Project Report

Yichu Yan

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Factors affecting Euro exchange rates in different EU countries

Background

Euro can be used in 19 EU countries: Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia and Spain. But exchange rates of Euro to Dollar varies in these countries and are affected by Forex trades. In this way, I set project topic as investigating factors affecting Euro exchange rates in EU countries.

Data collection

I collected 2000-2018 exchange rates, GDP, interest rates, and trade of goods data sheets of 10 EU countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Spain) on the International Monetary Fund website and organized data in Excel to make it readable. In order to arrange data easily, I renamed variables with abbreviations while reading into RStudio.

Time: "Time"
Country: "Country"
RealER: "Real Effective Exchange Rate, based on Consumer Price Index"
GDP: "Gross Domestic Product, Nominal, Domestic Currency"
HCE: "Household Consumption Expenditure, incl. NPISHs, Nominal, Domestic Currency"
GCE: "Government Consumption Expenditure, Nominal, Domestic Currency"
GFCF: "Gross Fixed Capital Formation, Nominal, Domestic Currency"
CinI: "Change in Inventories, Nominal, Domestic Currency"
EGS: "Exports of Goods and Services, Nominal, Domestic Currency"
IGS: "Imports of Goods and Services, Nominal, Domestic Currency"
GDPV: "Gross Domestic Product, Volume"
GDPD: "Gross Domestic Product, Deflator"
GDPN: "Gross Domestic Product, Nominal, Seasonally Adjusted, Domestic Currency"
HCE2: "Household Consumption Expenditure, incl. NPISHs, Nominal, Seasonally Adjusted, Domestic Currency"
GFCE: "Govenment Final Consumption Expenditure, Nominal, Seasonally adjusted, Domestic Currency"
GFCF2: "Gross Fixed Capital Formation, Nominal, Seasonally Adjusted, Domestic Currency"
CinI2: "Change in Inventories, Nominal, Seasonally Adjusted, Domestic Currency"
EGS2: "Exports of Goods and Services, Nominal, Seasonally Adjusted, Domestic Currency"
IGS2: "Imports of Goods and Services, Nominal, Seasonally Adjusted, Domestic Currency"
GDPV2: "Gross Domestic Product, Volume, Seasonally Adjusted"
GDPD2: "Gross Domestic Product, Deflator, Seasonally Adjusted"
GvmBonds: "Government Bonds"
HEAR: "Harmonized Euro Area Rates, Outstanding Amounts, Deposits, Households, Agreed Maturity, Up to 2 Years"
HEAR2: "Harmonized Euro Area Rates, Outstanding Amounts, Deposits, Non-Financial Corporations, Agreed Maturity, Up to 2 Years"
HEAR3: "Harmonized Euro Area Rates, Loans, Households, Consumer Credit and Other, Up to 1 Year"
HEAR4: "Harmonized Euro Area Rates, New Business, Loans, Households, Consumption, Floating Rate and

up to 1 Year"
HEAR5: "Harmonized Euro Area Rates, Loans, Households, House Purchase, Over 5 Years"
GDPV8: "Harmonized Euro Area Rates, Loans, Non-Financial Corporations, Up to 1 Year"
ExportUS: "Goods, Value of Exports, US Dollars"
ExportNC: "Goods, Value of Exports, National Currency"
ImportUS: "Goods, Value of Imports, CIF, US Dollars"
ImportNC: "Goods, Value of Imports, CIF, National Currency"

