Application of Principal Component Analysis (PCA) to Reduce Multicollinearity Exchange Rate Currency of Some Countries in Asia Period 2004-2014

Sri Rahayu
Diponegoro University, INDONESIA

Teguh Sugiarto*
Brawijaya University, INDONESIA

LudiroMadu
UPN 'Veteran' Yogyakarta, INDONESIA

Holiawati
UniversitasPamulang, INDONESIA

Ahmad Subagyo
GICI Business School, INDONESIA

Abstract: This study aims to apply the model Principal component Analysis to reduce multicollinearity on variable currency exchange rate in eight countries in Asia against US Dollar including the Yen (Japan), Won (South Korea), Dollar (Hongkong), Yuan (China), Bath (Thailand), Rupiah (Indonesia), Ringgit (Malaysia), Dollar (Singapore). It looks at yield levels of multicolinierity which is smaller in comparison with PCA applications using multiple regressions. This study used multiple regression test and PCA application to investigate the differences in multicollinearity at yield. From this research, it can be concluded that the use of PCA analysis applications can reduce multicollinearity in variables in doing research.

Keywords: *Principal component analysis (PCA), multiple regression, matrix var-cov, exchange rate.*

Introduction

In Indonesia's economy in particular, Bank of Indonesia (BI) predicts the exchange rate is in the range of Rp 13,500 to Rp 13,800. However, when seen as a point averages, the central bank predicts the rupiah will be at Rp 13,600 per US dollar by the end of 2016. "We predict the range of exchange rate from Rp 13,500 to Rp 13,800 (per dollar) in 2016. If we look at the dot is Rp 13,600 (per dollar), "said BI Governor Agus DW Martowardojo a working meeting with the House Commission XI on Tuesday (07/06/2016). Furthermore, Agus also said that the point estimate of the rupiah to note there are downside risks. According to Agus, if the US economy shows improvement, then the exchange rate can be weakened due to the risk of interest rate which beyond benchmark of the US Fed Funds Rate. BI Governor said that BI observed conditions in the US risks could be associated with exchange rates. The main risk is the risk of rising Fed Funds Rate is expected to rise as much as twice this year, namely in July and December 2016. "Turmoil existing conditions can not be avoided. Many authorities in the US give the message up or not," explains Governor of BI AgusMartowardoyo.

Dornbusch and Fisher (1980) says that exchange rate movements affect the international competitiveness and the balance of trade, and its consequences will also impact on the real output of the country which in turn will affect cash flow today and the future of the company. Equity, which is part of the company's assets, may affect the behavior of the exchange rate through the mechanism of the demand for money is based on the model of exchange rate determination by monetary expert (Gavin, 1989). The monetary approach to the development of the concept of purchasing power parity and the quantity theory of money. This approach emphasizes that an imbalance in foreign exchange rates occur because of imbalances in the monetary sector, namely the difference between the money demands with money supply (Mussa, 1976). The approach used to determine the factors that affect the exchange rate is the monetary approach. With the monetary approach to the studied variables influence the money supply in a broad sense, interest rates,

---

*****Corresponding author:**
Teguh Sugiarto, Faculty of Economics and Business, Brawijaya University, Jakarta, Indonesia,
✉ teguh_cpconsulting@yahoo.com

income levels, and variable price changes. US dollars were used as a comparison, because the US dollar is a strong currency and the US is the dominant trading partner in Indonesia. The concept of exchange rate determination begins with the concept of Purchasing Power Parity (PPP), and then developed the concept with the approach of the balance of payments (balance of payment theory).

Based on a brief review of the above adequately explains how the exchange rate can be made as a proxy in the macro-economic analysis. If we connect with the statistical analysis of one of the goals of this research is to answer the problem of data analysis in addition to that is the outlier. That data is contained multicollinearity outlier among the variables included in the model explained. When determining the population regression model it is possible that in a particular sample, some or all of the variables X highly collinear (has a linear relationship is perfect or nearly perfect). This condition is encouraging for the development of a method or technique that can be used to overcome the problem of multicollinearity in multiple regression analysis. One solution is by using principal component analysis (PCA). The use of PCA will generate new variable-variable which is a linear combination of the independent variables and the origin of this new intra-variable is independent. The new variables are called principal components, and they are, then, regressed to dependent variable.

