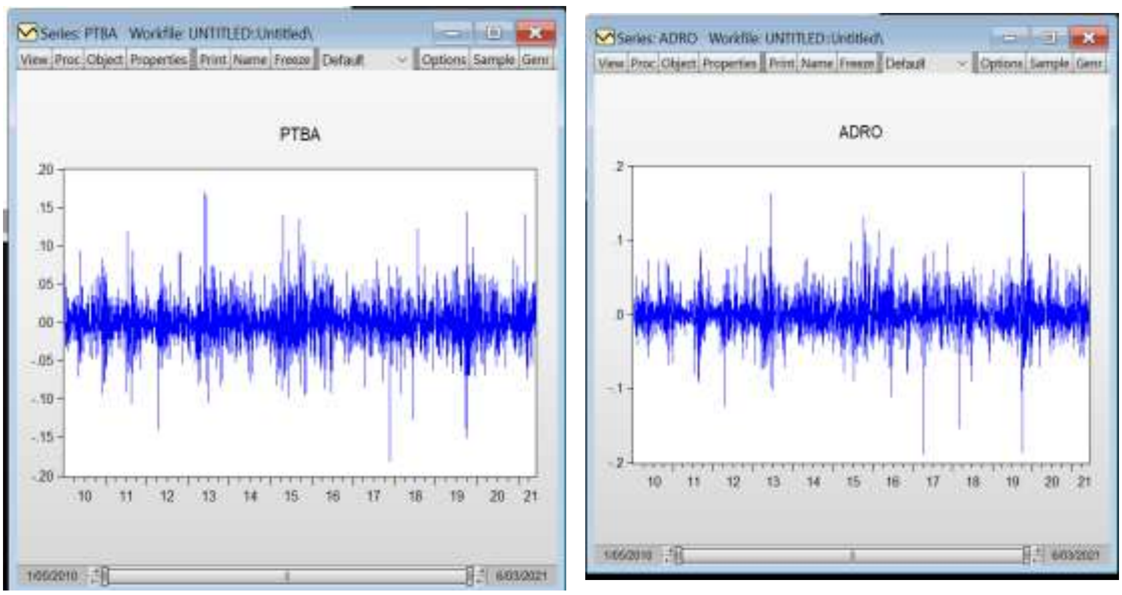


Fig. 1: Distribution of PTBA and ADRO Stock Returns
Source: Processed data (EViews 10)

Augmented Dickey-Fuller Unit Root Test on PTBA

Null Hypothesis: PTBA has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=28)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-54.09454	0.0001
Test critical values:	1% level	-3.432359	
	5% level	-2.862313	
	10% level	-2.567226	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(PTBA)
Method: Least Squares
Date: 09/13/22 Time: 14:43
Sample (adjusted): 1/06/2010 6/03/2021
Included observations: 2974 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PTBA(-1)	-0.992371	0.018345	-54.09454	0.0000
C	0.000272	0.000524	0.519281	0.6036

R-squared	0.496119	Mean dependent var	2.26E-05
Adjusted R-squared	0.495950	S.D. dependent var	0.040249
S.E. of regression	0.028576	Akaike info criterion	-4.271861
Sum squared resid	2.426817	Schwarz criterion	-4.267827
Log likelihood	6354.257	Hannan-Quinn criter.	-4.270409
F-statistic	2926.220	Durbin-Watson stat	1.998888
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on ADRO

Null Hypothesis: ADRO has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=28)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-54.05371	0.0001
Test critical values:	1% level	-3.432359	
	5% level	-2.862313	
	10% level	-2.567226	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ADRO)
Method: Least Squares
Date: 09/13/22 Time: 14:45
Sample (adjusted): 1/06/2010 6/03/2021
Included observations: 2974 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ADRO(-1)	-0.991784	0.018348	-54.05371	0.0000
C	0.000124	0.000483	0.256569	0.7975

R-squared	0.495742	Mean dependent var	-3.92E-07
Adjusted R-squared	0.495572	S.D. dependent var	0.037106
S.E. of regression	0.026354	Akaike info criterion	-4.433710
Sum squared resid	2.064175	Schwarz criterion	-4.429677
Log likelihood	6594.927	Hannan-Quinn criter.	-4.432259
F-statistic	2921.803	Durbin-Watson stat	1.999435
Prob(F-statistic)	0.000000		

Fig. 2: ADF unit-root test of PTBA and ADRO Stock Returns
Source: Processed data (EViews 10)