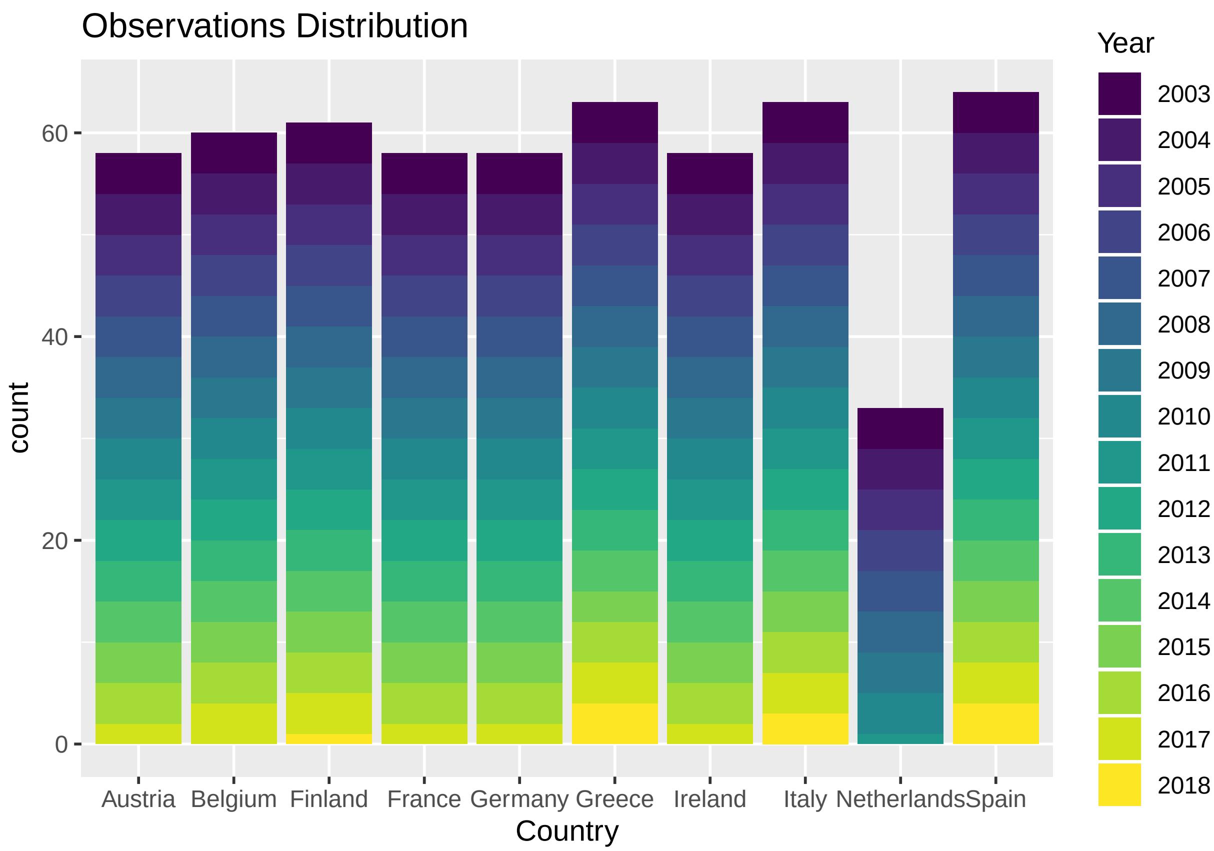
Data cleaning

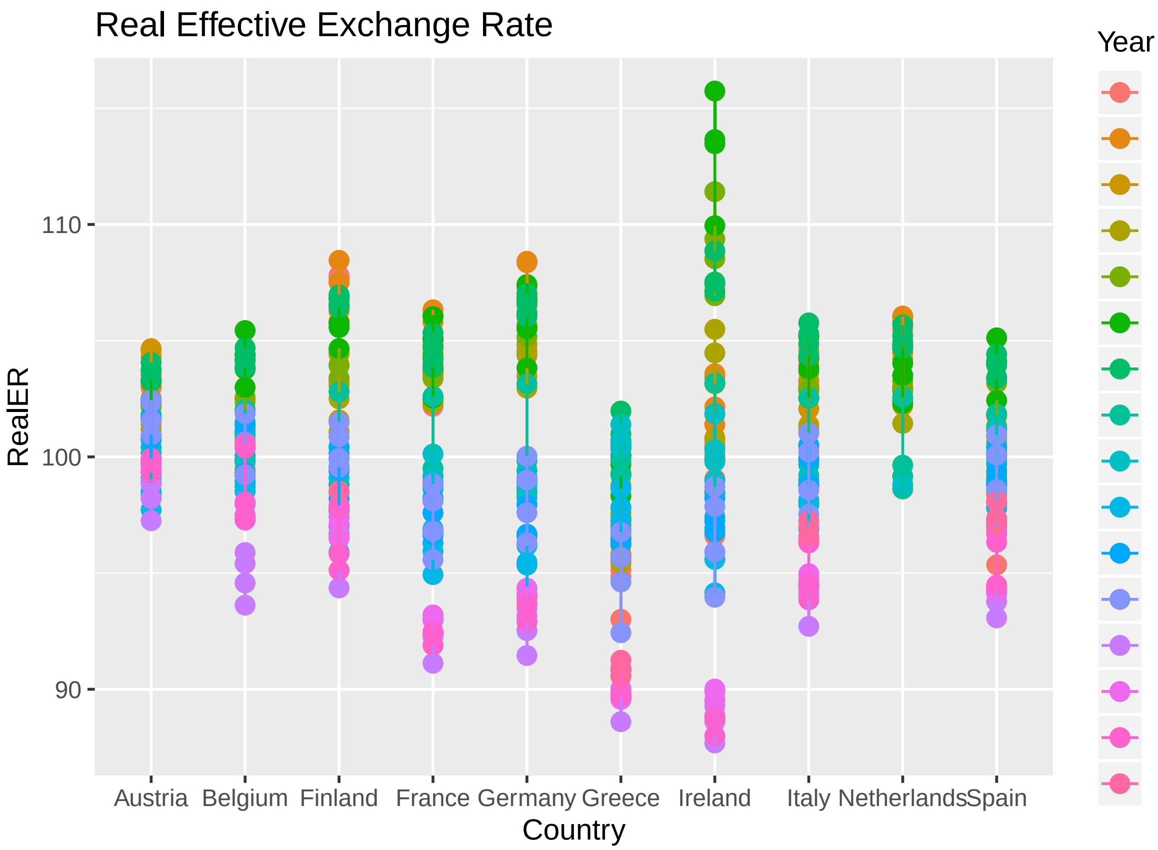
I summarized numbers of missing values in each variable and decided to remove such NAs from dataset.

```
## $vars_num_with_NA
##    variable q_na        p_na
## 1  GvmBonds   31 0.040789474
## 2      HEAR  120 0.157894737
## 3     HEAR2  120 0.157894737
## 4     HEAR3  120 0.157894737
## 5     HEAR4  152 0.200000000
## 6     HEAR5  120 0.157894737
## 7     GDPV8  120 0.157894737
## 8  ExportUS    4 0.005263158
## 9  ExportNC    4 0.005263158
## 10 ImportUS    4 0.005263158
## 11 ImportNC    4 0.005263158
##
## $vars_cat_with_NA
## [1] variable q_na     p_na
## <0 rows> (or 0-length row.names)
##
## $vars_cat_high_card
##   variable unique
## 1     Time     76
##
## $MAX_UNIQUE
## [1] 35
##
## $vars_one_value
## character(0)
##
## $vars_cat
## [1] "Time"    "Country"
##
## $vars_num
##  [1] "RealER"   "GDP"      "HCE"      "GCE"      "GFCF"     "CinI"
##  [7] "EGS"      "IGS"      "GDPV"     "GDPD"     "GDPN"     "HCE2"
## [13] "GFCE"     "GFCF2"    "CinI2"    "EGS2"     "IGS2"     "GDPV2"
## [19] "GDPD2"    "GvmBonds" "HEAR"     "HEAR2"    "HEAR3"    "HEAR4"
## [25] "HEAR5"    "GDPV8"    "ExportUS" "ExportNC" "ImportUS" "ImportNC"
##
## $vars_char
## [1] "Time"    "Country"
##
## $vars_factor
## character(0)
##
## $vars_other
## character(0)
```

