Evaluation of Models for predicting the average monthly Euro versus Norwegian krone exchange rate from financial and commodity information

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Chapter 1

Introduction

Trading started from the very beginning of human civilization. People used to trade with goods at the time but with advancement of development people started using gold, silver and finally money. The process is not restricted within a country. Some countries are powerful and some are not so as their currencies. Currency of another country becomes essential to buy things from that country. Here comes the roal of exchange rate. Buying powerful currencies requires large sum of weak currencies. All those economic activities that exist between countries create demand and supply of the currencies of those countries which consequently determine the exchange rate. The economic activities betwen countries is also called the balance of payment. Thus the balance of payment captures all the demand and supply of foreign currency (Fang and Kwong, 1991). When the domestic demand for foreign currency exceeds the foreign demand of domestic currency i.e. a deficit in the balance of payment, the domestic currency depreciate (*Balance of Payments Deficits and Surpluses*).

Any international trade is conducted through more than one currencies. Participants in the international trade require to exchange their currency which is performed by foreign exchange market. “The foreign exchange market (ForEx) is the mechanism that brings together buyers and sellers of different currencies” (Appleyard, 2014).

Chapter 2

Data and Material

Chapter 3

Models and Methods

3.1 A statistical Model

A statistical model describes the relationship between a cause and its effect. A vector $\mathbf{y}$ contains n number of responses. $\mathbf{X}$ be a $n \times p$ matrix whose columns are independent variables and each of them have n observations. These variables in $\mathbf{X}$ can affect $\mathbf{y}$ so, the relationship between $\mathbf{X}$ and $\mathbf{y}$ can be written in a functional form as,

$$\mathbf{y} = f(\mathbf{X}) + \epsilon \tag{3.1}$$

where, ϵ is a vector of unknown errors usually referred as 'white noise' when dealing with time-series data which is assumed to have zero mean and constant variance.

3.1.1 Linear Regression Model

The linear regression model with a single response ($\mathbf{Y}$) and p predictor variable $x_1, x_2, \ldots, x_p$ has form,

$$\underbrace{\mathbf{Y}}_{\text{Response}} = \underbrace{\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p}_{\text{Mean Response explained by predictors only}} + \underbrace{\epsilon}_{\text{Error Term}} \tag{3.2}$$

The model - 3.2 is linear function of p unknown parameters $\beta_1, \beta_2, \ldots, \beta_p$ which is generally refered as regression coefficients. The error term ϵ are assumed to follow,

$$\begin{aligned} \mathbf{E}(\epsilon_j) &= 0 \\ \mathbf{Var}(\epsilon_j) &= \sigma^2(\text{Constant}) \\ \mathbf{Cov}(\epsilon_j, \epsilon_k) &= 0 \; j \neq k \end{aligned} \tag{3.3}$$

In matrix notation, eqn (3.2) becomes (Johnson and Wichern, 2007),

$$\underset{n\times 1}{\mathbf{Y}} = \underset{n\times(p+1)}{\mathbf{X}} \underset{(p+1)\times 1}{\boldsymbol{\beta}} + \underset{n\times 1}{\boldsymbol{\epsilon}} \tag{3.4}$$

The assumption in (3.3) becomes,

$$\begin{aligned} \mathbf{E}(\boldsymbol{\epsilon}) &= \mathbf{0} \\ \text{and } \mathbf{cov}(\boldsymbol{\epsilon}) &= E(\boldsymbol{\epsilon}\boldsymbol{\epsilon}^{\boldsymbol{t}}) = \sigma^2\mathbf{I} \end{aligned} \tag{3.5}$$

Least Square Estimation

The unknown parameter $\boldsymbol{\beta}$ in (3.4) is obtained by minimizing the sum of square of residuals (Yeniay and Goktas, 2002), The sum of square of residuals is,

$$\boldsymbol{\epsilon}^t\boldsymbol{\epsilon} = (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^t(\mathbf{Y} - \mathbf{X}\boldsymbol{\beta}) \tag{3.6}$$

On minimizing eq - 3.6, we get the OLS estimate of $\boldsymbol{\beta}$ as,

$$\hat{\boldsymbol{\beta}}_{OLS} = (\mathbf{X}^t\mathbf{X})^{-1}\mathbf{X}^t\mathbf{Y} \tag{3.7}$$

Under the assumption in eq-3.5, the OLS estimate obtained from eq-3.7 is best linear unbiased estimator of β (Wooldridge, 2012).

Prediction

Using $\hat{\boldsymbol{\beta}}$ obtained in eq-3.7, following two matrices can be obtained,

$$\text{Predicted Values:}\hat{\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}(\mathbf{X^tX})^{-\mathbf{1}}\mathbf{X^tY} \tag{3.8a}$$

$$\text{Residuals:}\hat{\boldsymbol{\epsilon}} = \mathbf{Y} - \hat{\mathbf{Y}} = [\mathbf{I} - \mathbf{X}(\mathbf{X^tX})^{-\mathbf{1}}\mathbf{X^t}]\mathbf{Y} \tag{3.8b}$$

Here eq-3.8a gives predicted values of $\mathbf{Y}$ which on subtracting from the observed value give the error terms as is presented in eq-3.8b. Eq-3.8a can also be written as,

$$\hat{\mathbf{Y}} = \mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{HY} \tag{3.9}$$

Here, $\mathbf{H}$ is called Hat matrix and is the orthogonal projection of y onto the space spanned by X(Faraway, 2004).

3.2 Principal Component Analysis

The purpose of PCA is to express the information in $X = (X_1, X_2, \ldots, X_p)$ by a less number of variables $\hat{Z} = (Z_1, Z_2, \ldots, Z_q); q < p$ called principal components of X (Martens and Naes, 1992). These principal components are orthogonal and linearly independent. Since they are computed from the linear combination of X variables, the variation in these variables are compressed in first few principal components. In other words, the first principal components is the direction along which the X variables have the largest variance (Massart, 1998). In this situation, the multicollinearity in X is not a problem any more.

