Implementation of the Vector Autoregressive (VAR) Model in Electricity Supplier Companies

RR ERLINA¹, AYI AHADIAT¹, RIALDI AZHAR², LUTHFI FIRDAUS¹, TOTO GUNARTO³
¹Department of Management, University of Lampung, Bandar Lampung, INDONESIA
²Department of Accounting, University of Lampung, Bandar Lampung, INDONESIA
³Department of Economics Development, University of Lampung, Bandar Lampung, INDONESIA

Abstract: - The government's policy regarding setting special prices for coal as fuel for power plants is a dilemma for investors because if the policy is implemented there is a possibility that it will affect the company's profitability and impact the company's share price. Scientific forecasting of a company's future based on share price volatility with various considerations including political, social and economic aspects of the country are things that must be taken into account when making decisions. The method that will be used in this research is quantitative descriptive through the application of the VAR model to be able to describe the causal relationship between variables. The result is a VAR model for each variable that is used as a forecasting model for the daily share price volatility of companies supplying coal to PLN, so that investors can make strategic steps in investing.

Key-Words: - VAR Model, Energy Supplier, Daily Stock Volatility, Coal, Investment.

Received: April 19, 2023. Revised: April 25, 2024. Accepted: May 21, 2024. Published: June 24, 2024.

1 Introduction

The capital market is basically a market that is no different from markets in general, namely that there are sellers, buyers and price negotiations. The capital market is one way for companies to obtain additional funds to finance operational activities (Tandelilin, 2010: 26). The capital market must also facilitate capital investment by investors. Investment is a commitment to various funds or other resources carried out currently with the aim of achieving multiple profits in the future (Tandelilin, 2010: 3). Investing involves the decision to allocate a certain amount of money at a certain time and in the hope of getting a higher return in the future.

Investors in the capital market are very interested in investing their capital in the mining sector. The Investment Coordinating Board (BKPM) noted that investment realization funds for the basic metal industry sector, metal goods, non-machinery and equipment dominated the investment realization achievement for the third quarter of 2022, namely IDR 44.0 trillion. The coal mining sub-sector is of interest to researchers because it departs from government policy regarding setting special prices for coal used as generating fuel.

Furthermore, the main problem in investment activities in the coal mining sector is that investors are very interested in owning shares in PT Adaro Energy Tbk (ADRO), PT Indo Tambangraya Megah Tbk (ITMG), PT Indika Energy Tbk (INDY), and PT Bukit Asam Tbk (PTBA). Investor interest can be seen from the growth in market capitalization of these four shares, which can provide opportunities for investors to make a profit. However, the government's policy regarding setting a special price for coal as fuel for power plants is a dilemma for investors because if the policy is implemented there is a possibility that it will affect the company's profitability and impact the company's share price. Scientific forecasting of a company's future based on share price volatility with various considerations including political, social and economic aspects of the country are things that must be taken into account when making decisions.

There are several approaches to economic forecasting based on time series data according to Gujarati (2012:472-473). The five methods are Exponential Smoothing Method, Single-Equation Regression Method, Simultaneous-Equation Regression Model, Autoregressive Integrated Moving Average (ARIMA) Model, and Vector Autoregression. Researchers focus on time series data on stock price volatility because it is in accordance with the method used which requires more than one variable to be used. Apart from that, researchers chose the VAR model because it can test reciprocal relationships between variables because time series data variables will not only be influenced
by their own past data, but also past data from other variables that have a relationship.

Therefore, analysis of the reciprocal relationship between daily share price volatility of coal producing companies as suppliers of energy raw materials for the State Electricity Company (PLN) is important to carry out because it can be a reference in making decisions for investors who are interested in investing in PLN raw material supply companies. Analysis of the reciprocal relationship between these variables can be carried out using the Vector Autoregressive (VAR) model application.