There are several procedures that can be used to overcome the problem of multicollinearity, such as: the use of information a priori on the relationship several variables correlation, connecting the cross-sectional data and time series data, issuing a variable or multiple variables involved relationship collinear, transforming variable with difference procedure. Based on brief review of the background of the problems described in the introduction, where some of the macro variables have collinearity, ensuring the estimated standard error of the regression parameter estimates will be worth the huge investment that will affect the quality of the inferences. The purpose of this study was to obtain a regression model of investment that is free from the influence of multicollinearity. The results of this study are very useful as information material, inputs for education which deals mainly with research, in determining a suitable model for a macroeconomic analysis tool.

Literature

Understanding Multicollinearity

Multicollinearity term was first discovered by Frisch (1934), which means that the linear relationship is "perfect" or certainly among some or all of the independent variables of the multiple regression model.

Multicollinearity problems (Sumodiningrat, 1994: 282-283) can arise due to:

1. Properties contained in most of the economic variables that changed all the time and these variables are influenced by the same factors.

2. Use of Lag, distributed lag models (distributed lag)

Example: $C_t = f (Y_t, Y_{t-1}, \dots Y_1)$, Chances are there is a strong correlation between Yt and Y_{t-1}

Multicollinearity expected to appear in a plethora of economic relationships more often appear in time series data and may also appear in the data cross sectional. Furthermore, according to Montgomery and Peck 1982 (See Gujarati, 2003.323), which is caused by the emergence multicolinearities data collection method used (the method of data collection employed), the model specification (specification model) and models that are excessive (overdetermined model), ie situations where a specific estimation model, the number of explanatory variables more than the amount of data (observations).

Detection Multicollinearity

According to Gujarati (2003) Multicollinearity symptoms can be diagnosed in several ways, among others: Calculating the correlation coefficient (simple correlation) among the independent variables, if there is a simple correlation coefficient reaches or exceeds 0.8 then it identifies a problem multicollinearity in the regression.

Calculating the value of tolerance or VIF (Variance Inflation Factor), if the value of Tolerance is less than 0.1 or VIF exceeds 10 then it shows that multicollinearity is a problem that must happen between independent variables.

3. TOL tolerance to detect the size multicolliniarity

$$TOL_i = \frac{1}{VIF_i} = 1 - R^2{}_i \qquad \ldots\ldots \qquad (1)$$

4.With Eigenvalues and Conditions Index (CI)

Eigenvalues and Conditions Index for diagnosing Multicollinearity

Numbers Condition:.

$$K = \frac{\lambda_{Max}}{\lambda_{Min}} \qquad \ldots\ldots\ldots \qquad (2) \quad \lambda: \text{eigen value; Condition Index } i : \text{ID} = \sqrt{K}$$

Prevention Multicolinearity

Montgomery and Hines (1990) explains that the impact of multicolinearities can result in regression coefficients generated by multiple regression analysis becomes very weak or cannot provide the analysis results that represent the nature or effect of the independent variables concerned. In many ways the problem that leads to test multicollinearity could be insignificant. Whereas if each independent variable is regressed separately with the dependent variable (simple regression), the test showed significant result. It often led researchers to obtain results of analysis which were conducted in multiple regressions and simple regressions is not in line with or even very contradictory.

