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Causal relationship on volatility prices of coal-based enterprise and exchange rate

Fajrin Satria Dwi Kesumah[1]*
Rialdi Azhar[2]
Lis Andriani HR[1]

[1]Department of Management, University of Lampung, Lampung, Indonesia
[2]Department of Accounting, University of Lampung, Lampung, Indonesia

ABSTRACT

Stock prices movement of coal company is possible to be a reflection of its business performance that allow investors' decisions to invest. The study is aimed to examine the dynamic relationship of Indonesian coal sub-sector company and exchange rate. The novelty of this study is to examined the coal based-company stock prices dynamically to exchange rate. The method in this study used Vector Autoregressive (VAR) model. The results showed that the VAR(5) model was the best model in testing the causal relationship between PTBA stock price and the exchange rate. The VAR(5) model is also used to forecast data for the next 30 days. For further study, it suggested to extend the variables to some other macroeconomics indicators.

KEYWORDS

Coal Companies; Stocks Price: Exchange Rate: VAR Model: Forecasting

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Introduction

Currently, various countries are reducing their consumption of coal as an energy source with more environmentally friendly commodities. However, according to the (International Energy Agency, 2021), coal is one of the most important sources of energy for the survival of the community which is used as fuel for power plants that generate 37% of the world's electricity and an estimated 22% of the world's electricity by 2040. (World Coal Association, 2021) revealed that coal production in the Southeast Asia region is projected to generate 39% of internal electricity by 2040, while (Jiang et al., 2019) estimated that China's coal production will reach peak production of up to 5,000 tons by 2030.

(Tim Sekretaris Jenderal Dewan Energi Nasional, 2019) reported that energy demand, especially coal, is projected to continue to increase, while many countries lack this energy source to meet their energy needs. and energy import policies become one of the alternatives to maintain the needs of a country's internal stability. On the other hand, Indonesia as one of the coal producing countries is projected to have increased coal production, especially to meet domestic needs (power generation and industry) and external demand (exports) (Zhao & Alexandroff, 2019).

The development of coal production in Indonesia during the 2009-2018 period increased significantly, with production of 557 million tons in 2018 (Pusat Pengkajian Industri Proses dan Energi (PPIPE), 2021). Of the total production, the share of coal exports reached 357 million tons (63%), most of which was used to meet the needs of China and India. On the other hand, domestic coal consumption reached 115 million tons, below the domestic coal consumption target of 121 million tons. One of the causes of the decline in the realization of coal consumption is that some 35,000 MW steam power plants (PLTU) are not operating as planned and some industrial activities are declining (Pusat Pengkajian Industri Proses dan Energi (PPIPE), 2021).

Furthermore, the performance of companies with a coal production business base in meeting domestic and foreign needs can be seen from the volatility of their share prices (Badarau & Lapteacru, 2020). Therefore, the volatility of the company's stock price can be projected through an analysis of causality with macroeconomic variables, such as the rupiah exchange rate (Hamzah et al., 2020; Umpusinga et al., 2020; Warsono et al., 2019), using the Vector Autoregressive (VAR) model approach.

Methods

The study used data on shares of Indonesian government-owned coal companies listed on the Indonesia Stock Exchange (IDX) from 2017 to 2022, namely PT Bukit Asam (Persero) Tbk with the issuer code PTBA, and the exchange rate of the rupiah against the US dollar. The selected company is as it is the only government-owned company having the coal production as their main business. One of model to estimate causal relationship among variable are Vector Autoregressive (VAR) Model (Wei, 2006). VAR modeling in time series data, especially financial data, has been widely used and believed to have the ability to be able to analyze the two-way relationship between multivariate variables,

CONTACT Fajrin Satria Dwi Kesumah fajrin.satria@feb.unila.ac.id

as well as to forecast data (Tsay, 2014). The stages of VAR modeling in testing the causality of variables are as (Tsay, 2014) described is as follows.