EDA

Data plots

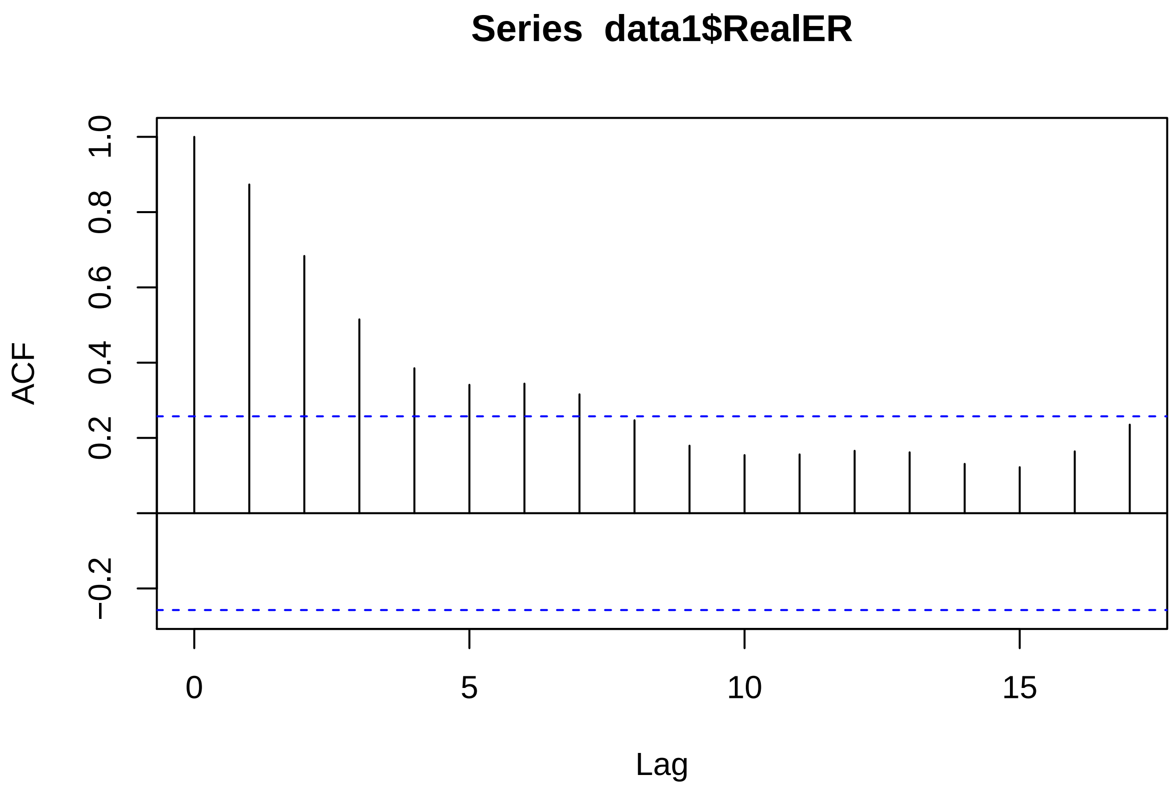


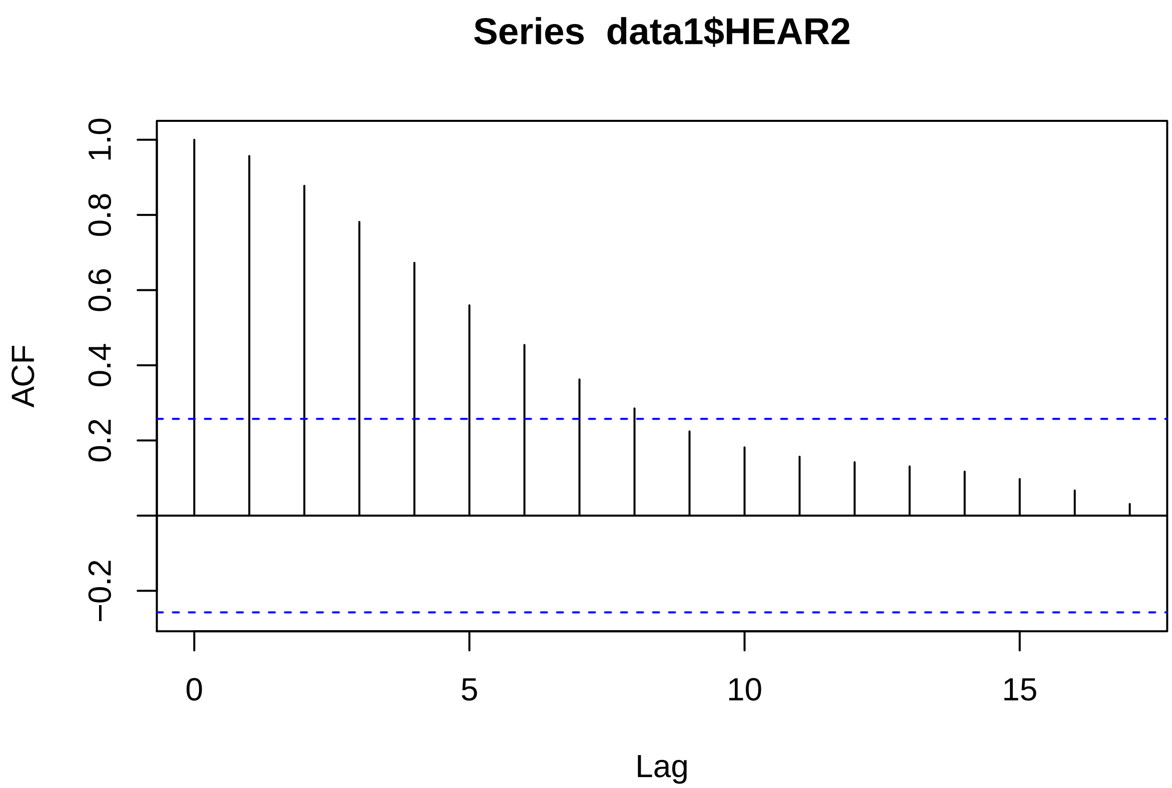


Time frame of cleaned data ranges from 2003 to 2018, although some factors related to exchange rates, GDP, interest rates, and trade of goods contains missing values in original data, after cleaning data, 10 countries still have plenty observations to fit models.

Concerns

Check stationary or non-stationary





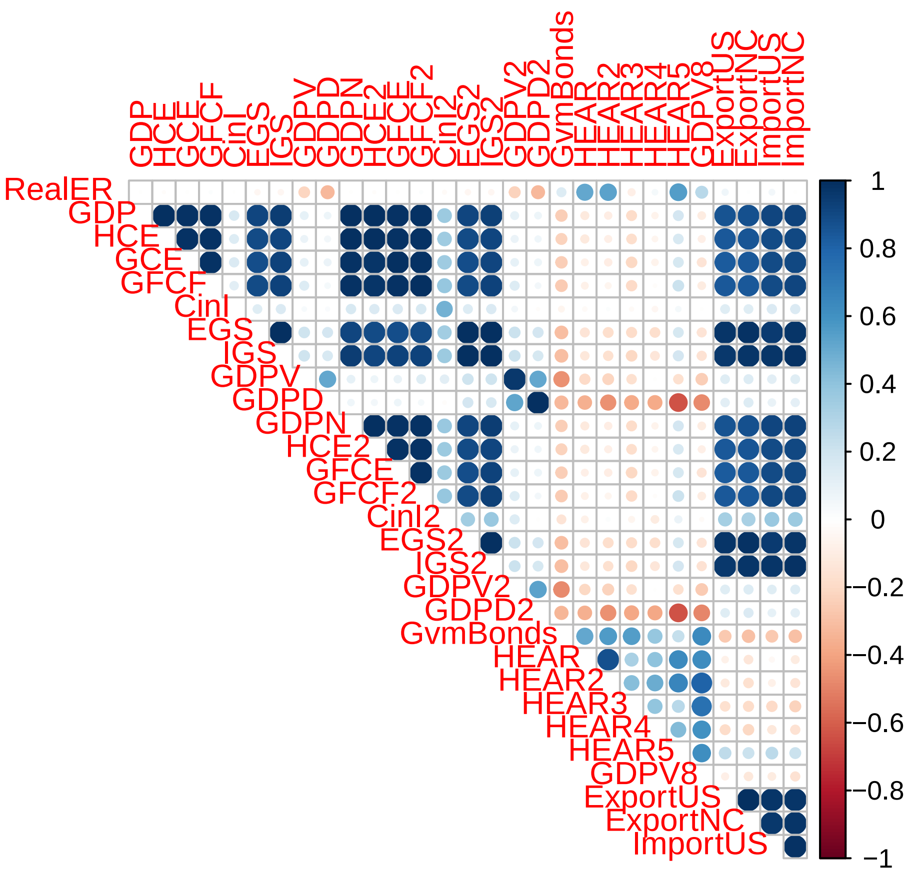
Non-stationary variables would give models large R square and makes estimates unreliable. Original data is time series data, even though I mixed 10 countries' data and deleted observations containing missing values, I still need to check ACF before and avoid using non-stationary variables to fit regressions, here are 2 examples.

Correlation

```r
sapply(mydata, is.numeric)
```

```
##      Time   Country    RealER       GDP       HCE       GCE      GFCF      CinI
##     FALSE     FALSE      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE
##       EGS       IGS      GDPV      GDPD      GDPN      HCE2      GFCE     GFCF2
##      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE
##     CinI2      EGS2      IGS2     GDPV2     GDPD2  GvmBonds      HEAR     HEAR2
##      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE
##     HEAR3     HEAR4     HEAR5     GDPV8  ExportUS  ExportNC  ImportUS  ImportNC
##      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE      TRUE
```

```r
cordata <- mydata[, sapply(mydata, is.numeric)]
cor.ma <- cor(cordata, method = "pearson")
corrplot::corrplot(cor.ma, method = "circle", type = "upper", diag = F)
```



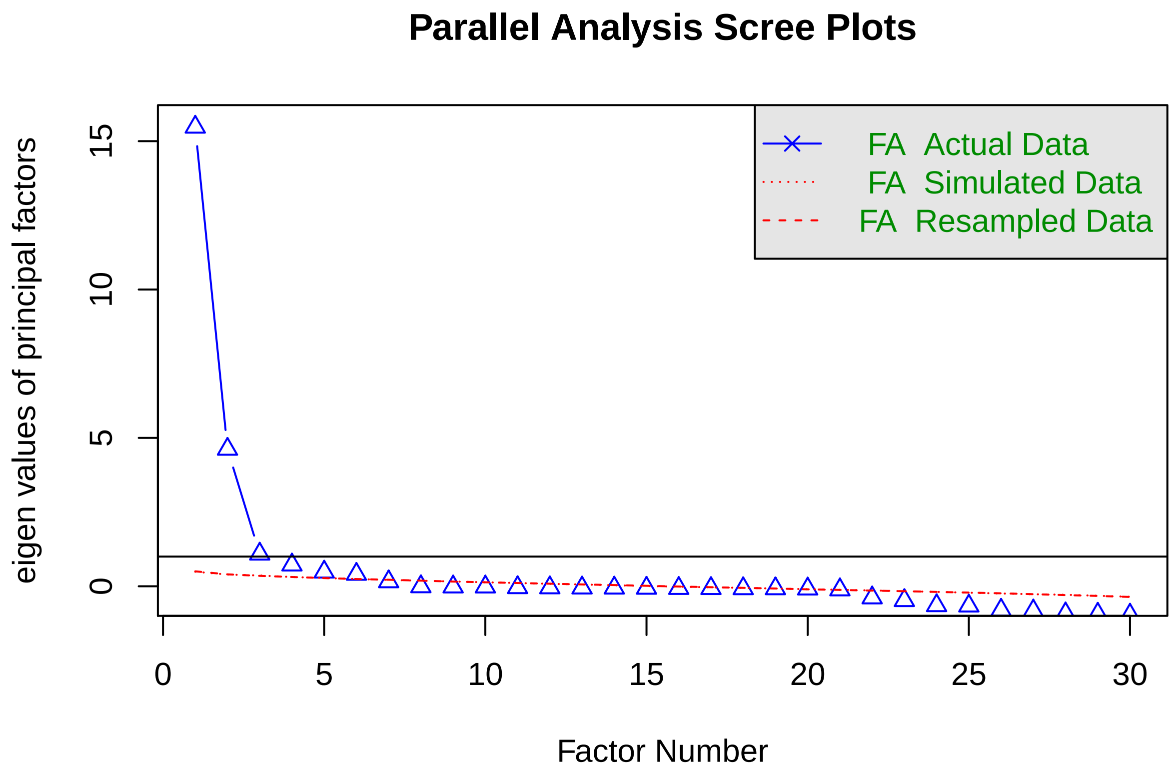
Some variables like ExportUS and ExportNC have high correlations beacuse they are both used to describe values of export. In this way, we need to consider only use part of them in models.

