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Empowering Innovative Science and Technology for
Future Environmental Perspective

ABSTRACT BOOK



Savana Hotel, Malang
October 26 to 27, 2022

Thursday, October 27th, 2022

Online, 12:45 – 15:00 WIB (Western Indonesia Time)

No	Time	Room 1 PIC: Mujahidin Ahmad	Room 2 PIC: Fachrur Rozi	Room 3 PIC: Arnelda Dwi Ridwan Majid
1	12:45 - 13:00	ID 214 Anwardi <i>Design Engineering and Economic Analysis of Magsor Cultivation as Basic Material for Pellet Manufacturing</i>	ID 355 Artmo Diharsono Lawangl <i>Summed spaces and its embeddings</i>	ID 329 Kamsah Dellawati Pandiangan <i>Synthesis of CaO/SiO_2 from Limestone and Pumice Silica Pumice as Catalyst for Transesterification of Rubber Seed Oil</i>
2	13:00 - 13:15	ID 344 Lud Wahyu <i>Detergent-tolerant Heterotrophic Bacteria Consortium Strain Decomposer to Improve Environmental Health</i>	ID 334 Satrya Adika Arif Alimaja <i>Commognitive-Based Creative Model Development in Controversial Mathematical Reasoning Activities</i>	ID 335 Alva Ika Nur Affah <i>The Study on Corrosion Inhibition Activities of Nitrogen Compounds Derived from Coconut Oil Methyl Ester Using Autoclave Method</i>
3	13:15 - 13:30	ID 323 Wastinton Simanjuntak <i>Catalytic Upgrading of Palm Oil Derived Biocrude Oil Using Protomated Zeolite-Y as Catalyst</i>	ID 350 Shakir Ali <i>Communting additive mappings in certain classes of rings</i>	ID 327 Dika Indah Alisla <i>Optimization of Zeolite-X Catalyzed Palm Oil Transesterification Using Response Surface Methodology</i>
4	13:30 - 13:45	ID 291 Sayyid Saifullah Akbar <i>Diversity of Soil Spiders in Simple and Complex Coffee Agroforestry in Mamosalam District Jombang Regency</i>	ID 254 Abdul Aziz <i>Ridge Regression Model Using Kibria Parameter</i>	ID 256 Dewi Sinta Megawati <i>Quantitative Structure-Activity Relationship (QSAR) of N-Benzoyl-N'-Naphthylurea Derivative Compounds by In Silico as Anticancer Through Inhibition of VEGFR2 Receptors</i>

ID ABSTRACT: 254

Ridge Regression Model Using Kibria Parameter**Mega Nur Royani¹, Abdul Aziz^{2*}, Nur Chamidah³**¹Universitas Islam Negeri Maulana Malik Ibrahim Malang²Universitas Airlangga, Surabayae-mail: abdulaziz@mat.uin-malang.ac.id**Abstract**

Stock prices in the economy, especially in Indonesia, is very important that so many people want to get benefits from investing stocks. The rate of return that owned by investor is called return investment. In this research, we are looking for return of stock model, which is useful for predicting return of stock at a certain time. Method that used forecasting of return is ridge regression using tuning parameter Kibria. The purpose of using this method is for eliminate multicollinearity that cannot be in OLS method. Model of return of JKSE is searched by following the steps in regression method and using tests to get the best model. Based on the result of the study, it was obtained that the equation of the ridge regression model with all the independent variables had a significant effect on return of stock. The tests that performed are normality test, multicollinearity test and parameter significant test. The VIF value obtained is also less than 10, namely $X_1 = 3,6310$, $X_2 = 0,8428$, $X_3 = 3,2148$, $X_4 = 2,1465$, $X_5 = 2,0458$, $X_6 = 1,4058$, dan $X_7 = 0,8270$ with a coefficient of determination is 0,9626 which means that all the independent variables on return of stock is 96,26% while 3,74% is influenced by other independent variables. Therefore, the ridge regression method using tuning parameter Kibria can be used to predict.