4.2 Optimal Lag Test

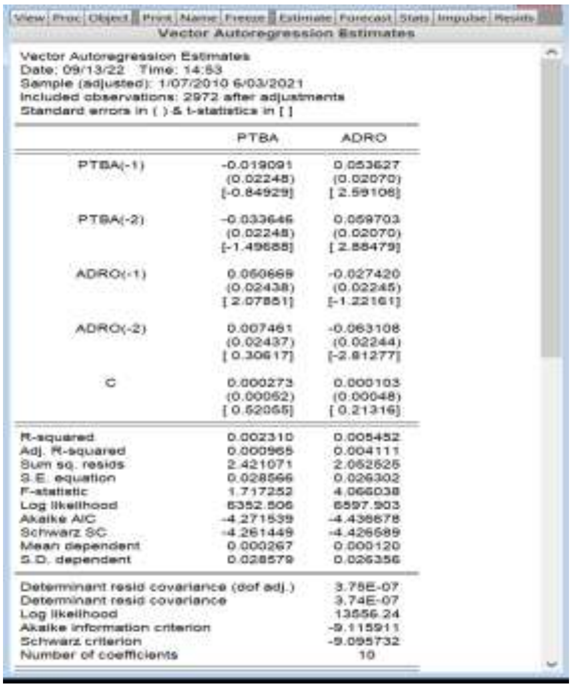
Determining the optimum lag in the VAR model is a necessary initial test because it can explain the dynamics model more accurately for the VAR model. Figure 3 shows the results of the optimal lag test for the estimation of the VAR model. Furthermore, from the VAR Lag Order output, the optimal lag length is then indicated by criteria marked with an asterisk, and in this case, the optimal lag length occurs in lag 2 (shown in Figure 3) because it has the highest number of criteria with asterisks. Then, after getting the optimal lag length in lag 2, the next step is to estimate the VAR lag 2 model, which is as Figure 4.

VAR Lag Order Selection Criteria
Endogenous variables: PTBA ADRO
Exogenous variables: C
Date: 09/13/22 Time: 14:49
Sample: 1/05/2010 6/03/2021
Included observations: 2968

Lag	LogL	LR	FPE	AIC	SC	HQ
0	13521.66	NA	3.79e-07	-9.110282	-9.106242*	-9.108826
1	13530.24	17.14816	3.78e-07	-9.113370	-9.101249	-9.109006
2	13543.09	25.64665*	3.75e-07*	-9.119330*	-9.099129	-9.112060*
3	13545.95	5.716281	3.76e-07	-9.118565	-9.090284	-9.108387
4	13546.98	2.046464	3.77e-07	-9.116561	-9.080200	-9.103475

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Fig. 3: Optimal Lag Testing of Var Model Estimation
Source: Processed data (EViews 10)



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Vector Autoregression Estimates

Vector Autoregression Estimates
Date: 09/13/22 Time: 14:53
Sample (adjusted): 1/07/2010 6/03/2021
Included observations: 2972 after adjustments
Standard errors in ( ) & t-statistics in [ ]

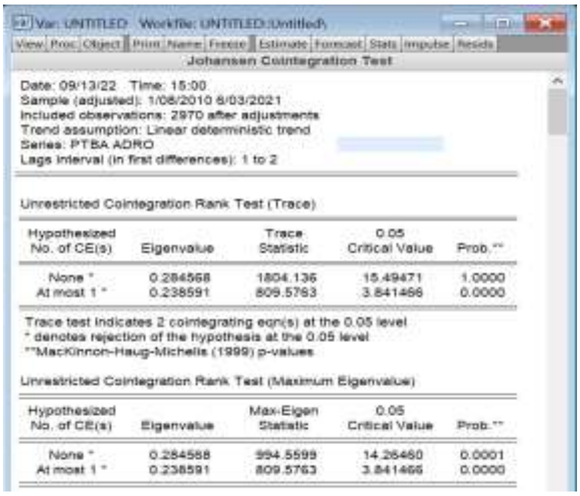
	PTBA	ADRO
PTBA(-1)	-0.019091	0.053627
	(0.02248)	(0.02070)
	[-0.84929]	[2.59106]
PTBA(-2)	-0.033646	0.059703
	(0.02248)	(0.02070)
	[-1.49688]	[2.88479]
ADRO(-1)	0.050669	-0.027420
	(0.02438)	(0.02245)
	[2.07851]	[-1.22161]
ADRO(-2)	0.007461	-0.063108
	(0.02437)	(0.02244)
	[0.30617]	[-2.81277]
C	0.000273	0.000103
	(0.00052)	(0.00048)
	[0.52055]	[0.21316]
R-squared	0.002310	0.005452
Adj. R-squared	0.000965	0.004111
Sum sq. resids	2.421071	2.052525
S.E. equation	0.028566	0.026302
F-statistic	1.717252	4.066038
Log likelihood	6352.506	6597.903
Akaike AIC	-4.271539	-4.436678
Schwarz SC	-4.261449	-4.426589
Mean dependent	0.000267	0.000120
S.D. dependent	0.028579	0.026356

