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Strategic Decision-Making on Mining Sector Company Stock Prices and Economic Variable (State Space Model Application)

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ABSTRACT

Energy sector is not excluded from the recession in global economics. However, one can be stable during such outbreak was gold prices which showed incredible stable prices and relatively increasing. That also affected on daily stock prices for the gold producing companies such as PT Aneka Tambang (issuer code: ANTM) that showed conversely increasing than other mining sector companies. This study aims to investigate causal relationships between ANTM stock prices and Indonesian exchange rates in order to have strategic decision-making for investors by employing State Space model and to provide forecasting daily data for both variables. The study found that the State Space model confirmed their dynamic relationship, in which ANTM was not only affected by itself but also by the movement of exchange rates. The forecasting graphs then provide the insight of strategic decision-making for investors to strongly invest on gold-based company as they have an increasing projection for the next 20 days.

Keywords: State Space Model, Strategic Decision-Making, Mining Sector, Gold-based Company, Exchange Rates
JEL Classifications: C1, C3, G17, Q4, Q47

1. INTRODUCTION

The world economy has suffered heavy losses due to the Covid-19 pandemic and the energy sector is no exception (Ganie et al., 2022). Concerns arising from the energy sector include declining global demand for oil and gas, due to travel restrictions and reductions in economic activity which have led to reduced demand for transportation and industry (Indupurnahayu et al., 2021), and have caused oil and gas prices to decline significantly. In addition, there are concerns about the long-term impact of the pandemic on investment in new and renewable energy, which could hamper the global transition towards a green environment (Kuzemko et al., 2020). On the other hand, one of sub-sector from the energy sector, which is classified as a commodity sub-sector, particularly gold, has experienced an increase during the Covid-19 pandemic because gold is considered stable as a haven asset in value in situations of economic uncertainty (Akhtaruzzaman et al., 2021; Baur and McDermott, 2016). Likewise, the movement of the stock price of a gold commodity producing company in Indonesia, PT Aneka Tambang (Emitent Code: ANTM), which tends to be stable during the Covid-19 pandemic (Adiningsih and Azib, 2021).

On the other hand, there are possible economic concerns arising after the pandemic including inflation growth, exchange rate and interest rate increases, which could reduce the demand for gold as a safe investment (Mensi et al., 2021). In addition, if the economy begins to recover and improve, investors may be more interested in investing in equities or other assets that are expected to provide higher returns than gold (Akkoc and Civcir, 2019). The decline in gold prices is likely to have an impact on gold producers' stock prices, so it is necessary to investigate more deeply the causal relationship of stock price volatility with macroeconomic determinants, such as exchange rates, inflation, and interest rates. Previous studies like Azhar et al. (2022) explained that the time series data of a variable can be influenced by the movement of the data itself from its past or have a reciprocal relationship from other data. Then, Hendrawaty et al. (2022) examined the level of economic growth on energy consumption in ASEAN countries.

This study aims to ensure that the energy variable represented by the daily stock price of the gold commodity sub-sector of mining companies does not stand alone but is supported by variables from the macroeconomic fundamental structure which consists of various types, one of which is the exchange rate, by applying the State Space model. This model can explain multivariate variables which have other additional variables, and some of which may not be directly observable. These additional variables can then be referred to as vectors. Variables and vectors can summarize information from the relevant current and past time series and then make predictions that describe the future (Akaike, 1970).

This study contributes to adding to the literature in the study of stock price forecasting studies which is useful for investors as strategic decision-making in considering their investment portfolios, especially investments in gold commodities and gold producing companies in Indonesia. As authors' observations, the implementation of the State Space model on the multivariate analysis of daily stock price models and macroeconomic variables in Indonesia is apparently a new thing, so that it can be a novel reference for recommendations for other researchers and investors.