Keywords: OLS, Ridge, Kibria, Return of Stock, Multicollinearity

Ridge Regression Model Using Kibria Parameter

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ABSTRACT

Stock prices in the economy, especially in Indonesia, is very important that so many people want to get benefits from investing stocks. The rate of return that owned by investor is called return investment. In this research, we are looking for return of stock model, which is useful for predicting return of stock at a certain time. Method that used forecasting of return is ridge regression using tuning parameter Kibria. The purpose of using this method is for eliminate multicollinearity that cannot be in OLS method. Model of return of JKSE is searched by following the steps in regression method and using tests to get the best model. Based on the result of the study, it was obtained that the equation of the ridge regression model with all the independent variables had a significant effect on return of stock. The tests that performed are normality test, multicollinearity test and parameter significant test. The VIF value obtained is also less than 10, namely $X_1 = 3,6310$, $X_2 = 0,8428$, $X_3 = 3,2148$, $X_4 = 2,1465$, $X_5 = 2,0458$, $X_6 = 1,4058$, dan $X_7 = 0,8270$ with a coefficient of determination is 0,9626 which means that all the independent variables on return of stock is 96,26% while 3,74% is influenced by other independent variables. Therefore, the ridge regression method using tuning parameter Kibria can be used to predict.

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INTRODUCTION

Mathematics can be used in various fields, one of which is finance. Financial instruments used in the capital market for a group of people who make buying and selling transactions, one of which is stock price [1]. Stock price is an important role of economic growth in Indonesia because it can be a very high investment. However, the investment made is not always profitable, due to their volatile nature. Therefore, from the economic events, alternatives are needed to assist investment activities. The result of investment activity is return. Return of stock or profits are given to investors for taking risks on the investments that have been made [2].

In general, method for forecasting of stock price uses ARIMA. However, this method has a weakness, cannot overcome heteroscedasticity. So, we need an alternative method that is able to overcome the problems or another problems in inferntial statistics, such as multicollinearity. One of methods that can solve multicollinearity is ridge regression which was proposed by Hoerl and Kennard (1962) [3]. Then, it was further developed by Kibria (2003) by using tuning parameter k to solve multicollinearity [4].

A ridge regression method is a modification of ordinary least square estimation, with a tuning parameter. The addition of tuning parameter will affect the magnitude of ridge estimator coefficient and produces a biased estimator [5]. Although it produces a biased regression estimator coefficient, the estimator can be closed to the actual value. It can be seen from

comparison of mean square error of ridge regression and mean square error of ordinary least square. Result of MSE using ridge estimator is smaller than MSE using OLS. In addition to tuning parameter Kibria, there are many tuning parameter can be used [6].

The use of the ridge model in stock price forecasting has been carried out by several researchers, such as Tanjung (2013) [7] who conducted research on stock price forecasting based on technical indicators using ridge regression and Kernel ridge regression models. Then, research on joint stock price modeling and forecasting at Bank Indonesia using the Generalized Ridge Regression (GRR) model. Results from these studies showed that the model can solve the problem GRR autocorrelation and multicollinearity by looking at VIF [8].

In addition, research on ridge regression with the selection of k ridge parameters was carried out by Muniz, et al (2012) [9], Karaibrahimoglu, et al (2014) [10], Arashi and Valizadeh (2014) [11], and Dorugade (2015) [12]. Based on these studies, the performance of the estimator depends on the error variance, the correlation between the explanatory variables, the number of samples, and the unknown coefficient. The results of this study indicate that the MSE of ridge estimator with k parameters is smaller than the MSE of OLS estimator.

Another study was also carried out by Mansson et al (2010) [13], Hefnawy and Farag (2013) [14], and Aslam (2014) [15] on the ridge model estimation method using Monte Carlo simulation Kibria. Results of these studies is the increase in the correlation between independent variables have a negative impact on the value of MSE, whereas the increase in the correlation between the explanatory variables have positive impact on the MSE. So, based on the results of the simulation, the ridge regression model with Kibria parameters is able to overcome multicollinearity.

METHODS

The steps in this study are as follows:

1. Implementation of ridge regression using tuning parameter Kibria.
 - a. Perform description data.
 - b. Perform classical assumption test:
 - i. Performing normality test on error of stock return.
 - ii. Performing multicollinearity test on independent variable.
 - c. Ridge estimator modeling:
 - i. Performing parameter estimation using least square method, including test for significance of parameter.
 - ii. Performing transformation data using centering and rescaling method.
 - iii. Performing parameter estimation using ridge regression with tuning parameter Kibria.
 - iv. Performing test for significance of parameter.
 - v. Performing goodness of fit model.
2. Forecasting for return of stock using tuning parameter Kibria:
 - a. Performing forecast for return of stock on ridge regression model.
 - b. Performing validation test.
 - c.

RESULTS AND DISCUSSION

The data used in this research is stock return data of JKSE – Jakarta Composite Index. These data are data that are assumed to follow ridge regression and the factors that are thought to have an effect on the return of the combined stock price. There are 7 independent variables used in this research that the stock price (close), VROC, BB, STCK, STCD, RSI, and MACD. This

study uses joint stock return data for the period April 2020 - February 2021 as training data and data for the period March 2021 to May 2021 as testing data.