However, in practice the procedure of prevention effect for multicollinearity often happens depends completely on research conditions, eg. procedures on the use of information. These procedures are highly dependent on the presence or absence of basic theory (literature), which is very strong for supporting the mathematical relationship between the independent variables. The variable is mutually multicollinearity, while procedures of issuing independent variable of multicollinearity often makes trouble for many researchers. Consequently, this procedure will reduce research objects and connect a cross-sectional and time series. Moreover, the procedure will be first difference and the addition of new data often only give the effect of counter-measures for small problems of multicollinearity. Therefore, we can use other techniques for eliminating multicollinearity problems without having to get the independent variables involved collinear relationship, namely with Ridge Regression method or the method of Principal Component Analysis (PCA) that exist in the factor analysis. This study will use the principal component analysis (PCA).

Research Methods

Data and Time Research

This research used data which were originally taken from daily currency exchange rate of 8 countries in Asia, namely China, Hong Kong, Japan, South Korea, Malaysia, Indonesia, Singapore, Thailand from 1 January 2004-31 December 2014. This study completed in January 2017. Other data were downloaded from various websites such as the IMF, WB,

Principle Component Analysis (PCA) Method

Principal Component Analysis (Principal Component Analysis) is a multivariate analysis that transforms the original variables that are correlated into new variables that are not correlated with the reduction of the number of variables that have smaller dimensions but can explain most of the diversity of the original variables.

The number of major components that are formed equals the number of original variables. Reduction (Simplification) dimensions do with the criteria of the percentage of diversity of the data described by some of the major components of the first. If the first few major components have explained more than 75% of the diversity of the original data is, then the analysis is done up to the main component. When the main component is derived from a population of multivariate normal random vector X = (X1, X2, ...,Xp) and vector average μ = (μ1, μ2, ..., μp) and covariance matrix Σ with root characteristic (eigenvalue) that λ1 ≥ λ2 ≥ ⋯ ≥ λp ≥ 0 obtained a linear combination of the main components is as:

$$Y_1 = e'_1 X = e'_{11} X_1 + e'_{21} X_2 + \cdots + e'_{p1} X_p$$
$$Y_2 = e'_2 X = e'_{12} X_1 + e'_{22} X_2 + \cdots + e'_{p2} X_p$$
$$\vdots$$
$$Y_p = e'_p X = e'_{1p} X_1 + e'_{2p} X_p + \cdots + e'_{pp} X_p$$

follows.

Then Var (Yi) = ei'Σei and Cov (Yi, Yk) = ei'Σei where i, k = 1, 2, ..., p.

Requirements to form the main component is a linear combination of variable X in order to have maximum variant is to select a feature vector (eigen vector) that e = (e1, e2, ..., ep) such that Var (Yi) = maximum ei'Σei and ei 'ei = 1.

• The first main component is a linear combination that maximizes e1'X Var (e1'X) provided e1'e1 = 1.

• The second major component is a linear combination that maximizes e2'X Var (e2'X) provided e2'e2 = 1.
• The main components of all i is a linear combination that maximizes ei'XVar (ei'X) provided ei'ek = 1 and Cov (ei'ek) = 0 for k <1.

The main components are uncorrelated and have the same variation with characteristic roots of Σ. Root characteristic of variance covariance matrix Σ is a variant of the main components of Y, so the variance covariance matrix of Y are:

$$\Sigma = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_p \end{bmatrix}$$

The total diversity of origin variable will be equal to the total diversity is explained by major components, namely:

$$\sum_{J=1}^{P} \text{var}(X_i) = \text{tr}(\Sigma) = \lambda_1 + \lambda_2 + \cdots + \lambda_p = \sum_{J=1}^{P} \text{var}(Y_i)$$

Depreciation dimensions of the original variable is done by taking a small number of components are able to explain the largest part of diversity data. If the main components are taken as the component q, where q <p, then the proportion of the total diversity can be explained by the main component to-i are:

$$\frac{\lambda_i}{\lambda_1 + \lambda_2 + \cdots + \lambda_p} \qquad i = 1, 2, \ldots, p$$

Decreasing the main components of the correlation matrix is conducted when the data was first transformed into a raw form Z. This transformation is performed on the data unit is not the same observation. When the size of the observed variables on a scale with a very wide differences or unit size is not the same, then these variables need to be standardized (standardized).