2. LITERATURE REVIEW

The Covid-19 pandemic that has occurred in recent years has had a broad impact on various sectors, including the energy sector as one of the vital sectors for human life. Previous studies such as Jiang et al. (2021) revealed that energy demand in general has decreased, so special policies are needed to seize opportunities for post-pandemic energy recovery. One example of an adaptive policy related to the energy sector during the Covid-19 pandemic was carried out by the government of the State of Kuwait through research conducted by Hamad et al. (2020). This study resulted in an economic and environmental model that was developed to be able to save the use of electricity and fuel energy which can reduce pollutant emissions released into the atmosphere. Furthermore, Szczygielski et al. (2022) claimed that the Covid-19 pandemic has caused a higher level of uncertainty in most of the national energy sector, where this level of uncertainty was measured through *Google Search Trends* which can quantify searches related to the pandemic.

However, there are energy commodities that tend to be stable during times of crisis. Akhtaruzzaman et al. (2021) examined the role of gold as an investment hedge amidst a weakening global economy. This study found that investment in gold is a safe haven asset investment during phase 1 of Covid-19 (December 2019–March 2020), so that investors can make gold investment a flight-to-safety asset during a crisis. Investments in gold as safe-haven assets have also been disclosed before the Covid-19 pandemic occurred. Baur and McDermott (2016) found the reason why gold is considered a safe-haven asset even though it is riskier than investment in US government bonds (US Treasury bills), because gold has unique features and biased behaviour of investors who still perceive gold as a foreign currency in the past. This is reinforced by research conducted by Salisu et al. (2021) which confirmed investing in gold as a safe-haven asset compared to investing in stocks in the United States during the economic crisis, even though the level of effectiveness is not as good as before the pandemic hit the world. However, the global economic recovery is likely to increase the risk level of gold investment and cannot be used as a safe-haven asset for volatility risks (Akkoc and Civcir, 2019).

Furthermore, Ganie et al., (2022) described the impact of Covid-19 on the stock market of 6 countries with the largest total victims infected with Covid-19. By applying different sub-periods in each country to identify the most volatile periods, the results of this study show that the Brazilian stock market experienced the largest decline almost 50% and the Mexican stock market index experienced the lowest decline among the six countries around 30% during the pandemic period. Study conducted by Mensi et al. (2021) also showed that there were significant price changes to the US and Chinese stock markets due to the pandemic using the Markov-switching vector autoregressive model approach. On the other hand, a study conducted by Godil et al. (2020) revealed differences in the behaviour of the Islamic stock market compared to the conventional stock market in the long term and it recommends as an alternative for investors in making investment decisions.

Many previous studies have been widely done on causality between variables (Abdullah et al., 2016; Acaravci and Ozturk, 2010; Dewi et al., 2018; Duarte et al., 2017; Iwata et al., 2010; Jiranyakul, 2013). More specifically (Mccarthy and Najand, 1993), tested the dynamic relationship between currency futures trading volume and price changes by applying the state space model. The results of this study indicated that the state space model is able to predict the direction of the relationship between variables which can be used as the best illustration in making future observations. Then the latest research related to the application of the state space model was carried out by (Azhar et al., 2022) who examined the dynamic relationship between gas and carbon prices by applying the state space model approach. The results of this study indicated that the state space model can explain more deeply the relationship between gas and carbon prices which can then be used as a predictor of future prices as one way to have strategic decision making on investment. Therefore, this study will examine the multivariable relationship between stock prices of gold producing companies and the rupiah exchange rate variable by applying a state space model approach to be able to provide a more comprehensive description and prediction of the direction of the relationship between the two variables.