Methods

Parallel Analysis

Dataset has 32 variables and I want to find out the number of factors that will be selected for later analysis.

```
library(psych)
library(GPArotation)
parallel <- fa.parallel(cordata, fm = 'minres', fa = 'fa') # parallel analysis
```

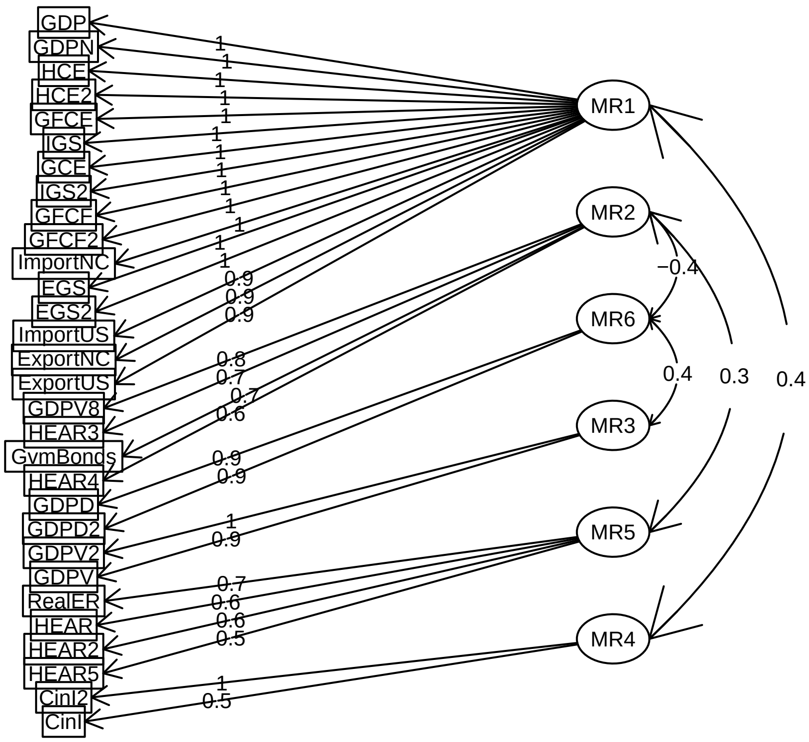



```
## Parallel analysis suggests that the number of factors =  6  and the number of components =  NA
```

The blue line shows eigenvalues of actual data and the two red lines (placed on top of each other) show simulated and resampled data. Here we look at the large drops in the actual data and spot the point where it levels off to the right. Also we locate the point of inflection – the point where the gap between simulated data and actual data tends to be minimum.

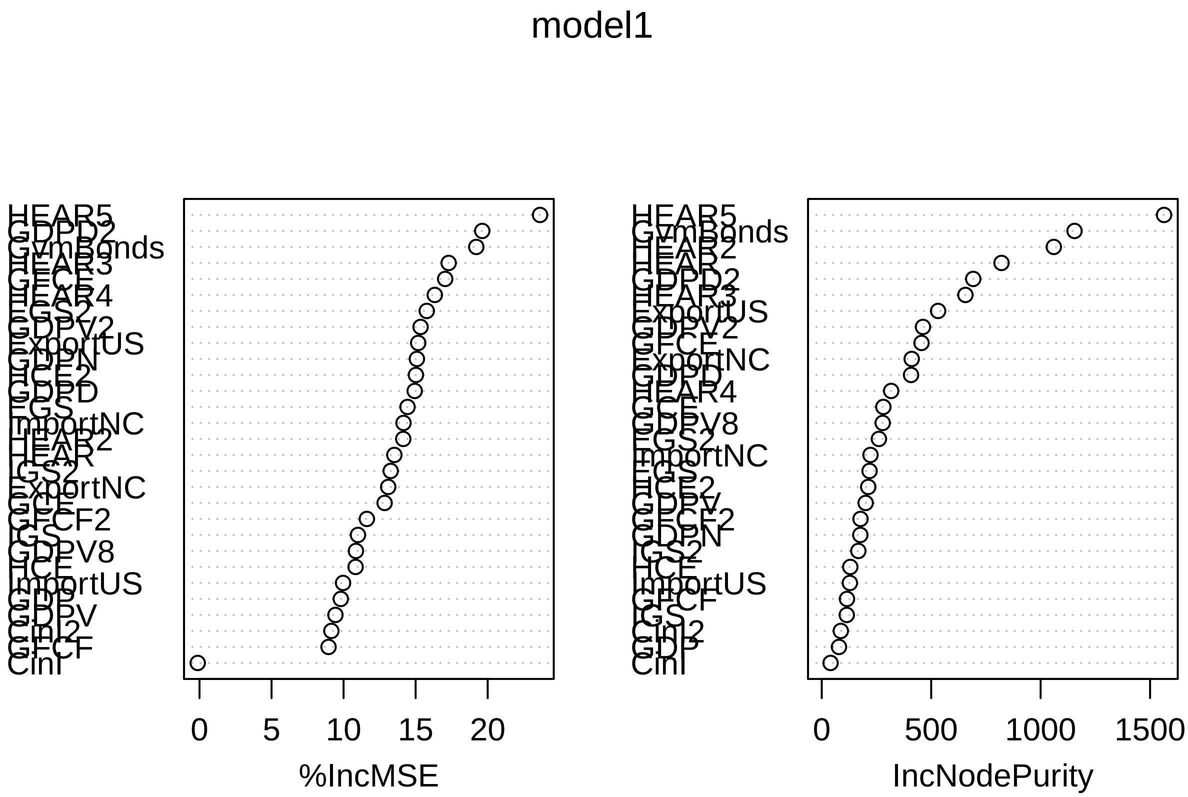
```
sixfactor <- fa(cordata,nfactors = 6,rotate = "oblimin",fm="minres") # 6 factor analysis
fa.diagram(sixfactor)
```

Factor Analysis

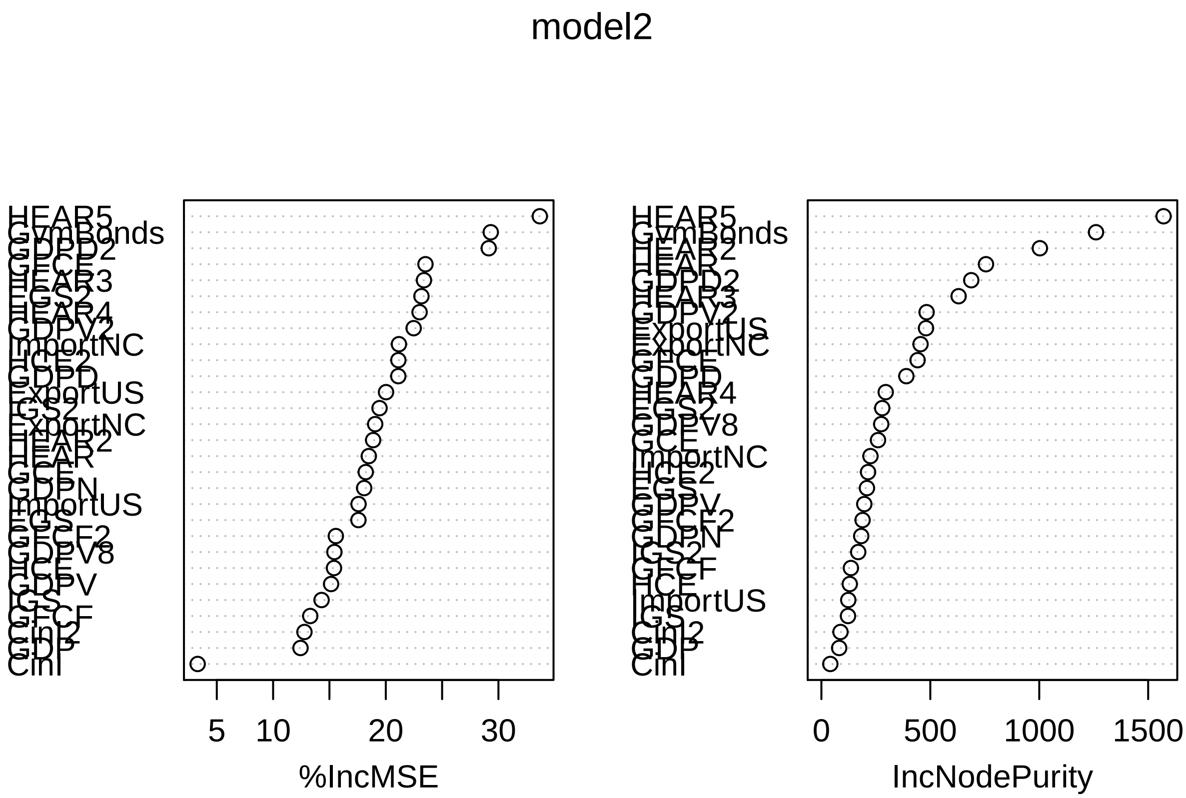


Random Forest

```
library(randomForest)
model1 <- randomForest(RealER~., data=cordata, importance=T, ntree=500)
model2 <- randomForest(RealER~., data=cordata, importance=T, ntree=1000)
varImpPlot(model1)
```




```
varImpPlot(model2)
```