Raw variable (Z) obtained from the transformation of the original variables in the following matrix:

$$Z = \left(V^{1/2}\right)^{-1} (X - \mu)$$

V1 / 2 is the standard deviation matrix with main diagonal elements are (αii) 1/2, while other elements are zero. The expected value E (Z) = 0 and diversity is

$$\text{Cov}(Z) = \left(V^{1/2}\right)^{-1} \Sigma \left(V^{1/2}\right)^{-1} = \rho$$

Thus the main components of Z can be determined from the feature vector obtained through the correlation matrix of variables ρ origin. To find the root traits and determine the vector as same as the matrix Σ. While trace matrix correlation will be equal to the number of variables used.

Selection of key components used are based on the value of the root of the characteristics, that is the main component to be used if the roots of character is greater than one.

Discussion

This chapter describes the results of calculations which are two of the three parts of the output. The first part gives a summary outlining the results of the original values of the correlation matrix, while the second part shows how the results of the corresponding vectors. However, in this view photo depicted another type of PCA, but will present actual value of output in the form of the estimated correlation matrix itself.

PCA Result with correlation

Table 1: Result PCA with Model

Principal Components Analysis

Eigenvalues: (Sum = 8, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	4.408876	2.832726	0.5511	4.408876	0.5511
2	1.576150	0.455220	0.1970	5.985026	0.7481
3	1.120930	0.485515	0.1401	7.105957	0.8882
4	0.635416	0.475316	0.0794	7.741372	0.9677
5	0.160100	0.112773	0.0200	7.901472	0.9877
6	0.047327	0.016367	0.0059	7.948799	0.9936
7	0.030960	0.010718	0.0039	7.979759	0.9975
8	0.020241	---	0.0025	8.000000	1.0000

Table 2: Result Eigenvectors Model

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
CHINA_YUAN	0.458926	0.102789	0.142805	-0.140992	0.075986	0.355091	-0.104803	0.771817
HONGKONG_$	0.153299	-0.545881	0.110674	0.802970	-0.142918	0.013941	0.002933	-0.029591
IND_RUPIAH	-0.106897	0.572916	-0.512805	0.427955	-0.341234	0.133608	-0.050307	0.278214
JAPAN_YEN	0.365507	-0.015683	-0.537786	0.118360	0.672758	-0.316615	0.100303	-0.005243
KOREAN_WON	-0.151257	0.486726	0.602058	0.363993	0.463232	-0.064963	0.119462	0.110360
MALAY_RINGGIT	0.446020	0.242206	0.060173	0.061091	0.082761	0.445078	-0.514029	-0.515637
PHIL__PESO	0.436992	0.194728	0.210525	-0.029046	-0.363072	-0.726021	-0.252470	0.057322
THAI_BAHT	0.456169	0.171710	0.068995	-0.033764	-0.226941	0.161859	0.796353	-0.211296

Table 3. Result ordinary correlation

Ordinary correlations:

	CHINA_YUAN	HONGKONG_$	IND_RUPIAH	JAPAN_YEN	KOREAN_WON	MALAY_ RINGGIT	PHIL__PESO	THAI_BAHT
CHINA_YUAN	1.000000							
HONGKONG_$	0.342418	1.000000						
IND_RUPIAH	-0.426932	-0.402723	1.000000					
JAPAN_YEN	0.647854	0.238613	0.115949	1.000000				
KOREAN_WON	-0.315256	-0.271297	0.238426	-0.540110	1.000000			
MALAY_RINGGIT	0.869471	0.130359	-0.013281	0.681786	-0.055176	1.000000		
PHIL__PESO	0.874037	0.146878	-0.143064	0.541277	-0.032175	0.930047	1.000000	
THAI_BAHT	0.903314	0.157407	-0.097786	0.662355	-0.148582	0.955860	0.949642	1.000000

Source: Proceed by author

Table 1 illustrates the calculation of the header information and two of the three parts of the output. The value of the results of the first part in the show, which describes the eight components of the first variable to approximately 90% of the total variance in the scale of values DCPCH between cross-sections. In the second part describes the combination hose linear coefficients. This study saw that the first principal component (labeled "PC1") is a linear combination of rough-together of all the eight countries per exchange. Eugen components in this matrix may be regarded as representing a common component in currency exchange rates from 8 countries. Here in view for the view of the model covariance.