2 Literature Review

When working with time series data, the initial step is to assess its stationarity. This involves two distinct methods for testing stationarity: firstly, a visual inspection of the time series data plot, and secondly, a statistical examination using the Augmented Dickey-Fuller Test (ADF Test), as outlined by P. Brockwell and Davis in 2002. The ADF Test employs a specific formula for this purpose.

\[
DF_t = \frac{\partial_i}{S\varepsilon_i}
\]

The hypothesis is defined as. H0: \(DF_t > 2.57 =\) non-stationary H0: \(DF_t < 2.57 =\) stationary.

Estimating a VAR (Vector Autoregressive) model with order p (VAR(p)) involves a mathematical representation as shown below.

\[
\begin{align*}
\theta_j &= \beta + \sum_{k=0}^{p} \gamma_k \theta_{j-k} + \epsilon_j \\
(\theta_{1j}) &= (\beta_1, \gamma_{11}^k, \gamma_{12}^k, \gamma_{13}^k) (\theta_{1j-k}) \\
(\theta_{2j}) &= (\beta_2, \gamma_{21}^k, \gamma_{22}^k, \gamma_{23}^k) (\theta_{2j-k}) \\
(\theta_{3j}) &= (\beta_3, \gamma_{31}^k, \gamma_{32}^k, \gamma_{33}^k) (\theta_{3j-k}) + \epsilon_j
\end{align*}
\]

Where k is 1,2,3,...,p; \(\gamma_k\) is the k x k matrix; and can be explained further below. The following is a bivariate VAR modeling of two variables as an example (\(A_x\) and \(B_x\)).

\[
A_x = C_0 + \sum_{k=1}^{p} C_k A_{j-k} + \sum_{k=1}^{p} D_k B_{j-k} + \epsilon_{1j}
\]

\[
B_x = N_0 + \sum_{k=1}^{p} N_k A_{j-k} + \sum_{k=1}^{p} M_k B_{j-k} + \epsilon_{2j}
\]

(Umpusinga et al., 2020) describes a linear model of Granger causality, where if Granger \(A_x\) causes \(B_x\), then historical data \(A_x\) can predict \(B_x\) better than just historical data \(B_x\) itself.

3 Result and Discussion

3.1 Stationarity

Stationarity in the context of a Vector Autoregression (VAR) model refers to a condition in which all variables in the model exhibit constant basic statistics over time. This is crucial because if the variables in a VAR are not stationary, the analysis and interpretation of the results become challenging and unreliable.

Table 1. Stationarity Test of Daily Stock Prices for PT PLN (Persero) Supplier Companies

<table>
<thead>
<tr>
<th>Method</th>
<th>Statistic</th>
<th>Prob.**</th>
<th>Cross-sections</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null: Unit root (assumes common unit root process)</td>
<td>Levin, Lin &amp; Chu t*</td>
<td>3.41495</td>
<td>0.9997</td>
<td>4</td>
</tr>
<tr>
<td>Null: Unit root (assumes individual unit root process)</td>
<td>Im, Pesaran and Shin W-stat</td>
<td>3.22541</td>
<td>0.9994</td>
<td>4</td>
</tr>
<tr>
<td>ADF - Fisher Chi-square</td>
<td>1.60507</td>
<td>0.9908</td>
<td>4</td>
<td>5208</td>
</tr>
<tr>
<td>PP - Fisher Chi-square</td>
<td>1.74190</td>
<td>0.9879</td>
<td>4</td>
<td>5208</td>
</tr>
</tbody>
</table>

Since in Table 1, the p-values of the unit root test are greater than 0.05, it can be concluded that the daily stock price data of the supplier companies of PT PLN is non-stationary. Therefore, it is necessary to perform data transformation or use differencing (calculating changes over time) to make it stationary before constructing a VAR model.