Try to fit models using top factors

Models

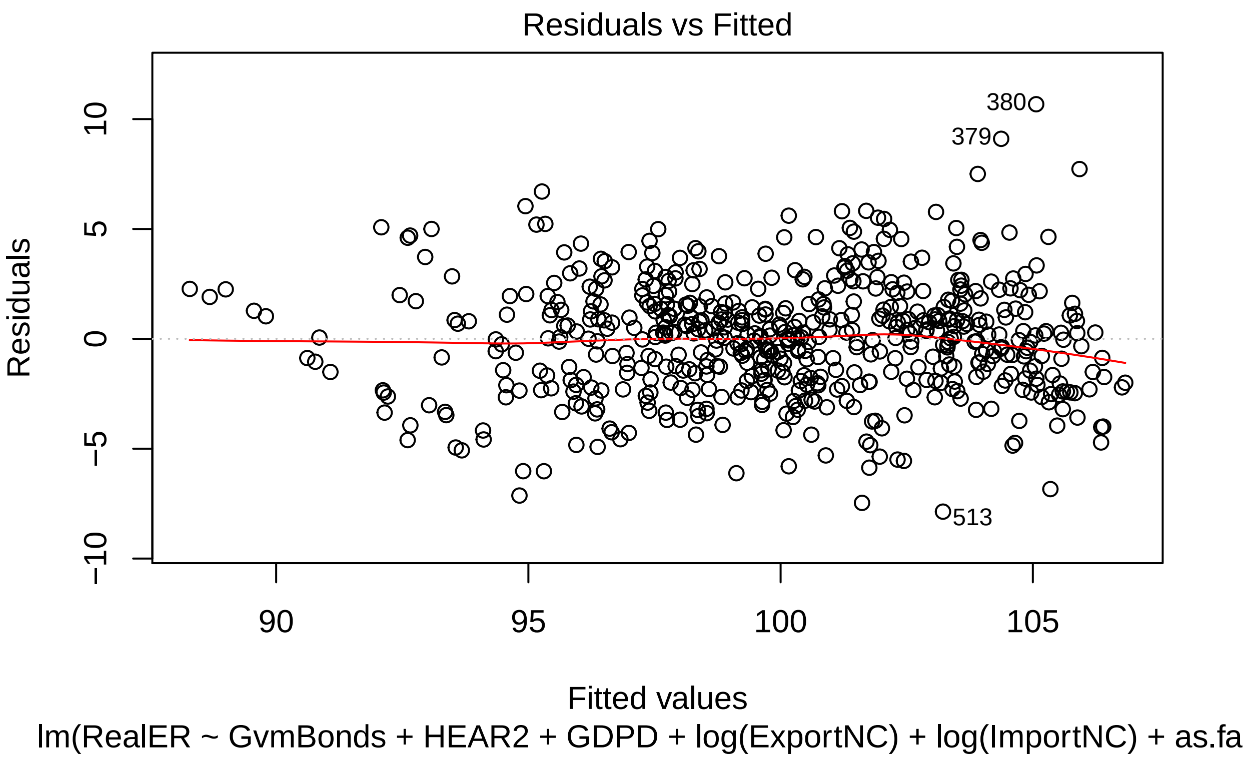
```r
library(plotly)
fit1 <- lm(RealER~GvmBonds+HEAR2+GDPD+log(ExportNC)+log(ImportNC)+as.factor(Country), data=mydata)
summary(fit1)
```

```
##
## Call:
## lm(formula = RealER ~ GvmBonds + HEAR2 + GDPD + log(ExportNC) +
##     log(ImportNC) + as.factor(Country), data = mydata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.8652 -1.8523  0.0819  1.5686 10.6769
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  206.63215    9.54856  21.640  < 2e-16 ***
## GvmBonds                       0.09868    0.07185   1.373  0.17020
## HEAR2                          2.02171    0.13274  15.231  < 2e-16 ***
## GDPD                           0.09900    0.03030   3.267  0.00115 **
## log(ExportNC)                 -5.83821    1.08333  -5.389 1.04e-07 ***
## log(ImportNC)                 -5.77247    1.40457  -4.110 4.55e-05 ***
## as.factor(Country)Belgium     10.64748    1.22079   8.722  < 2e-16 ***
## as.factor(Country)Finland     -8.42551    1.01820  -8.275 9.41e-16 ***
## as.factor(Country)France      13.32445    1.64349   8.107 3.26e-15 ***
## as.factor(Country)Germany     23.47793    2.28308  10.283  < 2e-16 ***
## as.factor(Country)Greece     -21.87098    1.45985 -14.982  < 2e-16 ***
## as.factor(Country)Ireland     -8.23730    1.08848  -7.568 1.57e-13 ***
## as.factor(Country)Italy       11.28357    1.38093   8.171 2.04e-15 ***
## as.factor(Country)Netherlands  11.70951    1.30216   8.992  < 2e-16 ***
## as.factor(Country)Spain        5.10566    1.06488   4.795 2.09e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.649 on 561 degrees of freedom
## Multiple R-squared:  0.6559, Adjusted R-squared:  0.6473
## F-statistic: 76.39 on 14 and 561 DF,  p-value: < 2.2e-16
```

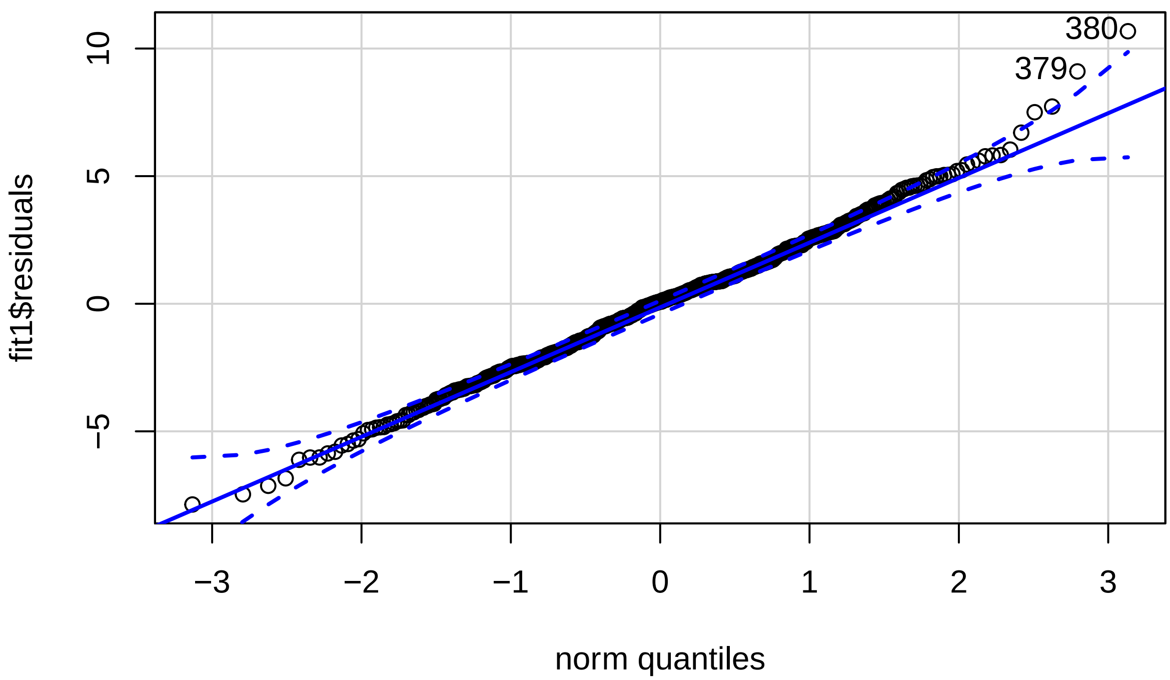
```r
AIC(fit1)
```

```
## [1] 2773.607
```

```r
plot(fit1,which=1)
```




```r
car::qqPlot(fit1$residuals)
```




```
## [1] 380 379
```

According to the residual plot, our model complies with the assumptions of normality and constant variance, so there is no issue about violating the model assumptions.