3. METHODS

3.1. State Space Model Representation of Dynamic Linear Systems

Kalman (1960) for the first time introduced a state-space model that is enabled to model and predict multiple time series data interconnected and interact dynamically. State Space models describe the multivariate through additional variables (state vectors), which consist of summarizing all the information about the past and present values of the time series, which is important for predicting future values (Chuang and Wei, 1991; Durbin and Koopman, 2013). The dynamic relationship between multivariate variables has been widely disclosed and tested in explaining the shape of time series data. The equations that make up this model can be appreciated by considering first-order autoregression. The state space represents the stochastic process from a stationary state and is defined as the state transition equation (Wei, 2006) with the input equation as follows.

$$z_{t+1} = Fz_t + Ge_{t+1} \quad (1)$$

$$t = 1,2,\ldots T \quad (2)$$

and output equation:

$$x_t = Hz_t \; or \; x_t = \left[I_r, 0\right] z_t \quad (3)$$

Where x is observation vector with dimension r × 1; z_t is a state vector with dimension s × 1 and s - r is the last element required for forecasting x_t future; F is a coefficient matrix of size s - s called the transition matrix, which determines the dynamic properties of the model; G is a coefficient matrix of size s × r called the input matrix, which determines the variance structure of the transition equation for model identification, the r rows and G columns are set into an identity matrix (I_r) of size r × r; H is a coefficient matrix measuring r × s, called the observation matrix; and e_i is a random residual vector, which is normally distributed with dimension r with mean 0 and covariance matrix e - e.

Then, the next stage is to determine the criteria for selecting the best model using the Information Criteria through the Akaike Information Criterion (AIC) approach which was first introduced by Akaike (1970) and the criterion for the best model is the model with the smallest AIC value.

3.2. Canonical Correlation Analysis

In the univariate case, the types of correlation commonly tested are simple, partial, and multiple correlations. Meanwhile, for multivariate variables, correlation analysis is better known as canonical correlation analysis. Canonical correlation analysis is used concurrently to identify and quantify the relationship between two sets of variables. Canonical correlation analysis is not as simple as partial and multiple correlations, so that in canonical correlation analysis, the correlation between independent and dependent clusters is not just the correlation between independent and dependent variables (Tsay, 2014).

The state vector elements were determined using canonical correlation analysis of the sample set of the auto covariance matrix. Lutkepohl (2013) stated that in the state space model, variables that are significantly correlated are included in the state vector, but variables that are not significant are excluded. Furthermore, Chuang and Wei (1991) claimed that the state vector is uniquely determined by canonical correlation analysis between sets of values from current and past observations (x_n, x_{n-1}, x_{np}) and the set of current observed values and future events (x_n, $x_{n+1|n}$, $x_{n+p|n}$), where P_n is a vector of the approximate value of x_{n+1} current and past of the predictor space f_n=(x_n, $x_{n+1|n}$, $x_{n+p|n}$) and f_n is a vector of current and future events. In canonical correlation analysis, submatrices are determined from covariance matrices based on block Hankel matrices as follows.

$$\Gamma = \begin{matrix} \Gamma(0) & \Gamma(1) & \Gamma(2) & \Gamma(\rho) \\ \Gamma(1) & \Gamma(2) & \Gamma(3) & \Gamma(\rho+1) \\ \vdots & \vdots & \vdots & \vdots \\ \Gamma(\rho) & \Gamma(\rho+1) & \Gamma(\rho+2) & \Gamma(2\rho) \end{matrix}$$

The components of the prediction vector $x_{n+i|n}$ allow non-independent linear relationships. Therefore, a canonical correlation analysis is performed for all components of the data space.

$$P_n = \left[x_{1,n}, x_{r,n}, x_{1,n-1}, x_{r,n-1}, x_{1,np}, \ldots x_{r,np}\right]$$

and the components of the predictor space is as follows.

$$f_n = \left[x_{1,n}, x_{r,n}, x_{1,n+1|n}, x_{r,n+1|n}, x_{1,n+p|n}, \ldots x_{r,n+p|n}\right]$$

Canonical correlation analysis will then form a series state vector of z_n^j, and to be able to calculate canonical correlation values needs a sequence f_n^j of subvectors f_n, tested to form a submatrix with the rows and columns corresponding to component f_n^j. The minimum canonical correlation is then used for state vector selection (Chuang and Wei, 1991).