The principal components can be performed on Covariance matrix or in Correlation matrix. If the variables are of same units and their variances do not differ much, we can use the covariance matrix. In this thesis, the correlation matrix is used to compute principal components since, the X variables are of different units and their variations have large difference. Calculation of Principal Component Analysis requires following steps:

1. Calculate the correlation of data matrix X

$$\text{cor}(X) = \frac{\text{cov}(X, Y)}{S_x S_y} = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2 \sum_{i=1}^{n} (Y_i - \bar{Y})^2}} \tag{3.10}$$

2. Calculate eigenvalue and eigenvector of the correlation matrix obtained in eq-3.10. An eigenvalue $\lambda_i; i = 1, \ldots p$ of a square matrix $\mathbf{A}$ of order p is a scalar which satisfies,

$$\mathbf{A}\mathbf{E}_i = \lambda_i \mathbf{E}_i \tag{3.11}$$

The vector $\mathbf{E}_i$ is called eigenvector(Harville, 2008).

It is equivalently written as, $|\mathbf{A} - \lambda_i \mathbf{I}_n|E = 0$ which can only be realized if $|\mathbf{A} - \lambda_i \mathbf{I}_n|$ is singular, i.e.,

$$|\mathbf{A} - \lambda_i \mathbf{I}_n| = 0 \tag{3.12}$$

Eq-3.12 is called the characteristic equation where, $\mathbf{A}$ is the correlation matrix obtained from eq-3.10. The root of the equation is called eigenvalues (Seber, 2008) and the vector $\mathbf{E}_i$ is called eigenvector corresponding to the eigenvalue λ_i.

3. The eigenvector obtaind from eq-3.11 is normalized, i.e. $||\mathbf{E}_i||^2 = 1$. In matrix form the eq-3.11 can be written as,

$$\mathbf{AE} = \mathbf{E\Lambda} \tag{3.13}$$

where,

$$\begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_p \end{bmatrix} \tag{3.14}$$

The matrix in eq-3.14 has eigenvalues of matrix A in its diagonal. In PCA these eigenvalues are arranged in descending order. i.e. $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_p$ and eigenvectors $\mathbf{E} = (\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_p)$ The eigenvalue decomposition of the matrix $\mathbf{A}$ is then written as,

$$\mathbf{A} = \mathbf{E\Lambda E}^{-1} = \mathbf{E\Lambda E}^T \tag{3.15}$$

Since, $\mathbf{E}$ is a orthogonal matrix generated from a symmetric and positive definite matrix $\mathbf{A}$

4. Since, the variation explained in data are accumulated in first few principal components, only k eigenvalues in descending order are considered while computing it. The corresponding eigenvectors of those eigenvalues is called projection matrix. The projection matrix is,

$$\mathbf{P} = \begin{pmatrix} \mathbf{E}_1^T \\ \mathbf{E}_k^T \\ \vdots \\ \mathbf{E}_k^T \end{pmatrix} \tag{3.16}$$

The projection matrix in eq-3.16 projects the datamatrix into low dimensional subspace $\mathbf{z}_i$. i.e.,

$$\mathbf{z}_i = \mathbf{P}\mathbf{X}_i \tag{3.17}$$

The new vectors $\mathbf{z}_i$ obtained from 3.17 are the orthogonal projections of data matrix $\mathbf{X}$ into k dimensional subspace. These components are the linear combination of the rows of matrix $\mathbf{X}$ such that the most variance is explained by the first component $\mathbf{z}_1$ and second component has less variance than the first one and so on. These components are also called scores.

3.3 Principal Component Regression

The components obtained from Principal Component Analysis

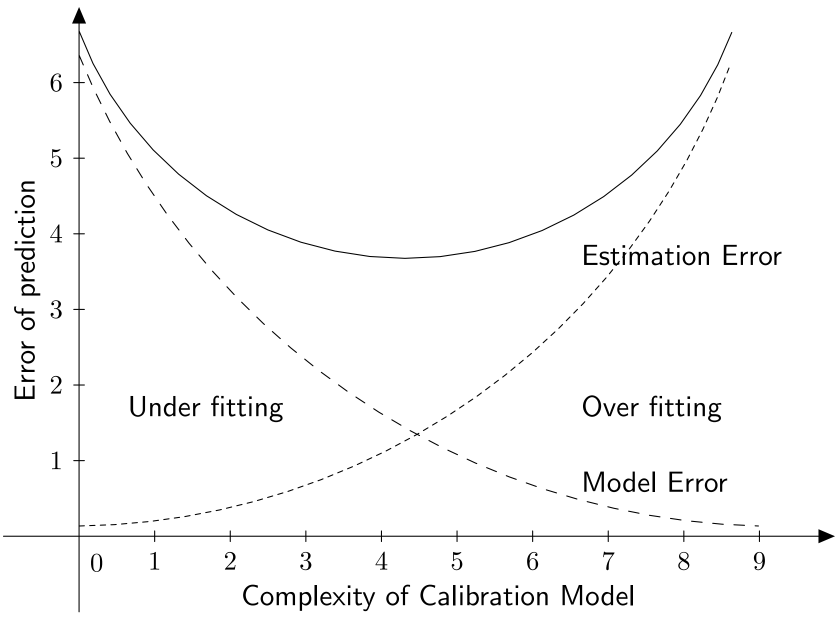


Figure 3.1: Model Error - Estimation Error and Prediction Error

3.4 Partial Least Square Regression

3.5 Ridge Regression

3.6 Comparision Criteria

3.6.1 PRESS (Predicted Residual Aum of Squares)

3.6.2 RMSEP (Root Mean Standard Error of Prediction)

3.6.3 R-squared for Prediction

3.6.4 Goodness of Fit

Chapter 4

Data Analysis

This chapter will present the analysis report obtained for different models and also compare those models with criteria like goodness of fit, prediction error, variation explained during prediction. During this analysis, only the observations from Jan 2000 to December 20012. The model will be exposed to predict the average monthly exchange rate of Euro vs Norwegian Krone and compare the prediction with original value for its accuracy.