Interpretation

The intercept is the predicted RealER in Austria if GvmBonds, HEAR2, GDPD, log(ExportNC) and log(ImportNC) are all equal to zero. Because these factors are never close to zero, the intercept has no direct interpretation.

The coefficient for GvmBonds is the predicted difference in RealER corresponding to a 1 unit difference in GvmBonds, if other vraiables equal to zero. Thus, the estimated predictive difference per unit of GvmBonds is 0.09868 for each country.

The coefficient for HEAR2 is the predicted difference in RealER corresponding to a 1 unit difference in HEAR2, if other vraiables equal to zero. Thus, the estimated predictive difference per unit of HEAR2 is 2.02171 for each country.

The coefficient for GDPD is the predicted difference in RealER corresponding to a 1 unit difference in GDPD, if other vraiables equal to zero. Thus, the estimated predictive difference per unit of GDPD is 0.09900 for each country.

The coefficient for log(ExportNC) is the predicted difference in RealER corresponding to a 1 unit difference in log(ExportNC), if other vraiables equal to zero. Thus, the estimated predictive difference per unit of log(ExportNC) is 5.83821 decrease for each country.

The coefficient for log(ImportNC) is the predicted difference in RealER corresponding to a 1 unit difference log(ImportNC), if other vraiables equal to zero. Thus, the estimated predictive difference per unit of log(ImportNC)s is 5.77247 decrease for each country.

Input variable that is used in these models is country, which is defined on a ten-point ordered scale:
Country = Austria: observations from Austria
Country = Belgium: observations from Belgium
Country = Finland: observations from Finland
Country = France: observations from Franc
Country = Germany: observations from Germany
Country = Greece: observations from Greece
Country = Ireland: observations from Ireland
Country = Italy: observations from Italy
Country = Netherlands: observations from Netherlands
Country = Spain: observations from Spain

This parameterization of the model allows for different real exchange rate corresponding to each category of country. The "baseline" category (Country = Austria) corresponds to country Austria; the average real exchange rate for Austria is estimated by the intercept, $206.63215 + 0.09868 \times GvmBonds + 2.02171 \times HEAR2 + 0.09900 \times GDPD$-$5.83821 \times log(ExportNC)$-$5.77247 \times log(ImportNC)$.

The average real exchange rate in the other countries is found by adding the corresponding coefficient to this baseline average. This parameterization allows us to see that the real exchange rate in Germany achieve the highest average real exchange rate, $206.63215 + 0.09868 \times GvmBonds + 2.02171 \times HEAR2 + 0.09900 \times GDPD$-$5.83821 \times log(ExportNC)$-$5.77247 \times log(ImportNC) + 10.64748$.

Appendix

Random Forest

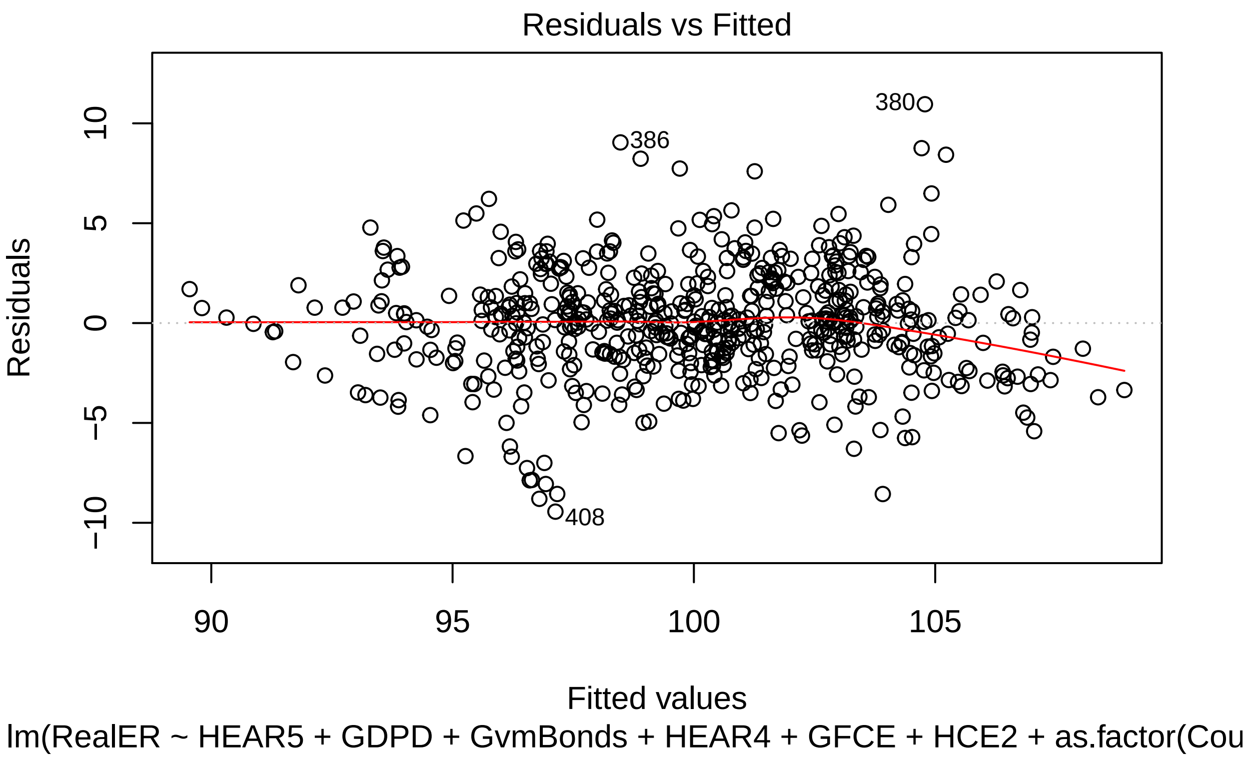
```r
fit2 <- lm(RealER~HEAR5+GDPD+GvmBonds+HEAR4+GFCE+HCE2+as.factor(Country), data=mydata)
summary(fit2)
```

```
##
## Call:
## lm(formula = RealER ~ HEAR5 + GDPD + GvmBonds + HEAR4 + GFCE +
##     HCE2 + as.factor(Country), data = mydata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.4414 -1.5185  0.0602  1.5300 10.9569
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   8.016e+01  3.377e+00  23.734  < 2e-16 ***
## HEAR5                         2.743e+00  1.913e-01  14.344  < 2e-16 ***
## GDPD                          1.420e-01  3.124e-02   4.545 6.74e-06 ***
## GvmBonds                      4.045e-01  5.691e-02   7.107 3.62e-12 ***
## HEAR4                        -3.176e-01  9.558e-02  -3.323  0.00095 ***
## GFCE                         -2.137e-05  5.752e-05  -0.372  0.71032
## HCE2                         -5.847e-05  2.941e-05  -1.988  0.04726 *
## as.factor(Country)Belgium    -1.390e+00  5.475e-01  -2.539  0.01138 *
## as.factor(Country)Finland     1.668e+00  5.962e-01   2.798  0.00532 **
## as.factor(Country)France      1.377e+01  2.543e+00   5.415 9.10e-08 ***
## as.factor(Country)Germany     1.814e+01  4.114e+00   4.411 1.24e-05 ***
## as.factor(Country)Greece     -6.541e+00  6.870e-01  -9.522  < 2e-16 ***
## as.factor(Country)Ireland    -2.803e+00  6.163e-01  -4.548 6.63e-06 ***
## as.factor(Country)Italy       1.220e+01  2.931e+00   4.163 3.63e-05 ***
## as.factor(Country)Netherlands  1.963e+00  8.159e-01   2.406  0.01646 *
## as.factor(Country)Spain       7.416e+00  1.760e+00   4.212 2.94e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.775 on 560 degrees of freedom
## Multiple R-squared:  0.6231, Adjusted R-squared:  0.613
## F-statistic: 61.71 on 15 and 560 DF,  p-value: < 2.2e-16
```