3.3. Selection of State Vector Components

To choose a state vector component, the thing to note is when there are no more elements from f_n added and removed from the state vector and determining the significance of the canonical correlation by selecting the smallest canonical correlation value (Hair et al., 2014). Then to test the significance level of canonical correlation can be done by applying the Chi-squared test approach with the following hypothesis:

$H_0 = 0$; $H_1 \neq 0$; if $X_{hit}^2 > X_{(db)}^2$, then H_0 is rejected which means canonical correlation is significant.

The further stage is to estimate the parameters once state space model determined. This procedure is performed iteratively, and estimates are obtained from canonical analysis and used to obtain efficient estimates of F and G. This estimation process requires that one element of F and G have a constant value (e.g., 0 or 1).

3.4. Kalman Filtering

Kalman Filter is a series of mathematical calculation techniques (algorithms) that provide efficient calculations in estimating process state by minimizing the average squared error (Mean Squared Error/MSE) (Kalman, 1960). Discrete Kalman filters are used in a system with discrete time, meaning that the distance between times is the same (constant). Filters are very useful in several aspects, being able to estimate past, present and future states. In Kalman Filter, Filter is assumed as a good tool to separate signals from other unwanted signals. In fact, the measurement results are inaccurate or contain unwanted signals (noise), so by using a filter against them, the measurement results will be close to the actual results (Aoki and Havenner, 1991).

4. RESULTS AND DISCUSSION

The data in this study are the daily stock prices of mining companies whose core business is in gold production and are listed on the Indonesian stock exchange, namely PT Aneka Tambang (issuer code: ANTM). The dynamic relationship will be tested with one of the macroeconomic variables of the exchange rate of rupiah against the US dollar. Time series data collection was carried out in the last 3 years from January 2020 to December 2022 which was taken secondary through www.yahoo.finance.com and Bank Indonesia.

4.1. Correlation Test

The study begins by describing the data used to understand the relationship between the two time series variables with the state space model. ANTM is a company engaged in mining and is one of the largest mining companies in Indonesia. Then the second variable that is strongly suspected of having a relationship with the movement of the mining entity is the currency exchange rate which is symbolized by IDR. Table 1 shows 298 data were observed over the last 3 years. The ANTM data range is from 363.86 to 3049 so that the average of the data is 1239, while the data range from IDR is 13204 to 16425 with an average of 14178.

Table 1: Descriptive statistics

Variable	n	Mean	SD	Sum	Minimum	Maximum
ANTM	298	1239	735.36578	369,212	363.86000	3049
IDR	298	14,178	538.55859	422,5120	13,204	16,425

SD: Standard deviation

Table 2: Pearson's correlation test

Pearson correlation coefficients, n=298 Probability > |r| under H0: Rho=0		
Variable	**ANTM**	**IDR**
ANTM	1.00000	0.23956 <0.0001
IDR	0.23956 <0.0001	1.00000

The state space model used in this study aims to observe and test whether two variables have a causal relationship. This conjecture must have a basis that is built from theory, it can also be proven earlier with a tool of the Pearson Correlation Test. More complete results are as follows.

The Pearson Correlation test (Table 2) provides an early chance that the conjecture of ATNM and IDR variables that are interconnected is proven. This can be seen by the significant test results of 1.0000, indicating the study can be continued with high confidence and the hypotheses formulated can be proven.

4.2. Stationarity and Differencing

To avoid unwanted effects of time series data, for example non-stationary data, several tests are carried out. Some indicators can be used to ensure the data is stationary, for example by testing unit-root of ADF test and visuals from the autocorrelation function (ACF) and partial ACF (PACF) graphs. Meanwhile in this study to have data stationary for ANTM and IDR, differencing data was carried out as with significant Pr < Rho and Pr < Tau values of 0.0001 (Table 3a and b).