The summary report of the variables that are in use during the analysis are in table (4.1),

Table 4.1: Summary Report of all the variables used in this report

	min	median	max	mean	stdev
PerEURO	7.30	8.00	9.40	8.02	0.37
KeyIntRate	1.25	2.25	7.00	3.41	2.05
CPI	104.60	118.50	137.40	120.52	9.42
EuroIntRate	0.02	2.07	5.06	2.13	1.56
LoanIntRate	2.25	4.00	9.00	4.90	2.32
ImpTot	20586.00	35096.00	57202.00	34325.09	8377.01
ImpExShip	20386.00	34472.00	56879.00	33537.63	8238.32

ImpExShipOilPlat	20386.00	34472.00	48711.00	33415.27	8196.36
ImpExcShipOilPlatCrd	20330.00	34472.00	48711.00	33132.77	8044.08
TotExp	34581.00	63117.00	90991.00	60482.33	14836.38
ExpExOldShip	34228.00	62772.00	90422.00	60135.93	14809.72
ExpExShip	34060.00	62457.00	90063.00	59831.67	14825.60
ExpExShipOilPlat	34060.00	62348.00	90063.00	59766.57	14869.77
MlandExp	14524.00	25479.00	33854.00	24364.58	5695.09
TrBal	10853.00	25106.00	48573.00	26157.26	8294.18
TrBalExShipOilPlat	11493.00	25443.00	47250.00	26351.35	8252.63
TrBalMland	-18150.00	-9262.00	-2766.00	-9050.70	3072.90
ImpShip	0.00	573.00	9729.00	787.45	942.74
ImpOldShip	0.00	103.00	8099.00	233.13	648.33
ImpNewShip	0.00	377.00	3011.00	554.35	630.02
ImpOilPlat	0.00	0.00	8914.00	122.37	803.28
ImpShipOilPlat	0.00	605.00	9729.00	909.80	1228.84
ExpCrdOil	13125.00	22630.00	37132.00	22811.93	4705.29
ExpNatGas	2457.00	11290.00	26420.00	11817.19	6511.09
ExpCond	0.00	751.00	2305.00	772.88	452.14
ExpCrdOilNatGasCond	18142.00	35765.00	56599.00	35401.99	9739.09
ExpShip	0.00	526.00	2619.00	650.67	528.82
ExpOldShip	0.00	214.00	1948.00	346.44	361.29
ExpNewShip	0.00	216.00	2326.00	304.25	365.74
ExpOilPlat	0.00	0.00	3069.00	65.11	368.38
ly.var	7.30	8.00	9.40	8.02	0.37

It is also desirable to see the time series plot of the related variables given in figure -(4.1)

The correlation plot in figure -(4.2a) will give some idea about the correlation among various predictor variables. In the plot, high correlation between independent variables indicates multicollinearity in the model.

Further, the fig-(4.2b) shows that only few of the predictor variables have significant correlation with response variable.