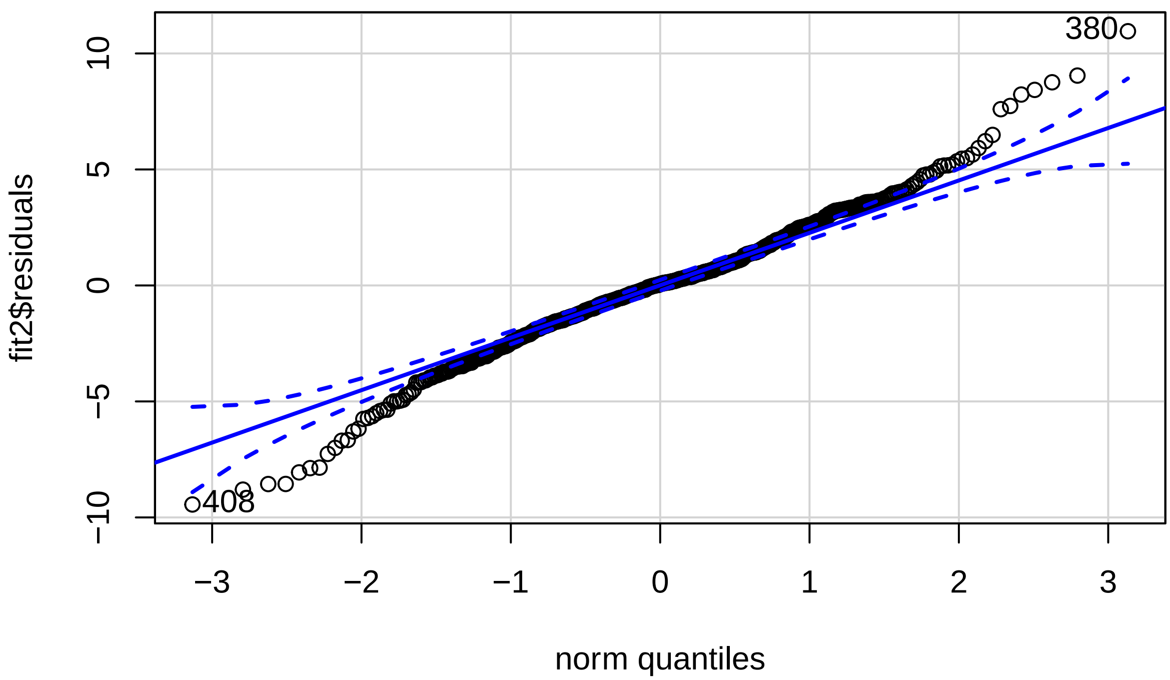
```r
AIC(fit2)
```

```
## [1] 2828.159
```

```r
plot(fit2,which=1)
```




```r
car::qqPlot(fit2$residuals)
```




```
## [1] 380 408
```

Multilevel model varying across countreis

```r
library(lme4)
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Registered S3 methods overwritten by 'lme4':
##   method                          from
##   cooks.distance.influence.merMod car
##   influence.merMod                car
##   dfbeta.influence.merMod         car
##   dfbetas.influence.merMod        car
```

```
mlfit1 <- lmer(RealER~GvmBonds+HEAR2+GDPD+log(ExportNC)+log(ImportNC)+(1|Country), data=mydata)
summary(mlfit1)
```

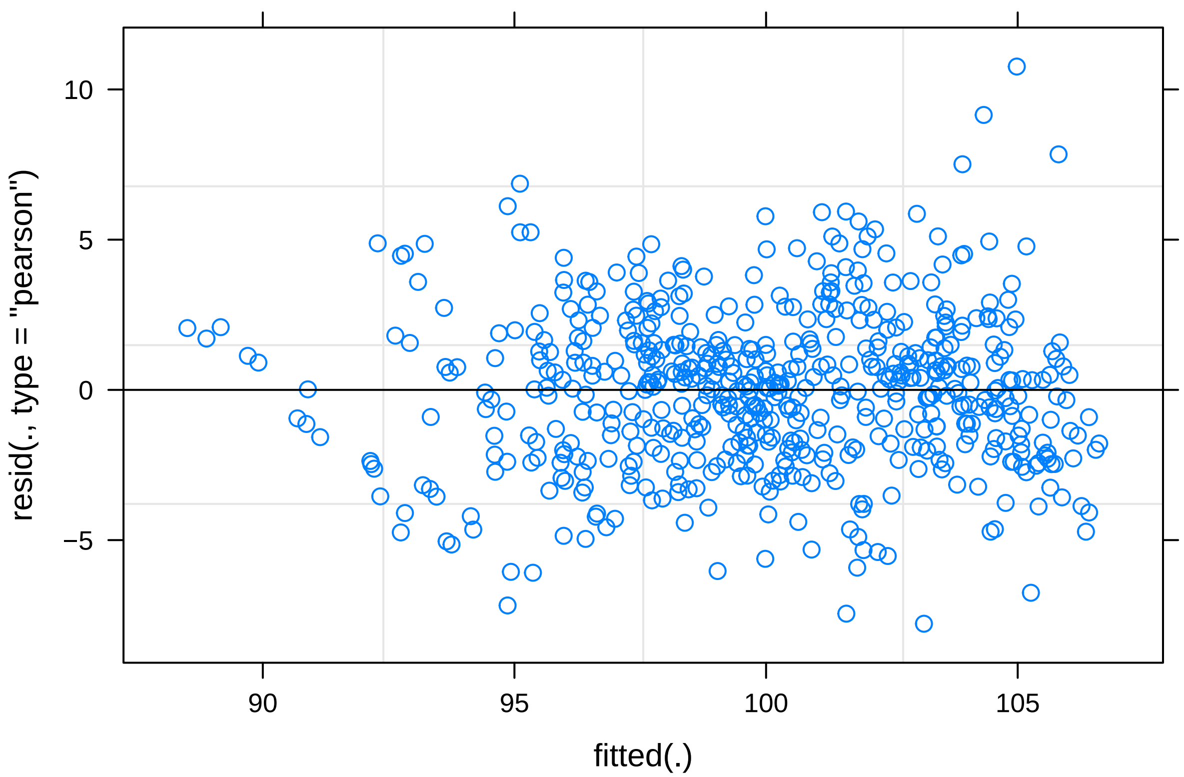
```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## RealER ~ GvmBonds + HEAR2 + GDPD + log(ExportNC) + log(ImportNC) +
##     (1 | Country)
##    Data: mydata
##
## REML criterion at convergence: 2827
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9370 -0.6875  0.0257  0.5744  4.0608
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Country  (Intercept) 157.762  12.56
##  Residual               7.023   2.65
## Number of obs: 576, groups:  Country, 10
##
## Fixed effects:
##                Estimate Std. Error t value
## (Intercept)   202.72077   10.54146  19.231
## GvmBonds        0.10501    0.07171   1.464
## HEAR2           2.00401    0.13250  15.125
## GDPD            0.08080    0.02968   2.722
## log(ExportNC)  -5.51714    1.07656  -5.125
## log(ImportNC)  -5.21413    1.38543  -3.764
##
## Correlation of Fixed Effects:
##             (Intr) GvmBnd HEAR2  GDPD   l(ENC)
## GvmBonds    -0.245
## HEAR2        0.159 -0.608
## GDPD         0.548 -0.134  0.380
## lg(ExprtNC) -0.146 -0.424  0.301 -0.196
## lg(ImprtNC) -0.602  0.522 -0.429 -0.439 -0.630
```

```
coef(mlfit1)
```

```
## $Country
```

```
##             (Intercept)  GvmBonds   HEAR2       GDPD log(ExportNC)
## Austria         199.4545 0.1050081 2.00401 0.08079799     -5.517144
## Belgium         209.2189 0.1050081 2.00401 0.08079799     -5.517144
## Finland         191.7158 0.1050081 2.00401 0.08079799     -5.517144
## France          211.5679 0.1050081 2.00401 0.08079799     -5.517144
## Germany         221.1603 0.1050081 2.00401 0.08079799     -5.517144
## Greece          178.4808 0.1050081 2.00401 0.08079799     -5.517144
## Ireland         191.7775 0.1050081 2.00401 0.08079799     -5.517144
## Italy           209.7238 0.1050081 2.00401 0.08079799     -5.517144
## Netherlands     210.2352 0.1050081 2.00401 0.08079799     -5.517144
## Spain           203.8730 0.1050081 2.00401 0.08079799     -5.517144
##             log(ImportNC)
## Austria          -5.214128
## Belgium          -5.214128
## Finland          -5.214128
## France           -5.214128
## Germany          -5.214128
## Greece           -5.214128
## Ireland          -5.214128
## Italy            -5.214128
## Netherlands      -5.214128
## Spain            -5.214128
##
## attr(,"class")
## [1] "coef.mer"
```

```
plot(mlfit1,which=1)
```