Table 1 Statistical Description of Each Variable

Variable	Mean	Standard Deviation
Y	0,1807	1,0524
X ₁	5338,7372	573,4888
X ₂	9,5862	2,4602
X ₃	5259,2920	549,1090
X ₄	62,9976	28,1648
X ₅	62,4826	23,4033
X ₆	57,8860	10,9456
X ₇	0,6963	5,3909

Furthermore, the normality test of the data is used to prove the assumption that the error must be normally distributed because the error data is normal.

Normality test was performed using the Jarque Bera (JB) test. The hypothesis used is.

H_0 : $JB \leq \chi^2(2)$ (error data is normally distributed)

H_1 : $JB > \chi^2(2)$ (error data is not normally distributed)

by using the significant level $\alpha = 5\% = 0,05$ and criteria test is reject H_0 if $JB \geq X_{tabel}^2$ or $p\text{ value} < \alpha$.

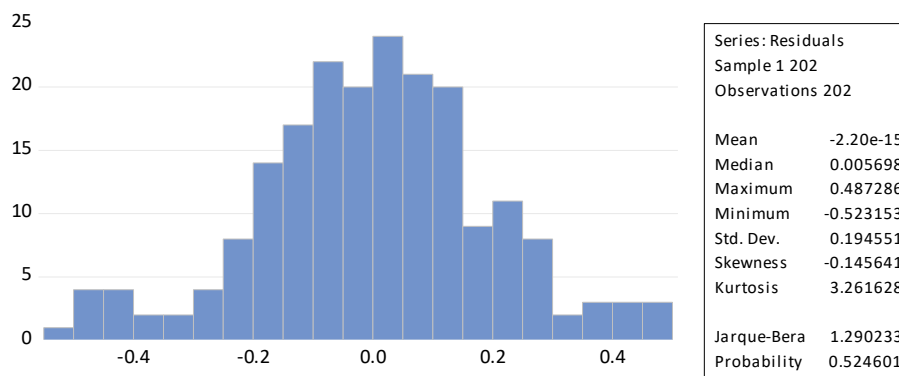


Figure 1 Normal Histogram Output on Normality Test

From Figure 1, the Jarque-Bera value is 1,2902 while the value of X_{tabel}^2 is 5,9915. This shows that $JB \leq X_{tabel}^2$ so H_0 be accepted. So, it can be concluded that the assumption of normality in this study is fulfilled.

The second test is multicollinearity. Multicollinearity test can be seen based on the value of the coefficient correlation and the value of VIF. The following is the multicollinearity test hypothesis:

H_0 : $VIF \leq 10$ (No Multicollinearity)

H_1 : $VIF > 10$ (There is a Multicollinearity)

The criteria for this test is if the value of $VIF > 10$, it can be said that there are symptoms of multicollinearity.

Table 3 Coefficient Correlation on Multicollinearity Test

Variable	Y	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇
Y	1	0,083	0,210	-0,003	0,656	0,313	0,340	0,962
X ₁		1	-0,012	0,970	0,219	0,252	0,484	0,084
X ₂			1	-0,135	0,395	0,510	0,426	0,119

X_3		1	0,094	0,110	0,280	0,016
X_4			1	0,808	0,595	0,531
X_5				1	0,653	0,221
X_6					1	0,280
X_7						1

Based on table 3 can be seen that all independent variables have a correlation to the dependent variable. The correlation between the two independent variables is also quite high, namely between X_1 and X_3 of 0.970 which indicates the existence of multicollinearity between the two independent variables. The correlation coefficient value greater than 0.9 results in a VIF value greater than 10, which can be seen in the following table.

Table 4 VIF Value on Multicollinearity Test

Independent Variable	VIF
X_1	102,7303
X_2	1,5224
X_3	86,1705
X_4	4,7423
X_5	4,4172
X_6	7,2581
X_7	1,7417

From on table 4, it can be said that the JKSE joint stock return data contains multicollinearity between independent variables. So, to overcome this problem an alternative method is needed, namely by using ridge regression.