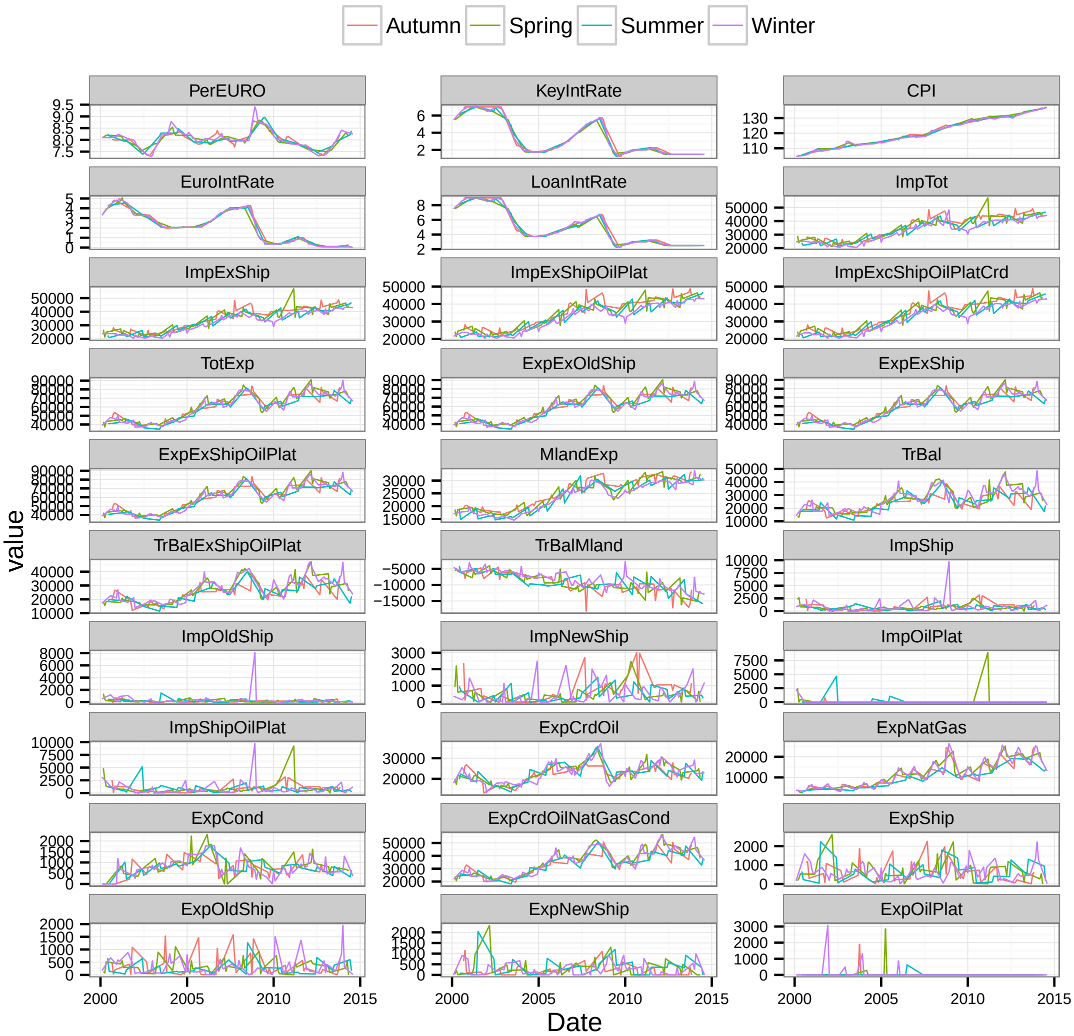
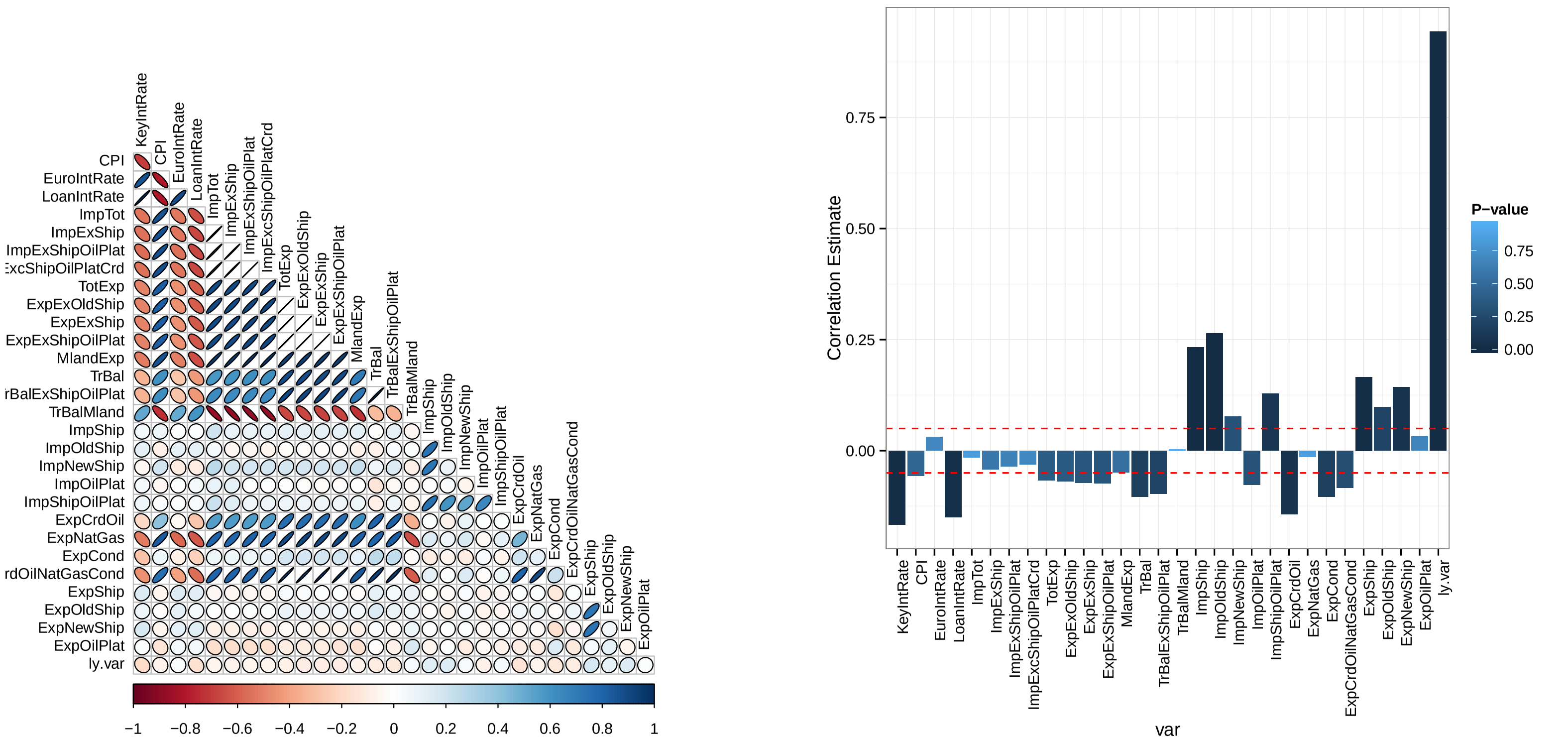


Figure 4.1: Time Series plot of different variables

4.1 Multiple Linear Regression

Lets denote the predictor variables by $\mathbf{X} = (X_1, X_2, \ldots, X_p)$ and Y for response variable. The detail explanation for the variables are in Appendix A. The linear model, as given in eq-(3.4),when fitted, shows that only few variables are significant. In other words `EuroIntRate, MlandExp, ly.var` are affecting the Euro vs



(a) Correlation Plot of different predictor variables

(b) Correlation betwen Response and Predictor Variables. The red dashed lines give the critical region of 0.05 significance level

Figure 4.2: Correlation Analysis of Dataset

Norwegian Krone exchange rate significantly. The table (4.2) gives the result for the fitted model.

The summary table in table-(4.2) can also be visualized by the bar plots of t-value we obtained which is shown in figure-(4.4a). The red bars are those coefficients which are only significant variables and are also separated by he red dashed lines representing the critical value of t at 0.05 level of significance.

Although, lots of coefficients are insignificant, the diagnostic plots in figure-(4.3) are satisfactory and indicates that the residuals are randomly distributed and the very few observations are influential but are out of danger zone.