Table 2. Stationarity Test of Daily Stock Prices for PT PLN (Persero) Supplier Companies (After Differencing)

<table>
<thead>
<tr>
<th>Method</th>
<th>Statistic</th>
<th>Prob.**</th>
<th>Cross-sections</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null: Unit root (assumes common unit root process)</td>
<td>Levin, Lin &amp; Chu t*</td>
<td>93.3754</td>
<td>0.0000</td>
<td>4</td>
</tr>
<tr>
<td>Null: Unit root (assumes individual unit root process)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Rr Erlina, Ayi Ahadiat, Rialdi Azhar, Luthfi Firdaus, Toto Gunarto

E-ISSN: 2945-1140

Volume 2, 2024
Table 3. indicates that the optimal lag occurs at lag 3. Hence, the next step can be initiated, which is the construction of the VAR model.

### 3.2 VAR Model Estimation

<table>
<thead>
<tr>
<th>La</th>
<th>LogL</th>
<th>LR</th>
<th>FPE</th>
<th>AIC</th>
<th>SC</th>
<th>HQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>.65</td>
<td>NA</td>
<td>14</td>
<td>86</td>
<td>82*</td>
<td>85*</td>
</tr>
<tr>
<td>1</td>
<td>.27</td>
<td>58</td>
<td>14</td>
<td>82</td>
<td>66</td>
<td>78</td>
</tr>
<tr>
<td>2</td>
<td>.08</td>
<td>41*</td>
<td>14*</td>
<td>99*</td>
<td>69</td>
<td>92</td>
</tr>
<tr>
<td>3</td>
<td>.39</td>
<td>66</td>
<td>14</td>
<td>28</td>
<td>85</td>
<td>18</td>
</tr>
<tr>
<td>4</td>
<td>.33</td>
<td>64</td>
<td>14</td>
<td>47</td>
<td>92</td>
<td>34</td>
</tr>
</tbody>
</table>

Table 3. indicates that the optimal lag occurs at lag 2, as it exhibits the most favorable criteria, as evidenced by the asterisks in the LR, FPE, and AIC criteria. Therefore, the VAR model (2) can be estimated in the next step to determine the best model. The estimation of the VAR (2) model is as follows:

### Table 4. Estimation of the VAR(2) Model

| D(ADRO(-2)) | 0.021804 | -0.040136 & -0.073418 & 0.022533 |
|-------------|----------|------------------|------------------|------------------|
| D(INDY(-1)) | 0.042730 & -0.011498 & 0.405325 & 0.034862 |
| D(ITMG(-1)) | -0.002680 & 0.008945 & -0.014322 & -0.002539 |
| D(PTBA(-1)) | 0.015180 & -0.017423 & -0.126878 & -0.080182 |
| D(PTBA(-2)) | -0.111913 & -0.136394 & -0.825543 & -0.122793 |
| C           | 1.814035 & -0.035869 & 18.07309 & 1.312876 |

In Table 4. it is evident that there are non-significant parameters. As Tsay (2005) explains, to address this issue, it suffices to eliminate the non-significant ones to improve the model. Thus, the VAR(2) model can be formulated as follows:

1. \( D(ADRO(-1)) = 1.814035 - 0.067019 \times D(ADRO(-1)) + 0.064932 \times D(INDY(-2)) - 0.111913 \times D(PTBA(-2)) \)
2. \[ D(\text{INDY}) = -0.035869 + 0.012991 \times D(\text{ADRO}(-1)) + 0.015501 \times D(\text{ITMG}(-2)) - 0.136394 \times D(\text{PTBA}(-2)) \]

3. \[ D(\text{ITMG}) = 18.07309 + 0.405325 \times D(\text{INDY}(-1)) - 0.825543 \times D(\text{PTBA}(-2)) \]

4. \[ D(\text{PTBA}) = 1.312876 + 0.044528 \times D(\text{ADRO}(-1)) + 0.082782 \times D(\text{INDY}(-2)) - 0.080182 \times D(\text{PTBA}(-1)) - 0.122793 \times D(\text{PTBA}(-2)) \]

3.3. Granger Causality Test

The Granger Causality Test plays a significant role in analyzing the daily stock prices of coal supplier companies in Indonesia. Its primary purpose is to determine if there exists a causal relationship between various variables within the VAR model used for this study. In this research context, the Granger Causality test will help assess whether specific variables can act as indicators influencing the stock prices of coal supplier companies or vice versa.