Multilevel model varying across countreis and years

```r
mlfit2 <- lmer(RealER~GvmBonds+HEAR2+GDPD+log(ExportUS)+(1|Country)+(1|Year), data=mydata)
summary(mlfit2)
```

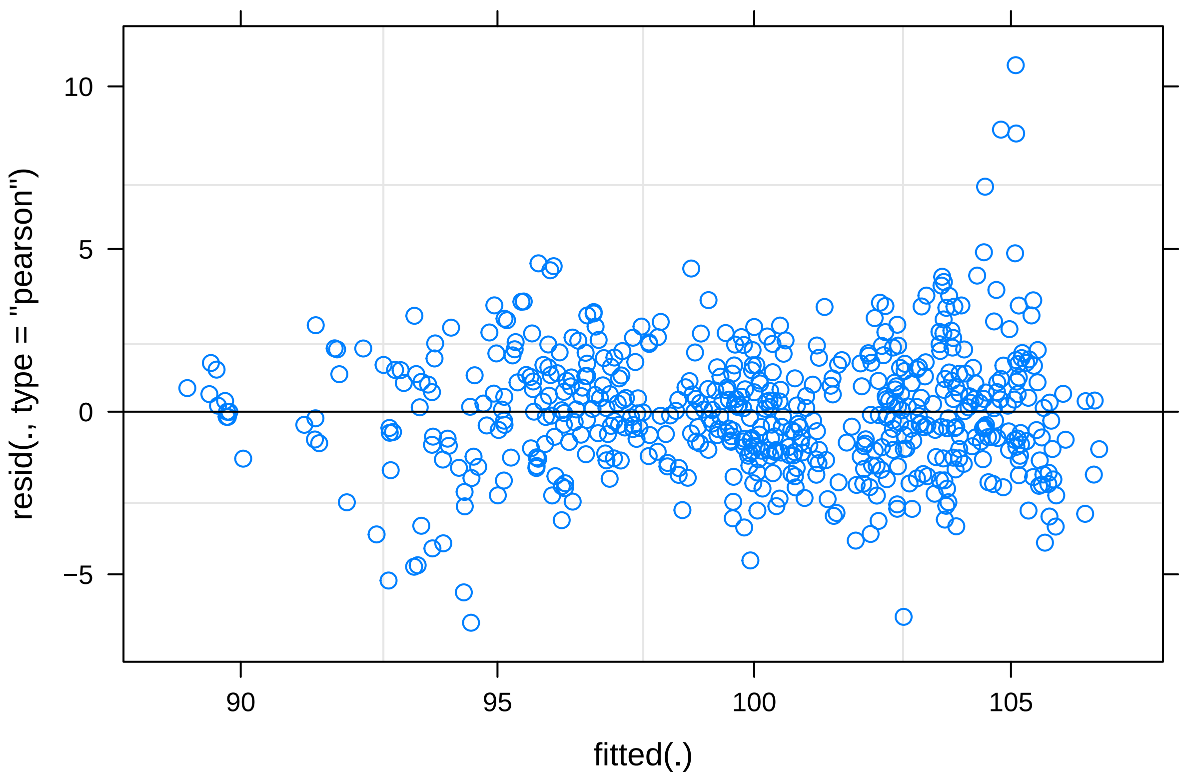
```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## RealER ~ GvmBonds + HEAR2 + GDPD + log(ExportUS) + (1 | Country) +
##     (1 | Year)
##    Data: mydata
##
## REML criterion at convergence: 2545.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.2548 -0.5951 -0.0372  0.5693  5.3438
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Year     (Intercept) 16.753   4.093
##  Country  (Intercept)  2.486   1.577
##  Residual              3.972   1.993
## Number of obs: 576, groups:  Year, 16; Country, 10
##
## Fixed effects:
##               Estimate Std. Error t value
## (Intercept)   59.64456    5.43891  10.966
## GvmBonds       0.32214    0.05887   5.472
## HEAR2          0.75540    0.22259   3.394
## GDPD           0.25088    0.02952   8.499
## log(ExportUS)  1.12898    0.41069   2.749
##
## Correlation of Fixed Effects:
##             (Intr) GvmBnd HEAR2  GDPD
## GvmBonds     0.001
## HEAR2       -0.044 -0.617
## GDPD        -0.517  0.106 -0.054
## lg(ExprtUS) -0.811 -0.058  0.022 -0.031
```

```r
coef(mlfit2)
```

```
## $Year
##      (Intercept) GvmBonds     HEAR2      GDPD log(ExportUS)
## 2003    64.34552 0.322137 0.7554043 0.2508818      1.128978
## 2004    65.46035 0.322137 0.7554043 0.2508818      1.128978
## 2005    63.93520 0.322137 0.7554043 0.2508818      1.128978
## 2006    62.40679 0.322137 0.7554043 0.2508818      1.128978
## 2007    62.14088 0.322137 0.7554043 0.2508818      1.128978
## 2008    62.50438 0.322137 0.7554043 0.2508818      1.128978
## 2009    64.53403 0.322137 0.7554043 0.2508818      1.128978
## 2010    60.03119 0.322137 0.7554043 0.2508818      1.128978
## 2011    58.58768 0.322137 0.7554043 0.2508818      1.128978
## 2012    55.40544 0.322137 0.7554043 0.2508818      1.128978
## 2013    57.71314 0.322137 0.7554043 0.2508818      1.128978
## 2014    58.24975 0.322137 0.7554043 0.2508818      1.128978
```

```
## 2015    53.08257 0.322137 0.7554043 0.2508818      1.128978
## 2016    54.38189 0.322137 0.7554043 0.2508818      1.128978
## 2017    54.74886 0.322137 0.7554043 0.2508818      1.128978
## 2018    56.78527 0.322137 0.7554043 0.2508818      1.128978
##
## $Country
##             (Intercept) GvmBonds     HEAR2      GDPD log(ExportUS)
## Austria        61.71834 0.322137 0.7554043 0.2508818      1.128978
## Belgium        59.79074 0.322137 0.7554043 0.2508818      1.128978
## Finland        62.62162 0.322137 0.7554043 0.2508818      1.128978
## France         59.01609 0.322137 0.7554043 0.2508818      1.128978
## Germany        59.08374 0.322137 0.7554043 0.2508818      1.128978
## Greece         57.60827 0.322137 0.7554043 0.2508818      1.128978
## Ireland        58.49511 0.322137 0.7554043 0.2508818      1.128978
## Italy          59.14478 0.322137 0.7554043 0.2508818      1.128978
## Netherlands    59.72650 0.322137 0.7554043 0.2508818      1.128978
## Spain          59.24040 0.322137 0.7554043 0.2508818      1.128978
##
## attr(,"class")
## [1] "coef.mer"
```

```
plot(mlfit2,which=1)
```



Discussion

According to the analysis using Linear Regression, we can conclude that dirrderent countries'Real Exchange Rates could be predicted by Government Bonds, Harmonized Euro Area Rates(Outstanding Amounts, Deposits, Non-Financial Corporations, Agreed Maturity, Up to 2 Years), Gross Domestic Product(Deflator), Goods Value of Exports in US Dollars and Goods Value of Import in US Dollars. And in Multilevel models, we choose to set up groups in different countries and different year and build linear regressions. Results of coef() show estimated model within each group. After comparing AIC of each model, we choose the linear regression with minimum AIC.