Since, there are a lot of variables that are not significant. So, it is better to use step-wise variable selection procedure. The backward elimination method choose some variables and a more variables are significant in this case.

The t-value plot in figure -(4.4b) summarize the results presented in table-(4.2), where the red bars represents the significant variables. The estimates are on the top of the bars.The critical region is separated by the red dashed lines.

From the correlation plot in fig-(4.2a) we can get some idea about multi-collineartiy. Since a multicollinearity problem can lead to false estimate in the models fitted above. The multicollineary can be measured using Variance Inflation Factor (VIF). For the linear model obtained from stepwise backward elimination process, the VIF obtained are in figure - (4.5). The red dashed line in the figure for the indication of VIF at 10 which is regarded as tolorence level as a rule of thumb. Since some of the variables have very high VIF comparing this tolorence level, It is better to adopt alternative approaches like Principal Component Regression, Partial Least Square Regression or Ridge Regression (Oâbrien, 2007).

4.2 Principal Component Analysis

Principal Component Analysis(PCA) creates a new set of mutually orthogonal and independent variables called components. The PCA analysis is done for centered and scaled x-variables (Predictor variables) that are considered in this analysis from Jan 2000 to Aug 2014. However, an observation of Jan 2000 is omitted due to introduction of lagged variable of response as a predictor variable.

The first seven component in the analysis are explaining the variation greater than the original variables (table-4.3). In addition, From figure - (4.6a), it can be seen that on considering twelve components, around 99 percent of variation in x-variables are captured.

However biplot (fig-4.6b) shows that the score at 108 row has second principle component.

4.3 Principal Component Regression

From the RMSEP and R2 plot in fig-4.7a, one can suggest to include only 16 component since, on taking 16 components RMSEP drops significantly down and R2Prediction increased dramatically. However, the increase does not stop there. On taking 25 components, R2prediction exceed 0.85 and RMSEP also decreases to 0.125. So, It is better taking 25 components and drop the remaining 5 components as residuals. The Measured vs Predicted plot of the Principal Component Regression taking those 25 components are plotted in figure-4.7b which is very much aligned to the diagonal line (line with slope of 45 degree).

4.4 Partial Least Square Regression

4.5 Ridge Regression

4.6 Prediction

4.6.1 Leave one out(LOO) cross-validation

4.6.2 Future Forecast

4.7 Comparison of Models

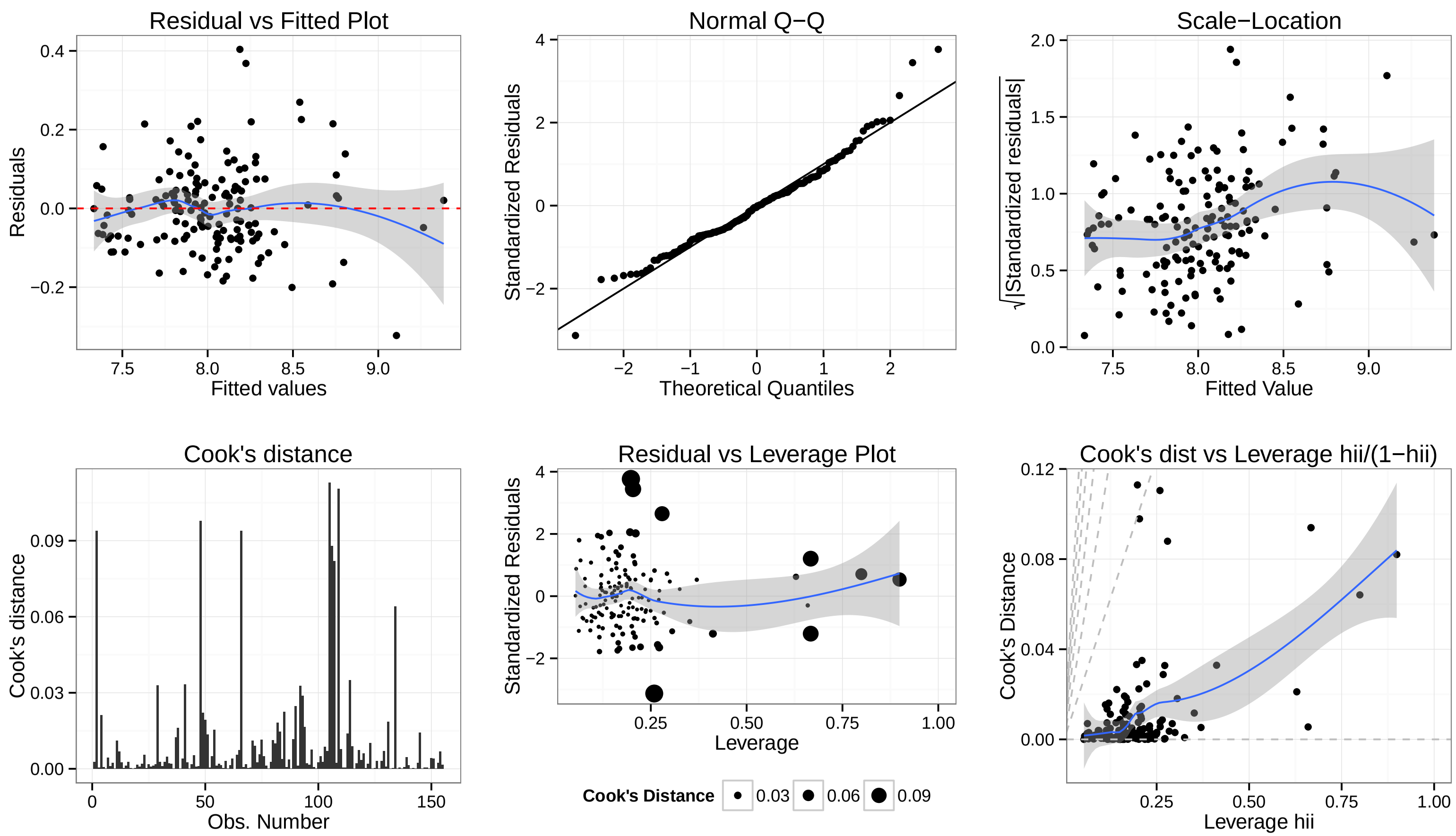
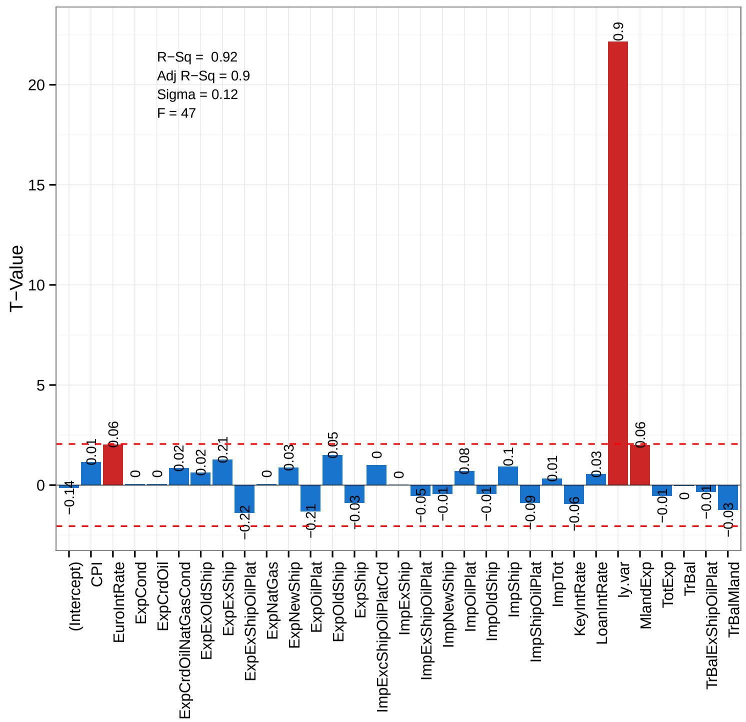