In Figure 1a and b, the ACF and PACF graphs show a rapidly decreasing visualization; this is evidence and a signal that ATNM and IDR have been stationary after differencing. Thus, we are allowed to go further on modelling state space for both variables.

4.3. State-Space Model Determination

We carried out our study by considering the AIC value in the autoregressive model to select the fittest state space model. From the results of data processing, we found the smallest AIC value at lag 10 for both data. For more clarity Table 4 is shown as follows:

Table 3a: ADF test for ANTM dan

Dickey-Fuller unit root tests for ANTM							
Type	**Lags**	**Rho**	**Pr<Rho**	**Tau**	**Pr<Tau**	**F**	**Pr>F**
Zero mean	0	−284.773	0.0001	−16.53	<0.0001		
Single mean	0	−285.124	0.0001	−16.53	<0.0001	136.58	0.0010
Trend	0	−285.271	0.0001	−16.51	<0.0001	136.25	0.0010

Table 3b: ADF test for IDR

Dickey-Fuller unit root tests for IDR							
Type	**Lags**	**Rho**	**Pr<Rho**	**Tau**	**Pr<Tau**	**F**	**Pr>F**
Zero mean	0	−111.328	0.0001	−8.25	<0.0001		
Single mean	0	−111.608	0.0001	−8.25	<0.0001	34.04	0.0010
Trend	0	−111.603	0.0001	−8.24	<0.0001	33.92	0.0010

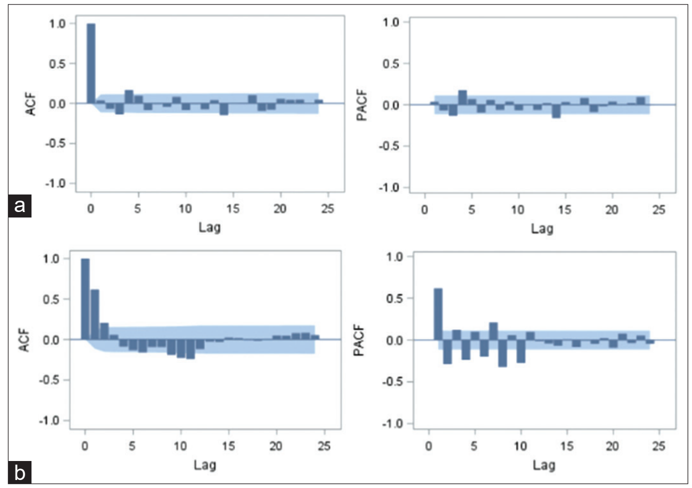
Table 4: Information criterion for autoregressive models

Lag=0	Lag=1	Lag=2	Lag=3	Lag=4	Lag=5	Lag=6	Lag=7	Lag=8	Lag=9	Lag=10
5999.136	5859.654	5840.915	5836.92	5816.656	5820.199	5811.099	5805.063	5772.317	5775.792	5755.841

Table 5: Yule-Walker estimates for minimum Akaike information criterion

Variable	Lag=1		Lag=2		Lag=3		Lag=4		Lag=5	
	ANTM	IDR	ANTM	IDR	ANTM	IDR	ANTM	IDR	ANTM	IDR
ANTM	0.036435	−0.05937	−0.04462	0.063345	−0.15333	−0.05523	0.171426	0.071521	0.054456	−0.09753
IDR	−0.05965	1.045054	−0.04272	−0.90753	−0.05246	0.863923	−0.06963	−0.92152	−0.07426	0.795794
Variable	**Lag=6**		**Lag=7**		**Lag=8**		**Lag=9**		**Lag=10**	
	ANTM	IDR	ANTM	IDR	ANTM	IDR	ANTM	IDR	ANTM	IDR
ANTM	−0.09085	0.051039	0.049585	−0.07317	−0.07117	0.083799	0.023527	−0.12896	−0.09382	0.026633
IDR	0.061679	−0.84773	−0.01646	0.773643	0.079794	−0.61594	−0.04594	0.350481	−0.050242	−0.28829