Stationary

Data Time series data is said to be stationary if the mean, variance and covariance in each lag are the same at all times. In this study, to test stationary data using the Augmented Dickey Fuller (ADF) unit root test (P. Brockwell & Davis, 2002; P. J. Brockwell & Davis, 1991).

Optimum lag test

Furthermore, to determine the lag in the VAR model, the optimum lag test is carried out, namely to see the behavior and relationships of variables in the short term. For this purpose, several criteria can be used to determine whether or not the lag is optimal. Some of these criteria are the Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Final Prediction Error (FPE), and Hannan Quinn (HQ) methods. The asterisk indicates the optimal lag recommended by the AIC, SIC, FPE and HQ criteria.

Var model estimation

The process of VAR modeling on order p (VAR(p)), can be written mathematically as follows (Engle, 1982).

$$\vartheta_t = \alpha + \sum_{k=0}^{p} \beta_k \vartheta_{t-k} + \varepsilon_t$$

Where ϑ_t m × 1 vector variable at time t; β_k is the k x k matrix; k is 1,2,3,…,p; and ε_t is white noise**.** It then can be described further below.

$$\begin{pmatrix} \vartheta_{1t} \\ \vartheta_{2t} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} + \begin{bmatrix} \beta_{11}^k & \beta_{12}^k \\ \beta_{21}^k & \beta_{22}^k \end{bmatrix} \begin{pmatrix} \vartheta_{1t-k} \\ \vartheta_{2t-k} \end{pmatrix} + \varepsilon_t$$

Results and discussion

Data description

The research data used is daily share data of coal companies with the issuer code PTBA and daily data on the rupiah exchange rate from 2017 to 2022. The graph of each data series is presented in the following figure.