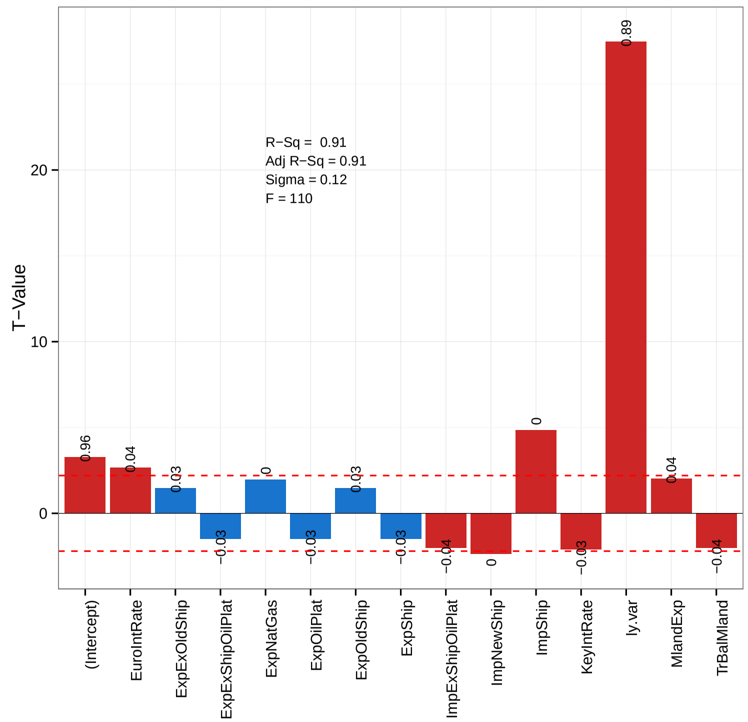
Figure 4.3: Diagnostic Plots for Linear Model

Table 4.2: Summary Report for Linear Models

	Dependent variable:	
	Full Model	Backward Eliminated
KeyIntRate	−0.057 (0.061)	−0.025** (0.012)
CPI	0.008 (0.007)	
EuroIntRate	0.061** (0.030)	0.044*** (0.017)
LoanIntRate	0.034 (0.064)	
ImpTot	0.009 (0.028)	
ImpExShip	0.001 (0.100)	
ImpExShipOilPlat	−0.053 (0.099)	−0.037** (0.018)
ImpExcShipOilPlatCrd	0.00004 (0.00004)	
TotExp	−0.015 (0.027)	
ExpExOldShip	0.018 (0.028)	0.029 (0.020)
ExpExShip	0.206 (0.163)	
ExpExShipOilPlat	−0.223 (0.161)	−0.029 (0.020)
MlandExp	0.056** (0.028)	0.037** (0.018)
TrBal	−0.001 (0.025)	
TrBalExShipOilPlat	−0.010 (0.029)	
TrBalMland	−0.032 (0.026)	−0.037** (0.018)
ImpShip	0.096 (0.104)	0.0001*** (0.00001)
ImpOldShip	−0.012 (0.028)	
ImpNewShip	−0.012 (0.028)	−0.0001** (0.00002)
ImpOilPlat	0.082 (0.118)	
ImpShipOilPlat	−0.093 (0.107)	
ExpCrdOil	0.001 (0.021)	
ExpNatGas	0.001 (0.021)	0.00001* (0.00000)
ExpCond	0.001 (0.021)	
ExpCrdOilNatGasCond	0.023 (0.028)	
ExpShip	−0.029 (0.034)	−0.029 (0.020)
ExpOldShip	0.045 (0.030)	0.029 (0.020)
ExpNewShip	0.027 (0.032)	
ExpOilPlat	−0.208 (0.159)	−0.029 (0.020)
ly.var	0.899*** (0.041)	0.885*** (0.032)
Constant	−0.136 (1.022)	0.962*** (0.293)
R^2	0.919	0.915
Adjusted R^2	0.899	0.906
Residual Std. Error	0.120 (df = 124)	0.116 (df = 140)
F Statistic	46.860*** (df = 30; 124)	107.000*** (df = 14; 140)
Note:		*p<0.1; **p<0.05; ***p<0.01



(a) Full Linear Model



(b) Model obtained from backward elimination

Figure 4.4: Plot of t-value for linear model. The red dashed line show the cretical region where the variable gets significant. The top of the bars includes the coefficients of the respective variables.