Determinant resid covariance (dof adj.)	3.75E-07
Determinant resid covariance	3.74E-07
Log likelihood	13556.24
Akaike information criterion	-9.115911
Schwarz criterion	-9.095732
Number of coefficients	10

Fig. 4: Results of VAR Lag 2 Model Estimation
Source: Processed data (EViews 10)

4.3 Cointegration Test

After getting the optimal lag on the VAR model, the next step is to perform a cointegration test on the VAR model estimation. The criteria for the VAR model to pass the cointegration test can be seen in the Prob** value, if it is less than 0.05 then the VAR model passes the cointegration test. The following are the results of the cointegration test for the estimation of the VAR model which has a probability value of less than 0.05, as shown in Figure 5.



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Johansen Cointegration Test

Date: 09/13/22 Time: 15:00
Sample (adjusted): 1/08/2010 6/03/2021
Included observations: 2970 after adjustments
Trend assumption: Linear deterministic trend
Series: PTBA ADRO
Lags interval (in first differences): 1 to 2

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.284568	1804.136	15.49471	1.0000
At most 1 *	0.238591	809.5763	3.841466	0.0000

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.284568	994.5599	14.26460	0.0001
At most 1 *	0.238591	809.5763	3.841466	0.0000

Fig. 5: Johansen Cointegration Test Output
Source: Processed data (EViews 10)

4.4 VAR Model Estimation

The optimal lag value is 2, it can be said that the VAR model estimation is the VAR(2) model. The following is the estimation result of the VAR(2) model for PTBA and ADRO stock returns, as shown in Table 1, and Table 2.

Table 1. Output Estimated Model VAR(2) for the dependent variable PTBA

Dependent Variable: PTBA
Method: Least Squares
Date: 09/13/22 Time: 15:06
Sample (adjusted): 1/07/2010 6/03/2021
Included observations: 2972 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000273	0.000524	0.520554	0.6027
PTBA(-1)	-0.019091	0.022478	-0.849290	0.3958
PTBA(-2)	-0.033646	0.022477	-1.496879	0.1345
ADRO(-1)	0.050669	0.024377	2.078513	0.0377
ADRO(-2)	0.007461	0.024367	0.306168	0.7595

R-squared	0.002310	Mean dependent var	0.000267
Adjusted R-squared	0.000965	S.D. dependent var	0.028579
S.E. of regression	0.028566	Akaike info criterion	-4.271539
Sum squared resid	2.421071	Schwarz criterion	-4.261449
Log likelihood	6352.506	Hannan-Quinn criter.	-4.267908
F-statistic	1.717252	Durbin-Watson stat	1.996560
Prob(F-statistic)	0.143286		

Table 2. Output Estimated Model VAR(2) for the dependent variable ADRO

Dependent Variable: ADRO
Method: Least Squares
Date: 09/13/22 Time: 15:10
Sample (adjusted): 1/07/2010 6/03/2021
Included observations: 2972 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000103	0.000482	0.213163	0.8312
PTBA(-1)	0.053627	0.020697	2.591063	0.0096
PTBA(-2)	0.059703	0.020696	2.884790	0.0039
ADRO(-1)	-0.027420	0.022445	-1.221614	0.2220
ADRO(-2)	-0.063108	0.022436	-2.812768	0.0049

R-squared	0.005452	Mean dependent var	0.000120
Adjusted R-squared	0.004111	S.D. dependent var	0.026356
S.E. of regression	0.026302	Akaike info criterion	-4.436678
Sum squared resid	2.052525	Schwarz criterion	-4.426589
Log likelihood	6597.903	Hannan-Quinn criter.	-4.433047
F-statistic	4.066038	Durbin-Watson stat	2.001770
Prob(F-statistic)	0.002731		

In the estimation output of the VAR(2) model for the dependent variables PTBA and ADRO, it can be seen that not all order lags have a significant coefficient, so the VAR(2) model for the dependent variable PTBA becomes:

PTBA = 0.000273 + 0.050669*ADRO(-1)

For the VAR(2) model, the dependent variable ADRO is:

ADRO = 0.000103 + 0.053627*PTBA(-1) + 0.059703*PTBA(-2) – 0.063108*ADRO(-2)

From the VAR model equation above, it can be concluded that PTBA stock returns are significantly affected only by stock returns ADRO first lag. Meanwhile, for the ADRO variable, the VAR(2) model shows that ADRO stock returns are significantly affected by PTBA stock returns in the first and second lag and ADRO stock returns in the second lag.