Table 4 Least Square Method Parameter Estimation

j	Variable	Estimation ($\hat{\beta}_j$)
0	Constant	0,0020
1	X_1	0,0008
2	X_2	0,0244
3	X_3	-0,0008
4	X_4	0,0132
5	X_5	-0,0081
6	X_6	-0,0099
7	X_7	0,1570

The estimation model using the least squares method has a significant effect and there is multicollinearity as follows:

$$\hat{Y}_{ols} = 0,0020 + 0,0008 X_1 + 0,0244 X_2 - 0,0008 X_3 + 0,0132 X_4 - 0,0081 X_5 - 0,0099 X_6 + 0,1570 X_7 \quad (1)$$

The model in equation (1) is a regression model that has multicollinearity problems. So that other methods are needed that can overcome these problems, one of which is ridge regression. The first step is to transform the data through the process of centering and scaling each variable. The results of the centering and scaling process are as follows:

Table 5 Transformation Data Using Centering and Rescaling

Y*	X1*	X2*	X3*	X4*	X5*	X6*	X7*
-1,71006	-1,52174	-0,47644	-1,0084	0,234158	0,369173	-1,68796	-1,96749

1,214831	-1,40727	-0,22027	-1,11024	-0,23726	0,260126	-1,49056	1,376783
1,732782	-1,24729	0,654937	-1,20264	1,268052	0,529443	-1,21865	1,054862
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
-0,89734	1,574675	1,587931	1,682069	-0,65233	-0,05533	-0,41987	-1,10103

After transforming the data using the centering and scaling method, the next step is to determine the value of the ridge parameter or can be called the tuning parameter Kibria. The tuning parameter of the bias constant is carried out using an iterative approach. The first step in the iteration process is to determine the tuning parameter using the canonical model estimator of least square. The initial tuning parameter obtained is used to estimate the ridge parameter. The iteration ends when $|(\hat{\alpha}_{ridge}^T \hat{\alpha}_{ridge})^i - (\hat{\alpha}_{ridge}^T \hat{\alpha}_{ridge})^{i-1}| \leq 0,01$. The following is the result of determining the canonical estimator of the least squares method.

Table 6 Canonical Estimator of Ordinary Least Square

j	$\hat{\alpha}_{ols,j}$
1	0,6471
2	0,1225
3	0,0617
4	-0,3226
5	0,7379
6	0,2120
7	0,3066

Based on table 6 which shows the canonical estimator of the least squares method, then the ridge parameter is determined using Kibria method $\left(\lambda = \text{median}\left(\frac{\sigma^2}{\hat{\alpha}_j}\right)\right)$. Then, the tuning parameter estimation results is obtained as follows:

Table 7 Output of Tuning Parameter Kibria and VIF Value

Iteration	λ	$\hat{\alpha}_{ridge}$	Error	$\hat{\beta}_{ridge}^*$	VIF
0	0,3767	0,4749	0,1968	0,3377	3,6393
		0,1205		0,0586	0,8428
		0,0614		-0,3270	3,2148
		-0,3214		0,3484	2,1465
		0,7383		-0,1765	2,0458
		0,2118		-0,0751	1,4058
		0,3064		0,8052	0,8270
1	0,3772	0,4747	1,4768e-04	0,3376	3,6310
		0,1205		0,0587	0,8420
		0,0614		-0,3269	3,2076
		-0,3214		0,3484	2,1429
		0,7383		-0,1765	2,0424
		0,2118		-0,0751	1,4040
		0,3064		0,8052	0,8261

From table 7, the model is

$$Y^* = 0,3376 X_1^* + 0,0587 X_2^* - 0,3269 X_3^* + 0,3484 X_4^* - 0,1765 X_5^* - 0,0751 X_6^* + 0,8052 X_7^* \quad (2)$$

Furthermore, each parameter is transformed into an early form. So that the estimation of ridge regression parameters is obtained using the method according to Kibria as follows.

Table 8 Ridge Regression Parameter Estimation

j	Variable	Estimation (β_j)
0	Constant	-0,0875
1	X_1	0,0006
2	X_2	0,0251
3	X_3	-0,0006
4	X_4	0,0130
5	X_5	-0,0079
6	X_6	-0,0072
7	X_7	0,1572

The parameter significance test in equation (2) was carried out partially and completely. Test the significance of the parameters partially by using the t test. The hypothesis used is

$H_0 : \beta_j = 0$ untuk $j = 1, 2, \dots, 6$ (Parameter β_j is not significant)

$H_1 : \beta_j \neq 0$ untuk $j = 1, 2, \dots, 6$ (Parameter β_j significant)

With significant level $\alpha = 5\% = 0,05$ and test criteria if $|t_{hitung}| > t_{tabel}$ or $\rho_{value} < \alpha$, then H_0 rejected, it means significant parameters.