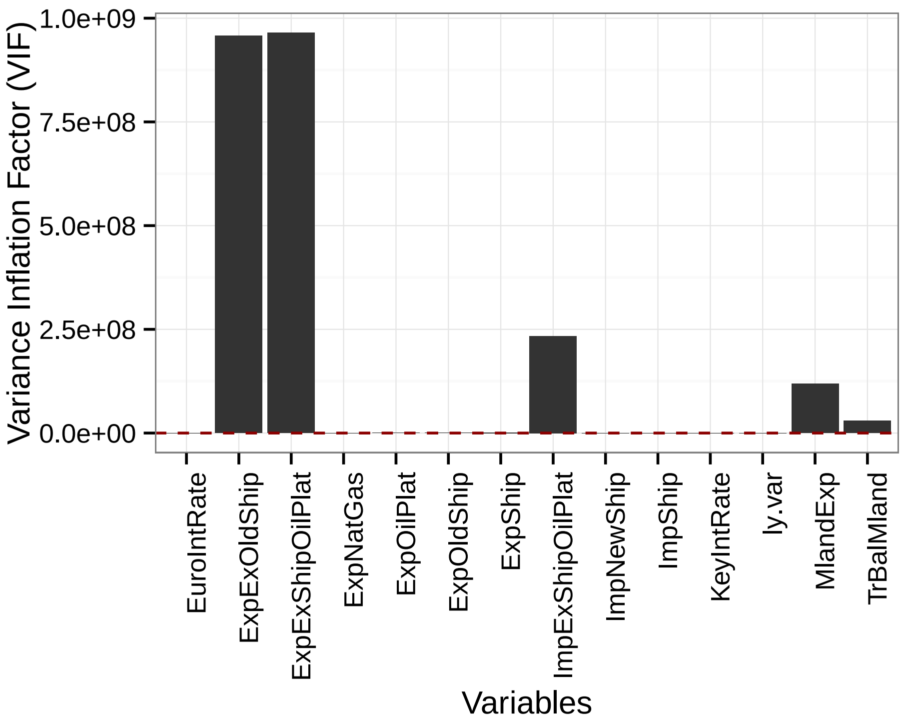
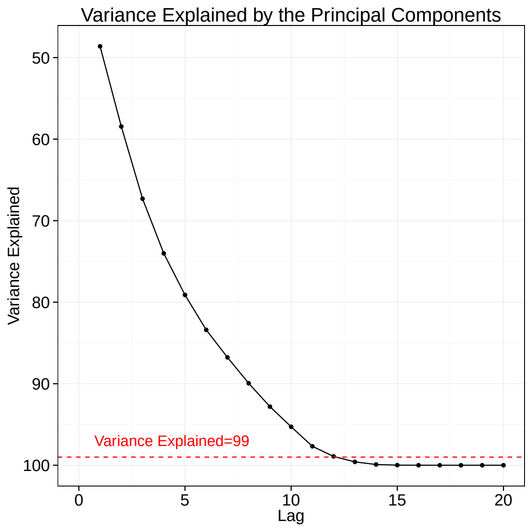


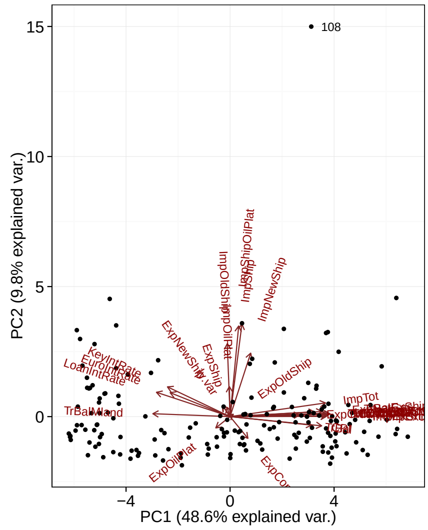
Figure 4.5: Variance Inflation Factor Plot for measuring Multicollinearity

Table 4.3: Summary table for variation explained with PCA

	Standard deviation	Proportion of Variance	Cumulative Proportion
PC1	3.819	0.486	0.486
PC2	1.717	0.098	0.585
PC3	1.630	0.089	0.673
PC4	1.418	0.067	0.740
PC5	1.236	0.051	0.791
PC6	1.134	0.043	0.834
PC7	1.007	0.034	0.868
PC8	0.976	0.032	0.899
PC9	0.927	0.029	0.928
PC10	0.861	0.025	0.953