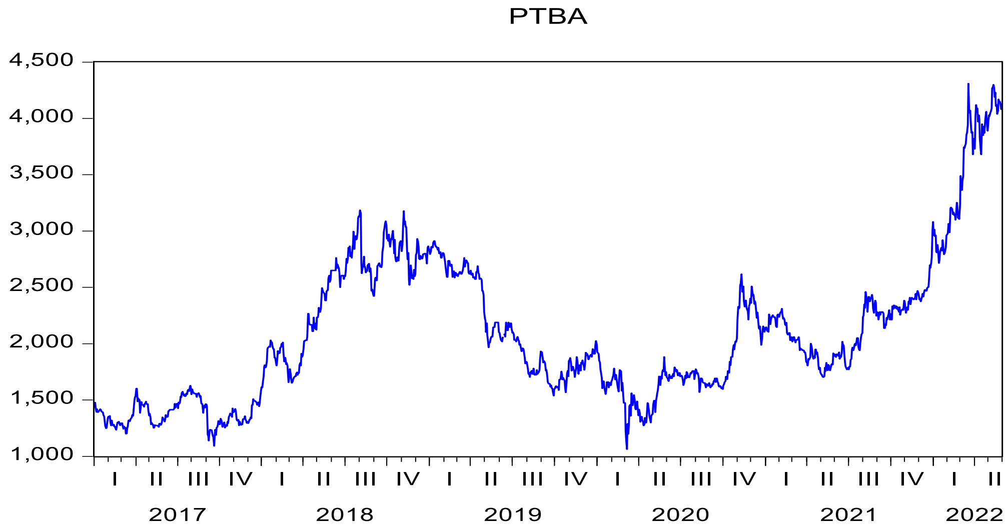

Figure 1. Plotting of Historical Data for PTBA

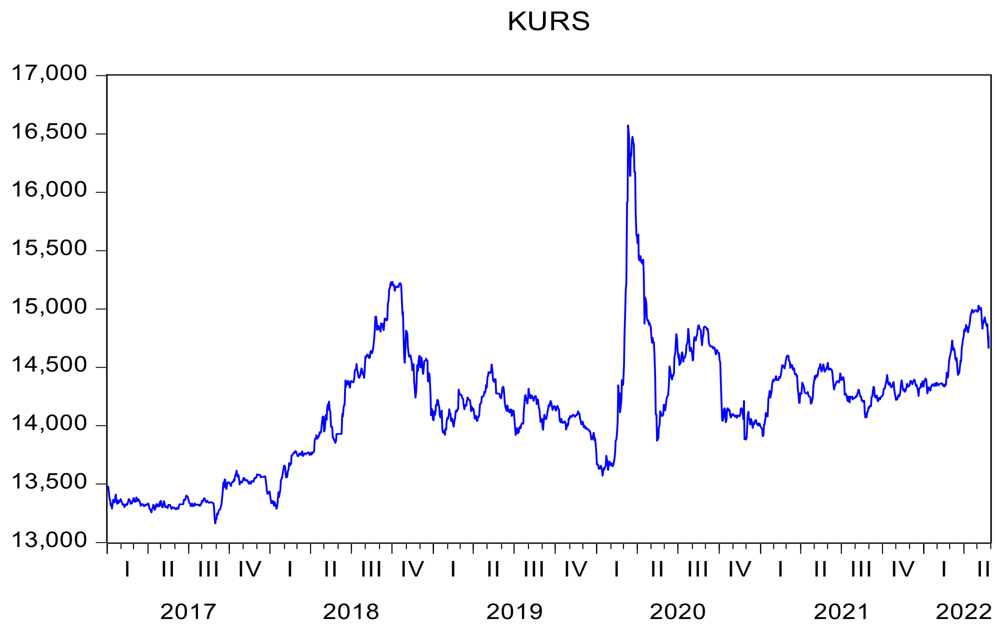

Figure 2. Plotting of Historical Data for KURS

In general, the PTBA stock price chart fluctuated and tended to increase from year to year. PTBA's share price increased in 2018, before experiencing a significant decline until mid-2020. The decline in PTBA's share price in 2020 was certainly one of the impacts of the covid 19 pandemic. However, after the implementation of the economic recovery policy, PTBA's shares crept up to reach level of 4.0000 until mid-2022. Meanwhile, the exchange rate of the rupiah against the US dollar also fluctuated and tended to increase. A significant increase occurred at the beginning of 2020, where the Covid-19 Pandemic caused a recession in the Indonesian economy and weakened the rupiah which reached up to 16,500 Rupiah per US Dollar. However, in the midst of Indonesia's economic recovery efforts, the value of the rupiah fell again below 15,000 and tends to fluctuate until mid-2022.

From the graph above, it can be said that visually, the plotting of the data series for the three variables is not around zero, or with In other words, these three variables have non-stationary data series. This statement is then proven by the ADF unit root test to ensure statistically stationary data. The results of the ADF test are as follows.

Table 1. The Results of the Unit Root Test for PTBA Shares and KURS

Group unit root test: Summary
Series: PTBA, KURS
Date: 09/14/22 Time: 13:53
Sample: 1/02/2017 5/31/2022
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 3 to 22
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.70544	0.9559	3	4183
Breitung t-stat	-0.48872	0.3125	3	4180
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.48472	0.3139	3	4183
ADF - Fisher Chi-square	10.5906	0.1019	3	4183
PP - Fisher Chi-square	8.10302	0.2307	3	4229

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

The output above shows a probability value above 5%, meaning that the data is not statistically stationary. It fits with visual findings through plotting data from each variable.

Transformation stationary data

The next step is to transform the data series into stationary by doing differencing. The following is the output of testing the data series after differencing 1st Level.

Table 2. Output Differencing 1st Level

Group unit root test: Summary
Series: PTBA, KURS
Date: 09/14/22 Time: 13:58
Sample: 1/02/2017 5/31/2022
Exogenous variables: Individual effects, individual linear trends
Automatic selection of maximum lags
Automatic lag length selection based on AIC: 8 to 21
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	26.9909	1.0000	3	4147
Breitung t-stat	-2.82857	0.0023	3	4144
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-15.5405	0.0000	3	4147
ADF - Fisher Chi-square	228.566	0.0000	3	4147
PP - Fisher Chi-square	790.172	0.0000	3	4224

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

From the output results above, it can be concluded that the data series of each variable is stationary at 1st (d = 1), which is indicated by the probability value of the ADF – Fisher Chi-square of 0.0000 (< 5 %). Furthermore, to further ensure that the data series is stationary, the autocorrelation function (ACF) and partial autocorrelation function (PACF) tests are carried out, as follows.