Table 9 Ridge Regression Parameter Significance Test with t Test

Variable	$SE(\beta)$	$t_{statistic}$	t_{table}	Conclusion
X_1	0,0002	2,5635	1,9723	Significant
X_2	0,0069	3,6589		Significant
X_3	0,0002	2,7108		Significant
X_4	0,0011	12,3157		Significant
X_5	0,0012	6,4650		Significant
X_6	0,0034	2,1448		Significant
X_7	0,0033	46,9630		Significant

From table 9 it can be seen that all $t_{statistic}$ value of the independent variable X are greater than the t_{table} value of 1,9723, so it can be stated that H_0 is rejected, meaning that these variables have a significant effect on the dependent variable..

Furthermore, regression testing or model suitability was carried out using the F test. The hypothesis used was:

$H_0 : \beta_0 = \beta_1 = \beta_2, \dots = \beta_7 = 0$ (regression model is not significant)

$H_1 : \exists \beta_j \neq 0, j = 1, 2, \dots, 7$ (regression model is significant)

With significant level $\alpha = 5\% = 0,05$ and test criteria if $F_{statistic} > F_{table}$ atau p-value $< \alpha$, then H_0 rejected.

Table 10 Ridge Regression Parameter Significance Test with F Test

Model	Df	Sum of Square	Mean Square	F
Regression	7	193,7108	27,6730	736,5043
Error	194	7,2892	0,0376	
Total	201	201		

From table 10 with an F_{table} value of 2,3218, then $F_{statistic}$ value greater than F_{table} value. So it can be concluded that the estimated ridge regression model has significant results on the estimated value of the dependent variable (Y). So, the model of ridge regression is

$$\hat{Y}_{ridge} = -0,0875 + 0,0006 X_1 + 0,0251 X_2 - 0,0006 X_3 + 0,0130 X_4 - 0,0079 X_5 - 0,0072 X_6 + 0,1572 X_7 \quad (3)$$

After that, the model suitability test was carried out. The following are the results of the MSE calculation, coefficient of determination (R^2) and *Adjusted R²* regression ridge with the help of MATLAB software as follows.

Table 11 Value of Adjusted R^2

Method	<i>Adjusted R²</i>
<i>Kibria</i>	0,9626

From table 11 it can be seen that the ridge regression model using the Kibria estimator is close to number 3 or it can be interpreted that the regression model is more in line with the actual data model because *Adjusted R²* value is 96,26%.

Forecasting of stock return can be done by inserting and testing the independent variables suspected to affect the dependent variable in the model which has been obtained previously. The following is a graph of forecasting stock returns JKSE.

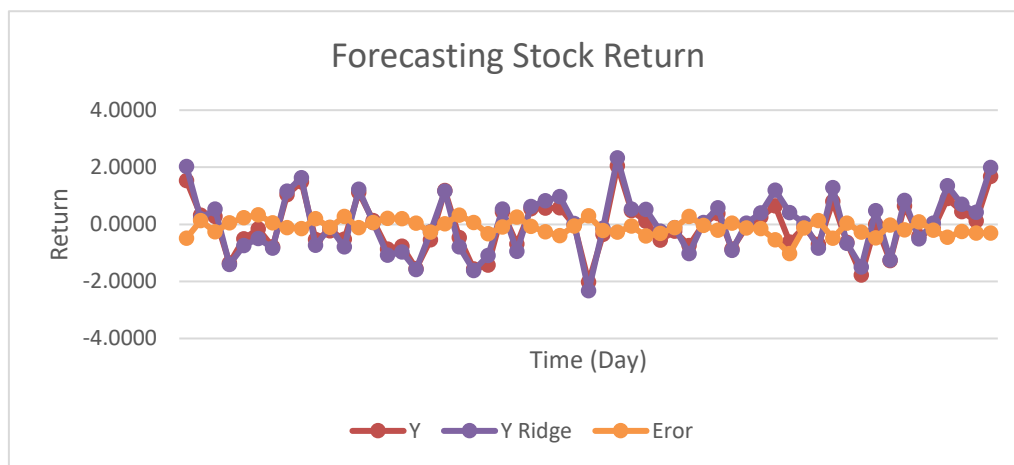


Figure 2 Plot Forecasting Testing Data

Based on the results of forecasting ridge regression model using the estimator Kibria in Figure 2, it can be seen that the error which is the difference of the actual data and the stock returns estimated using ridge regression model close to zero, so that it can be said that the model in number 3 is good to use.

Table 12 Validation Test

MSE	RMSE	MAPE
0,0591	0,2431	39,71%

Based on Table 12, it can be seen that the MSE value is 0.0591 and the RMSE is 0.2431, where both values are quite small and close to zero, while the MAPE value is 39.71%.

CONCLUSIONS

The ridge regression model using the tuning parameter Kibria can be used to predict the return of the JKSE joint stock with a fairly good level of accuracy.

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