PCA Result with Covariances

Table 4 : Result PCA analysis with covariances model

Principal Components Analysis
Eigenvalues: (Sum = 1018597, Average = 127324.6)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	1006411.	994377.7	0.9880	1006411.	0.9880
2	12033.16	11895.60	0.0118	1018444.	0.9999
3	137.5650	123.3140	0.0001	1018582.	1.0000
4	14.25099	13.62730	0.0000	1018596.	1.0000
5	0.623695	0.598717	0.0000	1018597.	1.0000
6	0.024978	0.022241	0.0000	1018597.	1.0000
7	0.002737	0.002251	0.0000	1018597.	1.0000
8	0.000486	---	0.0000	1018597.	1.0000

Table 5 : Result eugenvactor covariances model

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
CHINA_YUAN	-0.000326	-0.001561	0.050140	0.072957	0.078806	0.970455	-0.207613	-0.032616
HONGKONG_$	-1.05E-05	-4.30E-05	0.000457	-0.000917	-0.001637	0.018392	-0.071531	0.997267
IND_RUPIAH	0.999631	-0.026927	-0.002855	0.002130	-3.97E-05	0.000270	-6.03E-05	3.24E-06
JAPAN_YEN	0.001529	-0.072306	0.904362	-0.418771	-0.036815	-0.012953	-0.002601	-0.000810
KOREAN_WON	0.027106	0.997008	0.066758	-0.027973	0.001061	8.21E-05	-0.000451	-4.50E-05
MALAY_RINGGIT	-3.61E-06	-0.000146	0.020229	0.028857	0.026288	0.205550	0.975412	0.066233
PHIL__PESO	-0.000701	-0.000120	0.331550	0.765451	-0.550537	-0.031689	-0.007984	-0.000340
THAI_BAHT	-0.000353	-0.004411	0.254590	0.481427	0.829849	-0.120231	-0.016735	0.002705

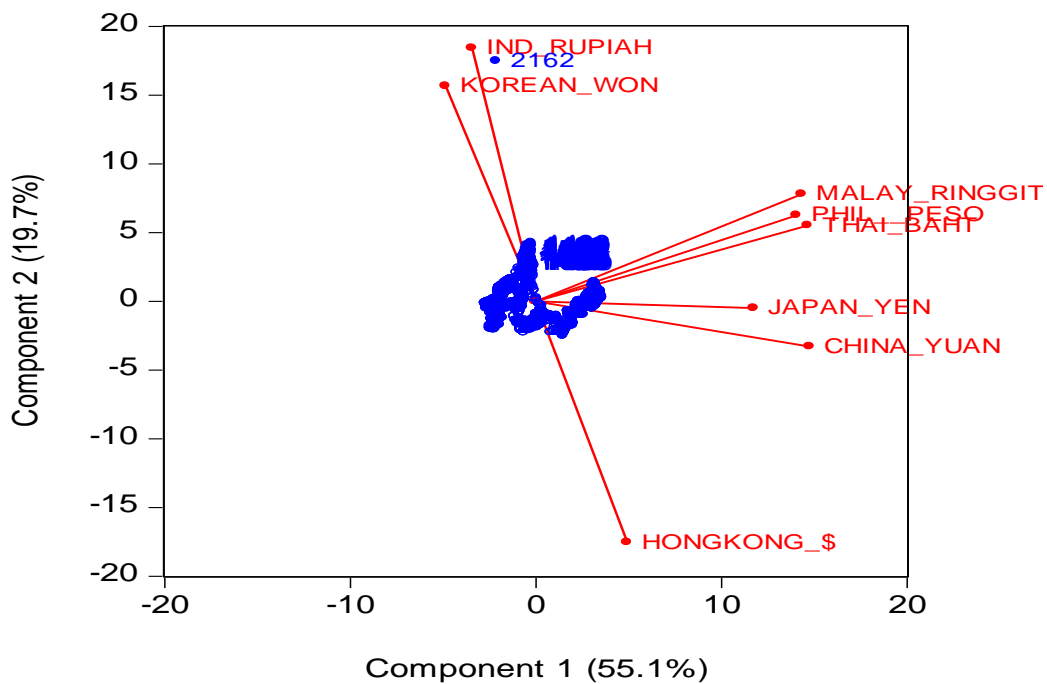*Table 6 : Result ordinary covariances model*