Table 3. Output ACF and PACF from PTBA and KURS

Correlogram of D(PTBA)

Date: 09/14/22 Time: 14:09
Sample: 1/02/2017 5/31/2022
Included observations: 1409

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.036	-0.036	1.8292	0.176
		2	-0.054	-0.056	5.9789	0.050
		3	0.064	0.060	11.800	0.008
		4	0.006	0.007	11.844	0.019
		5	0.020	0.027	12.391	0.030
		6	-0.038	-0.039	14.384	0.026
		7	-0.046	-0.047	17.343	0.015
		8	0.031	0.021	18.722	0.016

Correlogram of D(KURS)

Date: 09/14/22 Time: 14:09
Sample: 1/02/2017 5/31/2022
Included observations: 1411

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.124	0.124	21.825	0.000
		2	0.186	0.173	70.784	0.000
		3	-0.000	-0.043	70.784	0.000
		4	0.110	0.086	87.806	0.000
		5	0.061	0.050	93.067	0.000
		6	0.050	0.004	96.627	0.000
		7	0.004	-0.015	96.652	0.000
		8	0.028	0.016	97.759	0.000

From table correlogram PTBA and KURS, after 1st differencing, it can be seen that the probability value of correlogram for both variables is below 5%, as shown on autocorrelation (ACF) and partial correlation (PACF column which indicates that the variables have stationary data at 1st level differencing.

Optimum lag test

After making sure the data series is stationary, the next step is to perform the optimum lag test which aims to determine the amount of lag in the estimated 1st differencing VAR model(d=1). The optimum lag test output is presented below.

Table 4. Optimum Lag Test Results

VAR Lag Order Selection Criteria
Endogenous variables: D(PTBA) D(KURS)
Exogenous variables: C
Date: 09/14/22 Time: 14:17
Sample: 1/02/2017 5/31/2022
Included observations: 1393

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-20065.11	NA	6.54e+08	28.81279	28.82407*	28.81701
1	-20043.71	42.66384	6.43e+08	28.79499	28.84013	28.81187
2	-20012.43	62.25714	6.23e+08	28.76300	28.84198	28.79253*
3	-20002.11	20.48423	6.21e+08	28.76111	28.87394	28.80330
4	-19995.00	14.09609	6.23e+08	28.76381	28.91050	28.81866
5	-19981.99	25.71113*	6.20e+08*	28.75806*	28.93860	28.82557
6	-19975.52	12.76645	6.22e+08	28.76169	28.97608	28.84185
7	-19969.64	11.58150	6.25e+08	28.76617	29.01440	28.85899
8	-19964.18	10.71233	6.28e+08	28.77126	29.05334	28.87673

* 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

From the output above, it can be concluded, lag 5 is the optimum lag, because it has the most asterisks in the lag selection criteria, namely LR, FPE, and AIC criteria. Therefore, the estimated VAR 1st Differencing model is at lag 5, or VAR(5).

Model estimation of VAR(5)

The VAR(5) model estimation of each variable is presented in the following table.