4.4 Granger Causality

The hypothesis of the Granger causality test is to test whether the correlation value of a variable is only influenced by itself and not by the historical value of other variables. The following are the results of the Granger causality test from the VAR(2) model, as shown in Table 3.

Table 3. Granger Causality Test Statistics Model VAR(2)

Pairwise Granger Causality Tests
Date: 09/13/22 Time: 15:26
Sample: 1/05/2010 6/03/2021
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
ADRO does not Granger Cause PTBA	2972	2.18100	0.1131
PTBA does not Granger Cause ADRO		7.16395	0.0008

From the output of Granger Causality Tests Model VAR(2) above, it can be concluded that the PTBA variable with a probability value of more than 0.05 PTBA return value variable is not influenced by itself and is influenced by historical data of other variables. Meanwhile, for the ADRO stock return value variable with a probability value less than 0.05, it can be said that ADRO's stock return is influenced by its own historical data as well as the historical data of other variables.

4.5 Forecasting Stock Return Value

The next step is to forecast the stock return value from the estimated VAR(2) model. The following graphs presented at Figure 6 illustrate the projected stock return value of each variable.

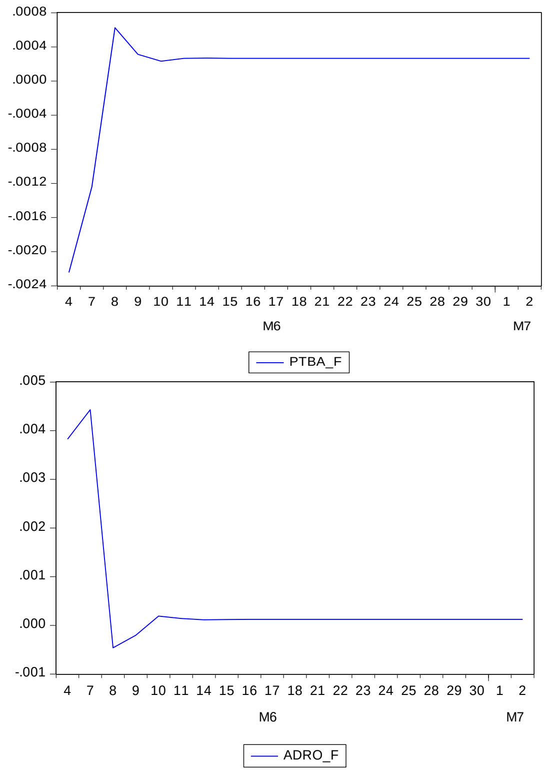

Fig. 6: Forecasting of PTBA and ADRO Stock Returns for the Next One Month

5 Conclusion

This study aims to examine more deeply the implementation of strategic risk control which is described by the stock returns of the coal production subsector for each group of companies. This is achieved by looking at the dynamic relationship with the VAR model approach. We emphasize on how the rate of return from one company is influenced by the rate of return from each company, thus, it can be used as a reference in future planning of strategic risk. From the results of this study, the most suitable model used to describe the relationship is the VAR(2) model. Analytically, the VAR(2) model can be applied to predict the behaviour of each variable over the next 30 days. On the one hand, it is worth mentioning that before doing our forecasting analysis, the model was tested for the univariate model using the Granger causality. Based on the univariate model, our model shows significant enhancements with a probability value of less than zero. On the other hand, Granger causality explains that each variable does not only affect itself but is also influenced by other variables. Finally, the forecasting model is very well fitted where the prediction line closely matches the actual data plot, which indicates that the VAR(2) model is the most suitable model used for forecasting.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Ayi Ahadiat was the main conceptor of the study and conducting analysis on discussion part.
Ribhan was responsible for writing introduction and literature reviews.
Fitra Dharma and Fajrin Satria Dwi Kesumah carried out collecting and analysis data.

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Conflict of Interest

The authors have no conflict of interest to declare.