Figure 1: (a) Autocorrelation function (ACF) and partial ACF (PACF) for ANTM and (b) ACF and PACF for IDR



With information from the smallest AIC value, Table 5 presents an identifiable tenth-order autoregressive model. The Yule–Walker estimation for the autoregressive model is carried out to provide the output of the coefficient matrix of the autoregressive vector model for each lag as follows:

From Table 5, it can be constructed the equation as follows.

$$\begin{bmatrix} x_i \\ y_i \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} 0.036435 & -0.05937 \\ -0.05965 & 1.045054 \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix}$$
$$+ \begin{bmatrix} -0.04462 & 0.063345 \\ -0.04272 & -0.90753 \end{bmatrix} \begin{bmatrix} x_{t-2} \\ y_{t-2} \end{bmatrix}$$
$$+ \begin{bmatrix} -0.15333 & -0.05523 \\ -0.05246 & 0.863923 \end{bmatrix} \begin{bmatrix} x_{t-3} \\ y_{t-3} \end{bmatrix}$$
$$+ \begin{bmatrix} 0.171426 & 0.071521 \\ -0.06963 & -0.92152 \end{bmatrix} \begin{bmatrix} x_{t-4} \\ y_{t-4} \end{bmatrix}$$
$$+ \begin{bmatrix} 0.054456 & -0.09753 \\ -0.07426 & 0.795794 \end{bmatrix} \begin{bmatrix} x_{t-5} \\ y_{t-5} \end{bmatrix}$$
$$+ \begin{bmatrix} -0.09085 & 0.051039 \\ 0.061679 & -0.84773 \end{bmatrix} \begin{bmatrix} x_{t-6} \\ y_{t-6} \end{bmatrix}$$
$$+ \begin{bmatrix} 0.049585 & -0.07317 \\ -0.01646 & 0.773643 \end{bmatrix} \begin{bmatrix} x_{t-7} \\ y_{t-7} \end{bmatrix}$$
$$+ \begin{bmatrix} -0.07117 & 0.083799 \\ 0.079794 & -0.61594 \end{bmatrix} \begin{bmatrix} x_{t-8} \\ y_{t-8} \end{bmatrix}$$
$$+ \begin{bmatrix} 0.023527 & -0.12896 \\ -0.04594 & 0.350481 \end{bmatrix} \begin{bmatrix} x_{t-9} \\ y_{t-9} \end{bmatrix}$$
$$+ \begin{bmatrix} -0.09382 & -0.026633 \\ 0.050242 & -0.28829 \end{bmatrix} \begin{bmatrix} x_{t-10} \\ y_{t-10} \end{bmatrix}$$

4.4. Canonical Correlation Analysis

A series of canonical correlations is used to determine the state vector with the aim of exploring the relationship between two variables or multivariate vectors at the same data set size.

Figure 2: Forecasting graph for (a) ANTM and (b) IDR for the next 20 days

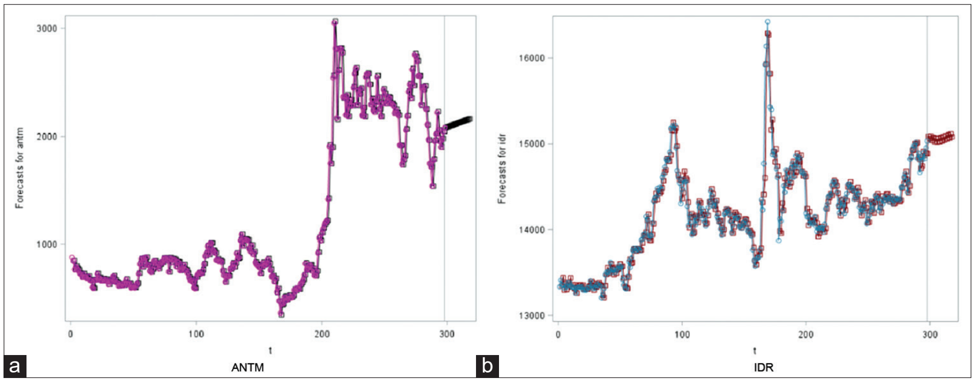


Table 6: Canonical correlations analysis

ANTM (T; T)	IDR (T; T)	IDR (T+1; T)	IDR (T+2; T)	Information criterion	χ^2	DF
1	1	0.719408	0.373041	6.354572	42.93103	19