Table 5. Estimation Results of VAR(5) Model for PTBA Variable

Dependent Variable: D(PTBA)
Method: Least Squares
Date: 09/14/22 Time: 14:41
Sample (adjusted): 1/10/2017 5/31/2022
Included observations: 1399 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.965311	1.500212	1.310022	0.1904
D(PTBA(-1))	-0.031301	0.027118	-1.154282	0.2486
D(PTBA(-2))	-0.061930	0.027132	-2.282548	0.0226
D(PTBA(-3))	0.059602	0.027151	2.195170	0.0283
D(PTBA(-4))	-0.000364	0.027148	-0.013402	0.9893
D(PTBA(-5))	0.032286	0.027109	1.190936	0.2339
D(KURS(-1))	-0.008689	0.027464	-0.316389	0.7518
D(KURS(-2))	-0.023212	0.027574	-0.841816	0.4000
D(KURS(-3))	0.054817	0.027908	1.964228	0.0497
D(KURS(-4))	-0.063332	0.027528	-2.300658	0.0216
D(KURS(-5))	0.068403	0.027476	2.489576	0.0129

R-squared	0.023430	Mean dependent var	1.916891
Adjusted R-squared	0.012838	S.D. dependent var	56.19908
S.E. of regression	55.83718	Akaike info criterion	10.89413
Sum squared resid	4311905.	Schwarz criterion	10.95410
Log likelihood	-7604.442	Hannan-Quinn criter.	10.91655
F-statistic	2.212047	Durbin-Watson stat	1.998579
Prob(F-statistic)	0.004780		

Table 6. Estimation Results of VAR(5) Model for EXCHANGE Variables

Dependent Variable: D(KURS)
Method: Least Squares
Date: 09/14/22 Time: 14:45
Sample (adjusted): 1/10/2017 5/31/2022
Included observations: 1400 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.894534	1.466802	0.609853	0.5421
D(PTBA(-1))	0.042625	0.026519	1.607321	0.1082
D(PTBA(-2))	-0.094129	0.026538	-3.546971	0.0004
D(PTBA(-3))	0.013121	0.026557	0.494062	0.6213
D(PTBA(-4))	-0.004876	0.026551	-0.183650	0.8543
D(PTBA(-5))	-0.026773	0.026512	-1.009857	0.3127
D(KURS(-1))	0.116423	0.026841	4.337440	0.0000
D(KURS(-2))	0.160924	0.026964	5.968047	0.0000
D(KURS(-3))	-0.062585	0.027297	-2.292782	0.0220
D(KURS(-4))	0.077572	0.026925	2.881052	0.0040
D(KURS(-5))	0.056419	0.026866	2.099970	0.0359

R-squared	0.069198	Mean dependent var	1.112500
Adjusted R-squared	0.059110	S.D. dependent var	56.30443
S.E. of regression	54.61501	Akaike info criterion	10.84986
Sum squared resid	4128194.	Schwarz criterion	10.90979
Log likelihood	-7578.900	Hannan-Quinn criter.	10.87226
F-statistic	6.859345	Durbin-Watson stat	2.002961
Prob(F-statistic)	0.000000		

The equation estimation matrix of the VAR(5) model can be described as follows.

$$\vartheta_t = \begin{bmatrix} 1.965311 \\ 0.894534 \end{bmatrix} + \begin{bmatrix} -0.031301 & 0.042625 \\ -0.008689 & 0.116423 \end{bmatrix} \vartheta_{t-1} + \begin{bmatrix} -0.061930 & -0.094129 \\ -0.023212 & 0.160924 \end{bmatrix} \vartheta_{t-2} + \begin{bmatrix} 0.059602 & 0.013121 \\ 0.054817 & -0.062585 \end{bmatrix} \vartheta_{t-3} + \begin{bmatrix} -0.000364 & -0.004876 \\ -0.063332 & 0.077572 \end{bmatrix} \vartheta_{t-4} + \begin{bmatrix} 0.032286 & -0.026773 \\ 0.068403 & 0.056419 \end{bmatrix} \vartheta_{t-5} + \varepsilon_t$$

Then, from the two outputs and the equation matrix above, in each variable (as the dependent variable), it can be seen that there are independent variables that are not significant, so that the estimation of the VAR(5) model for each dependent variable will only contain the coefficient significant independent variable (p-value < 5%). The estimation equation for the VAR(5) model of each dependent variable is as follows.