Ordinary covariances:

	CHINA YUAN	HONGKONG $	INDIAN RUPIAH	JAPAN YEN	KOREAN WON	MALAY RINGGIT	PHIL. PESO	THAI BAHT
CHINA_YUAN	0.585574							
HONGKONG_$	0.006839	0.000681						
IND_RUPIAH	-327.626104	-10.541012	1005677.103009					
JAPAN_YEN	6.656330	0.083620	1561.220204	180.274084				
KOREAN_WON	-27.188116	-0.798024	26946.780525	-817.284826	12701.338173			
MALAY_RINGGIT	0.179180	0.000916	-3.586883	2.465232	-1.674614	0.072525		
PHIL__PESO	3.287210	0.018841	-705.126696	35.718457	-17.821868	1.230990	24.155345	
THAI_BAHT	2.493143	0.014818	-353.691886	32.075627	-60.395926	0.928443	16.833863	13.008730

Sources : Proceed by author

Similar to the above format, the previous table. In the header describes the observation sample (table 2), the method used to calculate the dispersion matrix, and information about the number of components is maintained (in this case, all no 8). The next section summarizes the eigenvalues, showing values, differences developed in eigen, and the proportion of the total variance explained. As we do a major component of the correlation matrix, the amount of the variance scale to 8 variables are not equal. If read out the main first order component accounts for 98% of the total variance (1006411 / 8.00 = 125,000), while the second accounts for 1.1% (12033.16 / 8.00 = 1500) of the total. The first two components account for over 100% of the total variation.

For the second table column describes the combination of linear coefficients. Can be seen that the first principal component (labeled "PC1") is a linear combination of rough-together of all eight of the exchange rate; may reasonably be interpreted as a general return rate. The second major component (labeled "PC2") have a negative burden for the 8 countries (China, Hong Kong, Japan, South Korea,), and the exchange rate of the country (Singapore, Indonesia, Thailand, Malaysia).


Figure 1. Abnormal loading PCA

In figure 1 above score component is displayed as a circle and variable load is displayed as a line from the origin to the variable label. Biplot clearly shows that the first component has a positive burden for all five variables (common stock return indices interpretation). The second component has a variable load is positive for energy stocks, and a negative charge on chemical stocks; when energy stocks did well relative to chemical stocks, the specific component to be positive, and vice versa.