Determination of the elements of the state vector through a series of canonical correlation analyzes from an autocovariance matrix with order 10. Negative IC values are excluded from the state vector, while positive IC values are included. Based on significance test using chi square (X^2) is obtained X^2hit = 42.93103 > $X^2_{0,05(19)} = 30.14$. This means the canonical correlation is significant, so that these components can be included in the state vector. From testing the significance of canonical correlation analysis, the real component is obtained x_t, y_t, $y_{t+1|t}$ and this component becomes the final state vector component as follows:

$$z_t = \begin{bmatrix} x_t \\ y_t \\ y_{t+1|t} \\ y_{t+2|t} \end{bmatrix}$$

The equation above can be built based on Table 6 as follows.

4.5. State Space Model Estimation

The steps for selecting the VAR order and determining the state vector by going through the stages in a series of canonical correlation analyzes have been carried out. The selection ends with setting the state space model parameters. Parameter estimation was carried out using the maximum likelihood approach. The results of the maximum likelihood can be seen in Table 7 as follows:

With all the supporting conditions, the suitable state space model has been calculated with the maximum iterative shown in Table 8 as follows:

The initial estimate obtained is then used as the initial value for the parameter estimation process iteratively. Efficient estimator for obtained with 6 iterations. After experiencing 5 iterations, the coefficient matrix is obtained as follows:

$$\hat{F} = \begin{bmatrix} 0.026591 & -0.01096 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -0.01646 & -0.23367 & 0.206405 & 0.779716 \end{bmatrix}$$

$$\hat{G} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -0.04649 & 0.86496 \\ -0.08199 & 0.141269 \end{bmatrix}$$

$$\hat{\Sigma} = \begin{bmatrix} 13318.79 & -3788.99 \\ -3788.99 & 23060.04 \end{bmatrix}$$

The State Space model is described as follows:

$$z_{t+1} = Fz_t + Ge_{t+1}$$

$$\begin{bmatrix} x_t \\ y_t \\ y_{t+1|t} \\ y_{t+2|t} \end{bmatrix} = F\begin{bmatrix} 0.026591 & -0.01096 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -0.01646 & -0.23367 & 0.206405 & 0.779716 \end{bmatrix}\begin{bmatrix} x_t \\ y_t \\ y_{t+1|t} \\ y_{t+2|t} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ -0.04649 & 0.86496 \\ -0.08199 & 0.141269 \end{bmatrix}\begin{bmatrix} e_{1.t+1} \\ n_{t+1} \end{bmatrix}$$

and

$$var\begin{bmatrix} e_{t+1} \\ n_{t+1} \end{bmatrix} = \begin{bmatrix} 13318.79 & -3788.99 \\ -3788.99 & 23060.04 \end{bmatrix}$$

$$y_{t+2|t+1} = -0.01646x_t - 0,23367y_t + 0206405y_{t+1|t}$$
$$+0,779716y_{t+2|t} - 0.08199e_{1,t+1} + 0.141269n_{t+1}$$

4.6. Discussion and Forecasting

After obtaining the fitted state space model, the next step is forecasting using the Kalman Filter method. Forecast results