PTBA = 1.96 - 0.06*D(PTBA(-2)) + 0.05*D(PTBA(-3)) + 0.05*D(KURS(-3)) - 0.06*D(KURS(-4)) + 0.06*D(KURS(-5))

D(KURS) = 0.89 - 0.09*D(PTBA(-2)) + 0.11*D(KURS(-1)) + 0.16*D(KURS(-2)) - 0.06*D(KURS(-3)) + 0.07*D(KURS(-4)) + 0.05*D(KURS(-5))

Model (Eq.1) also explains that the value of PTBA shares is influenced by the PTBA stock price itself at lag 2 (t-2) and lag 3 (t-3), and is also influenced by the rupiah exchange rate against the dollar at lag 3 (t-3), lag 4 (t-4), and lag 5 (t-5). While the Model (Eq.3) explains that the rupiah exchange rate against the dollar is negatively affected by PTBA's stock price at lag 2 (t-2), and is also influenced by the rupiah exchange rate against the dollar itself at each lag (t-1 to t -5).

Forecasting

VAR(5) model is then used to estimate forecasting data for the next month. The following is a graph of the forecasting results in each variable from the VAR(5) model for a period of one month.

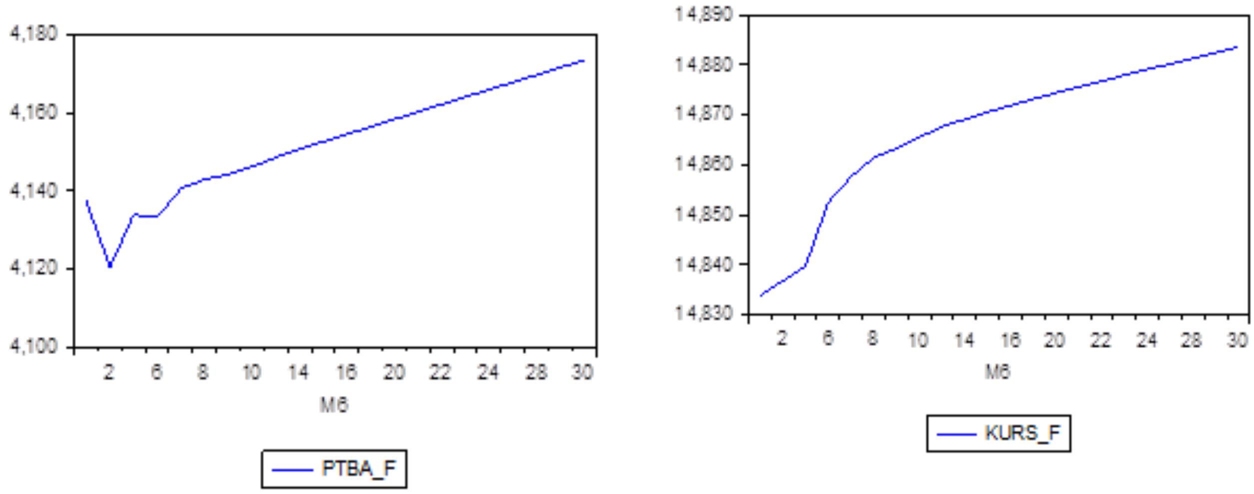

Figure 2. Forecasting data of PTBA and KURS for the Next 30 Days

The image above shows the estimated results of forecasting data from each variable for a time horizon of one month. In PTBA's stock price forecasting, the forecast chart shows a significant decline in the first week, but the next day it is projected that PTBA's stock price will increase gradually. Meanwhile, in the graph of the projection of the exchange rate of the EXCHANGE, it can be seen that the exchange rate is projected to gradually increase over the next one month.

Conclusion

In this study, we examined the causality of the stock price of the coal sub sector in Indonesia from 2017 to 2022, taking into account the factor of the rupiah exchange rate against the dollar using the VAR model approach. The VAR(5) model is the best model from a series of tests that we have done in the analysis of stock price causality relationships. The findings were then used to forecast the stock prices of PTBA when the shock of interest rate applied. For further study, it is suggested to for further study, it suggested to extend the variables to some other macroeconomics indicators.

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