Score 3 label indicates that the observation is an outlier, with a high value for the exchange rate, and the value of a relatively neutral for the sector index. In contrast, observations of 20 is a period in which the exchange rate overall was positive, with high returns on the currency exchange rate for the East Asian region relative to the currency exchange rate in the Southeast.
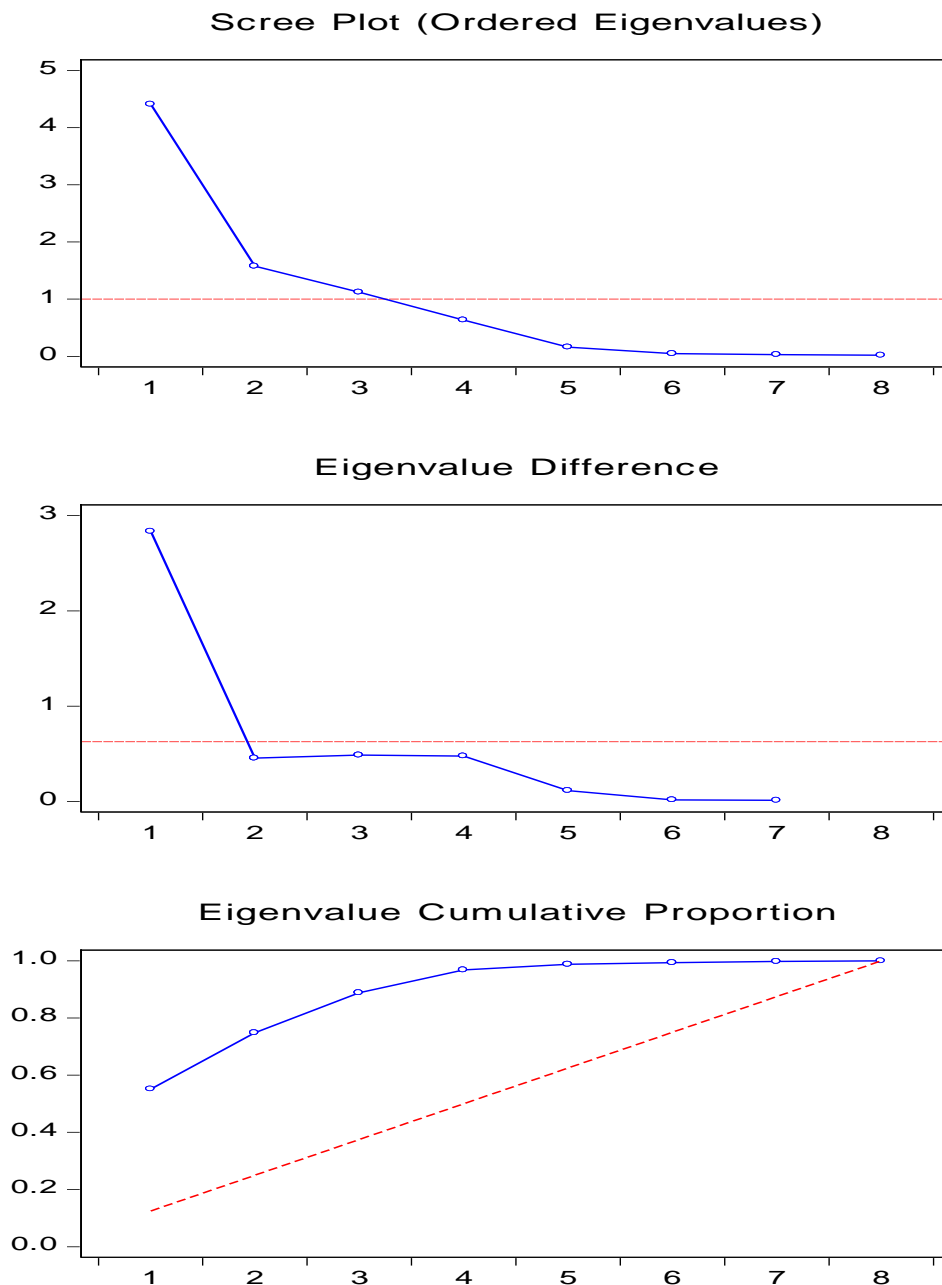
Source: Proceed by author

Figure 2. Eigenvalue loading PCA

Figure 2 shows results ordered Eigen line by selecting Eigenvalues plot on the main dialog display. Dialog will change to offer a choice of displaying the plot of one: eigenvalues (scree plot), a difference of eigenvalues, the cumulative proportion of variance explained.