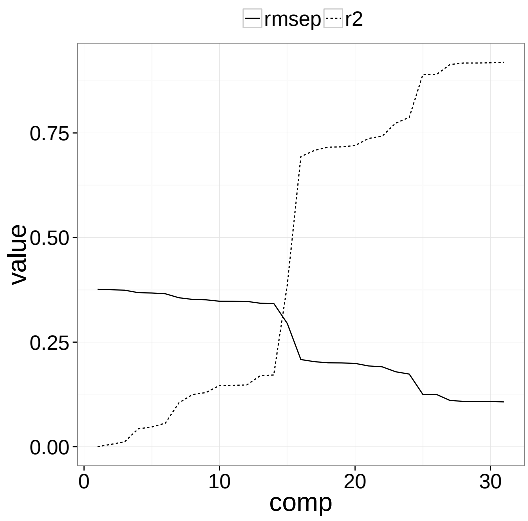


(a) Scree Plot showing the variation explained by each components

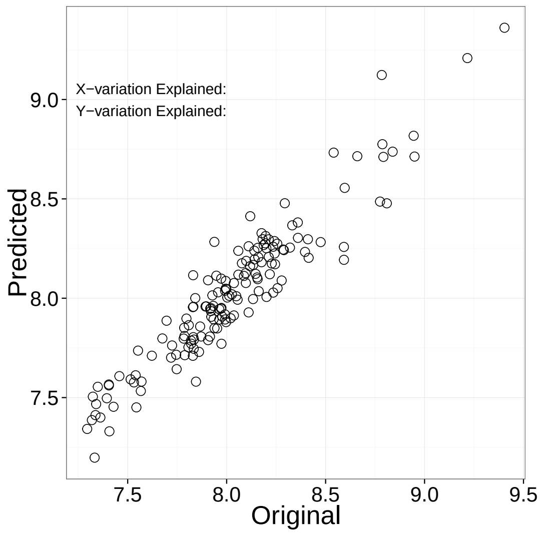


(b) Biplot of PCA analysis on predictor variables

Figure 4.6: Principal Component Analysis Plots



(a) RMSEP and R2 plot to determine the required components to consider



(b) Measured vs Prediction plot. The points aligned to the line with slope of 45 degree are considered to be fitted better

Figure 4.7: Fitted Results for Principal Component Regression

Bibliography

[App14] D.R. Appleyard. *International Economics*. The McGraw-Hill series economics. McGraw-Hill Education, 2014. ISBN: 9781259010576. URL: http://books.google.no/books?id=kUFTMAEACAAJ.

[Far04] Julian J Faraway. *Linear models with R*. CRC Press, 2004.

[FK91] Hsing Fang and K Kern Kwong. "Forecasting Foreign Exchange Rates". In: *THE JOURNAL OF BUSINESS* 92 (1991).

[Har08] David A Harville. *Matrix algebra from a statistician's perspective*. Springer, 2008.

[JW07] R.A. Johnson and D.W. Wichern. *Applied Multivariate Statistical Analysis*. Pearson Education International. Pearson Prentice Hall, 2007. ISBN: 9780135143506. URL: http://books.google.no/books?id=SJZnPwAACAAJ.

[Mas98] D.L. Massart. *Handbook of Chemometrics and Qualimetrics*. Data handling in science and technology pt. 1. Elsevier, 1998. ISBN: 9780444897244. URL: http://books.google.no/books?id=0u7vAAAAMAAJ.

[MN92] H. Martens and T. Naes. *Multivariate Calibration*. Wiley, 1992. ISBN: 9780471930471. URL: http://books.google.no/books?id=6lVcUeVDg9IC.

[Oâ07] RobertM. Oâbrien. "A Caution Regarding Rules of Thumb for Variance Inflation Factors". English. In: *Quality & Quantity* 41.5 (2007), pp. 673–690. ISSN: 0033-5177. DOI: 10.1007/s11135-006-9018-6. URL: http://dx.doi.org/10.1007/s11135-006-9018-6.

[Seb08] George AF Seber. *A matrix handbook for statisticians*. Vol. 15. John Wiley & Sons, 2008.

[Sur] Steve M. Suranovic. *Balance of Payments Deficits and Surpluses*. URL: http://internationalecon.com/Finance/Fch80/F80-8.php.

[Woo12] Jeffrey Wooldridge. *Introductory econometrics: A modern approach.* Cengage Learning, 2012.

[YG02] Ozgür Yeniay and Atill Goktas. “A comparison of partial least squares regression with other prediction methods”. In: *Hacettepe Journal of Mathematics and Statistics* 31.99 (2002), p. 111.

Appendix A

Data Description

The variables used in this paper are listed in following table along with the code used for them.

Code	Description
`PerEURO`	Exchange Rate of NOK per Euro
`PerUSD`	Exchange Rate of NOK per USD
`KeyIntRate`	Key policy rate (Percent)
`CPI`	Consumer Price Index
`ImpTot`	Total imports
`ImpExShip`	Imports excl. ships
`ImpExShipOilPlat`	Imports excl. ships and oil platforms
`ImpExcShipOilPlatCrd`	Imports excl. ships, oil platforms and crude oil
`TotExp`	Total exports
`ExpExOldShip`	Exports excl. elderly ships
`ExpExShip`	Exports excl. ships
`ExpExShipOilPlat`	Exports excl. ships and oil platforms
`MlandExp`	Mainland exports
`TrBal`	Trade balance (Total exports - total imports)
`TrBalExShipOilPlat`	Trade balance (Exports - imports, both excl. ships and oil platforms)
`TrBalMland`	Trade balance (Mainland exports - imports excl. ships and oil platforms)
`ImpShip`	Imports of ships
`ImpOldShip`	Imports of elderly ships
`ImpNewShip`	Imports of new ships
`ImpOilPlat`	Imports of oil platforms
`ImpShipOilPlat`	Imports of ships and oil platforms
`ExpCrdOil`	Exports of crude oil

Code	Description
ExpNatGas	Exports of natural gas
ExpCond	Exports of condensates
ExpCrdOilNatGasCond	Exports of crude oil, natural gas and condensates
ExpShip	Exports of ships
ExpOldShip	Exports of elderly ships
ExpNewShip	Exports of new ships
ExpOilPlat	Exports of oil platforms
ExpShipOilPlat	Exports of ships and oil platforms
EuroIntRate	Money market interest rates of Euro area (EA11-2000, EA12-2006, EA13-2007, EA15-2008, EA16-2010, EA17-2013, EA18)
LoanIntRate	Overnight Lending Rate (Nominal)

```
dataDescription<-read.xls(path.expand(
  file.path(dirname(dirname(getwd())),
            "Datasets", "CompleteDataSet.xlsx")), sheet = 2)
```