Table 7: Iterative fitting: Maximum likelihood estimation

Iter	Half	Determinant	Lambda	F (1, 1)	F (1, 2)	F (4, 1)	F (4, 2)	F (4, 3)	F (4, 4)	G (3, 1)	G (3, 2)	G (4, 1)	G (4, 2)	Sigma (1, 1)	Sigma (2, 1)	Sigma (2, 2)
0	0	2.9798E8	0.1	0.02533401	−0.011168	−0.018903	−0.224804	0.18001747	0.75898868	−0.047722	0.8360432	−0.085786	0.15052123	13318.9388	−3663.547	23380.0566
1	3	2.9312E8	1	0.02632422	−0.0111797	−0.0170938	−0.2332874	0.20247839	0.77551126	−0.0463554	0.85839081	−0.0827433	0.14445061	13318.758	−3756.726	23067.7509
2	3	2.9282E8	10	0.026645	−0.010888	−0.01641	−0.233609	0.2076504	0.78092595	−0.046718	0.8670136	−0.081625	0.14009729	13318.8015	−3799.611	23069.3772
3	2	2.9278E8	100	0.02658129	−0.0109853	−0.0164193	−0.2337237	0.20599872	0.77936467	−0.0463626	0.86425735	−0.0821507	0.14166914	13318.7791	−3785.6638	23058.6709
4	0	2.9278E8	10	0.02660387	−0.0109429	−0.0164603	−0.233654	0.20673244	0.78002821	−0.0465601	0.86551087	−0.081893	0.14095584	13318.7896	−3791.7592	23061.8266
5	4	2.9278E8	100	0.02658801	−0.0109673	−0.0164585	−0.2336835	0.20631381	0.77963318	−0.0464674	0.86480398	−0.0820266	0.14135738	13318.784	−3788.2303	23059.6514
6	3	2.9278E8	1000	0.02659087	−0.010962	−0.016463	−0.233674	0.20640532	0.77971616	−0.046491	0.86495966	−0.081994	0.14126863	13318.7853	−3788.988	23060.0429

Table 8: Selected state-space form and fitted model

State vector			
ANTM (T; T)	IDR (T; T)	IDR (T+1; T)	IDR (T+2; T)
Estimate of transition matrix			
0.026591	−0.01096	0	0
0	0	1	0
0	0	0	1
−0.01646	−0.23367	0.206405	0.779716
Input matrix for innovation			
1			0
0			1
−0.04649			0.86496
−0.08199			0.141269
Variance matrix for innovation			
13318.79			−3788.99
−3788.99			23060.04

for the next 20 days can be seen in the following graph (Figure 2a and b).

Form the State Space Model, it can be seen visually that the forecasting graph for ANTM (Figure 2a) shows the increasing trend, so does IDR with slower increase (Figure 2b). State space model provides the relationship between those variables and with simultaneously increasing trend they show the interrelationship. This is evidence that stock price of ANTM jointly effected not only by itself but also by the trend of the exchange rate. This causal relationship is apparent as one of business activities on ANTM is to export the raw material of gold produced (bauxite) mainly to Southeast Asian, East Asian, and Sout Asian. A weak rupiah exchange rate can cause stock prices to fall, because it makes domestic products more expensive for foreign buyers, and conversely, a strong rupiah exchange rate can increase stock prices (Kumar, 2019). Therefore, from this study, it can be recommended that investors should take strong consideration on the fluctuations in exchange rates if they have decision to put their fund on stock prices with the basis of gold production company.

5. CONCLUSION

Overall, the study provided an insight in strategic decision-making for investors who have interest on investment in stock with gold-based company in Indonesia. With the shock economics during Pandemic Covid-19, ANTM showed significant upward trend, so did IDR. The study employed state space model to picture the dynamics of both variables and found that ANTM stock prices were not only affected by itself but also from the fluctuations in exchange rates. The study also provided the estimation of daily stock prices of ANTM and the movement of exchange rates for the next 20 days. Both forecasting graphs showed an increasing trend, that proved the data were fit the model. Lastly, the result of this study is aimed to be one reference for investors to take action on gold-based company in Indonesia.

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