Prevention Multicollinearity

Previous sections have described how there are problems of colinearity in the data, then the countermeasures to solve the problem by using the procedures Principal Component Analysis (PCA), which aims to simplify the observed variables by reducing its dimensions. To determine whether or not the factor analysis is done, do a test Kaiser-Meyer-Olkin (KMO). Once it searched values of loading: It can be obtained main components and functions through R program can be seen through the scree plot, function main components are:

Table 7 : Result regression analysis model

Dependent Variable: CHINA_YUAN

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-5.524698	0.905279	-6.102759	0.0000
HONGKONG_$	1.092170	0.115269	9.474980	0.0000
IND_RUPIAH	-0.000267	3.41E-06	-78.24919	0.0000
JAPAN_YEN	0.004637	0.000447	10.37946	0.0000
KOREAN_WON	-0.000726	3.85E-05	-18.86120	0.0000
MALAY_RINGGIT	1.265865	0.042482	29.79738	0.0000
PHIL__PESO	0.012007	0.001978	6.070170	0.0000
THAI_BAHT	0.062456	0.003275	19.06939	0.0000
R-squared	0.969315	Mean dependent var		7.050292
Adjusted R-squared	0.969235	S.D. dependent var		0.765371
S.E. of regression	0.134246	Akaike info criterion		-1.175307
Sum squared resid	48.29924	Schwarz criterion		-1.157758
Log likelihood	1587.613	Hannan-Quinn criter.		-1.168960
F-statistic	12094.07	Durbin-Watson stat		0.098411
Prob (F-statistic)	0.000000			

Sources : Proceed by author

Then it will be the calculated value of F 1.3972 is less than the value of F 12094.07 at the table. There is no correlation between the exchange rate variable. If we compare the value of F arithmetic with F table that has been generated, it can be explained that these values, are greater than the value of the degree of correlation of PCA applications that have been implemented. As explained, the model equations are derived from a regression that was made.

Substituted Coefficients:
=========================
CHINA_YUAN = -5.52469757633 + 1.09216991545*HONGKONG_$ - 0.000267174974015*IND_RUPIAH + 0.00463694598481*JAPAN_YEN - 0.00072602004864*KOREAN_WON + 1.26586503157*MALAY_RINGGIT + 0.0120071183121*PHIL__PESO + 0.0624558145377*THAI_BAHT

Conclusion

Based on the results of the analysis showed that the cumulative value of the proportion of variance principal component can explain 98% which means that by taking just one component that is the main component of one is sufficient but if until two main components, the cumulative value of the proportion of the variance can be explained 1% .Would be better if up with three main components that can explain the value of the cumulative variance proportion of 0.00%. To get a better model, the authors cannot be advised to use a variable exchange rate which is the best to be made as the dependent variable. But in this study, author obtained the best to be made as the dependent variable is Yuan (China).

Reference

Dornbusch, R, (2004), *Macroeconomics* (8th ed.). New York, NY: McGraw-Hill, Inc.

Dornbusch, R., & Fischer, S. (1980). Exchange rates and the current account. *American Economic review, 70*(5), 960–971.

Gavin, M. (1989). The stock Market and exchange rate dynamics. *Journal of international money and finance, 8*(2) 181-200.

Gujarati, D. (2003). *Basic Economertics* (4th ed.). New York, NY: McGraw-Hill, Inc.

Johnson, R. A., & Wichern, D. W. (2002). *Applied multivariate statistical analysis* (5th ed.). London, UK: Pearson.

Kutner, N., Nachtsheim, C., & Neter, J. (2004). *Applied linear regression models* (4th ed.). New York, NY: McGraw-Hill Education.

Myers, R. A., & Milton, J. S (1991). *A first course in the theory of linier statistical models*. Boston, MA: PWS-KENT Publishing Company.

Mussa, M. L. (1976). The exchange rate, the balance of payments and monetary and fiscal policy under a regime of controlled floating. *Scandinavian Journal of Economics, 78*(2), 229-248. https://doi.org/10.2307/3439926

Sumodiningrat, G. (1998). *Membangun perekonomian rakyat* [Build people's economy]. Yogyakarta, Indonesia: Pustaka Pelajar Publishing.