<table>
<thead>
<tr>
<th>Null Hypothesis:</th>
<th>Obs</th>
<th>F-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>INDY does not Granger Cause ADRO</td>
<td>1300</td>
<td>1.61443</td>
<td>0.1994</td>
</tr>
<tr>
<td>ADRO does not Granger Cause INDY</td>
<td></td>
<td>1.22448</td>
<td>0.2943</td>
</tr>
<tr>
<td>ITMG does not Granger Cause ADRO</td>
<td>1300</td>
<td>0.31393</td>
<td>0.7306</td>
</tr>
<tr>
<td>ADRO does not Granger Cause ITMG</td>
<td></td>
<td>2.39795</td>
<td>0.0913</td>
</tr>
<tr>
<td>PTBA does not Granger Cause ADRO</td>
<td>1300</td>
<td>1.02319</td>
<td>0.3597</td>
</tr>
<tr>
<td>ADRO does not Granger Cause PTBA</td>
<td></td>
<td>3.76080</td>
<td>0.0235</td>
</tr>
<tr>
<td>ITMG does not Granger Cause INDY</td>
<td>1300</td>
<td>2.09101</td>
<td>0.1240</td>
</tr>
<tr>
<td>INDY does not Granger Cause ITMG</td>
<td></td>
<td>1.71339</td>
<td>0.1807</td>
</tr>
<tr>
<td>PTBA does not Granger Cause INDY</td>
<td>1300</td>
<td>0.13329</td>
<td>0.8752</td>
</tr>
<tr>
<td>INDY does not Granger Cause PTBA</td>
<td></td>
<td>4.18698</td>
<td>0.0154</td>
</tr>
<tr>
<td>PTBA does not Granger Cause ITMG</td>
<td>1300</td>
<td>0.46675</td>
<td>0.6271</td>
</tr>
<tr>
<td>ITMG does not Granger Cause</td>
<td></td>
<td>3.75272</td>
<td>0.0237</td>
</tr>
</tbody>
</table>

4 Conclusion

Complex Interconnections: This study emphasizes the intricate nature of the relationship between the stock prices of coal supplier companies and various influencing factors. The analysis using VAR reveals that stock price fluctuations are influenced not only by internal company factors but also by external variables such as coal commodity prices, global market conditions, and other economic factors. Association with Coal Prices: The results of the Granger Causality test indicate a cause-and-effect association between coal commodity prices and the stock prices of coal supplier companies. This suggests that fluctuations in coal prices can have a significant impact on these companies' stock prices. Implications for Decision-Makers: The outcomes of this research carry significant implications for investors, financial managers of coal supplier companies, and capital market regulators in Indonesia. Investors can apply this knowledge to enhance portfolio risk management, while financial managers can devise more effective business strategies by considering external factors that influence stock prices. Capital market regulators can also use these findings to formulate improved policies aimed at upholding stock market stability.

Acknowledgement:
The authors wish to extend their thanks to the Financial Exchange for their willingness to furnish the data for this study. Furthermore, they appreciate the University of Lampung for its institutional funding support, which has made this research possible.

References:


https://doi.org/10.1177/04866134902100308


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

Rr Erlina and Ayi Ahadiat, carried out the concept of the study. Toto Gunarto and Rialdi Azhar, collected and run the data analysis. Luthfi Firdaus, was responsible for the Statistics.

Alternatively, the following text will be published:

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.
Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

The authors also wish to express their gratitude to the University of Lampung for providing institutional funding, which has enabled the research to be conducted.

Conflict of Interest

The authors have no conflict of interest to declare.

Creative Commons Attribution License 4.0 (Attribution 4.0 International, CC BY 4.0)
This article is published under the terms of the Creative Commons Attribution License 4.0
https://creativecommons.org/licenses/by/4.0/deed.en_US