

ARIMA Model GBP And JPY

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Forecasting Exchange Rate Using ARIMA Model for British Pound And Japanese Yen

Reading GBP and JPY Currency into r

```
library(readr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
GBPJPYARIMA <- read.csv ("GBPJPY_Candlestick_1_D_BID_01.01.2000-31.12.2020.csv")%>%
  select('GMT.TIME', CLOSE)%>%
  rename(Date = ('GMT.TIME'), RateGBPJPY = ("CLOSE"))
```

```
head(GBPJPYARIMA)
```

```
##           Date RateGBPJPY
## 1 2000-01-03      166.01
## 2 2000-01-04      168.81
## 3 2000-01-05      171.34
## 4 2000-01-06      173.37
## 5 2000-01-07      172.56
## 6 2000-01-10      171.98
```

Conversion of Gmt time to date format

```
library(dplyr)
library(lubridate)
```

```
##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:base':
##
##   date, intersect, setdiff, union
```

```
GBPJPYARIMA$Date <- lubridate::ymd(GBPJPYARIMA$Date)
head(GBPJPYARIMA)
```

```
##           Date RateGBPJPY
## 1 2000-01-03    166.01
## 2 2000-01-04    168.81
## 3 2000-01-05    171.34
## 4 2000-01-06    173.37
## 5 2000-01-07    172.56
## 6 2000-01-10    171.98
```

```
##Checking for obvious errors or missingg value
```

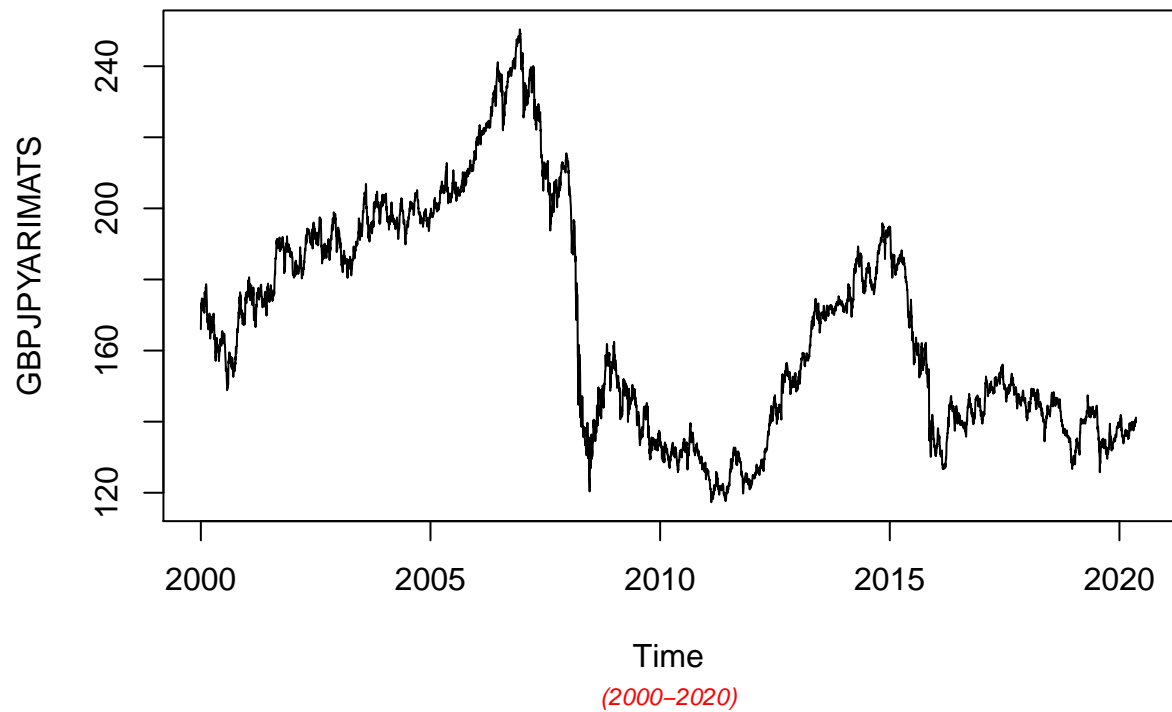
```
#Checking for obvious errors
which(is.na(GBPJPYARIMA))
```

```
## integer(0)
```

```
##Converting the data set into time series object
```

```
#Converting the data set into time series object
GBPJPYARIMATS<- ts(as.vector(GBPJPYARIMA$Rate), frequency = 314, start= c(2000,01,03))
plot.ts(GBPJPYARIMATS)
title("Time Series plot of GBPJPYTimeseries ", sub = "(2000-2020)",
      cex.main = 1.5, font.main= 4, col.main= "blue",
      cex.sub = 0.75, font.sub = 3, col.sub = "red")
```

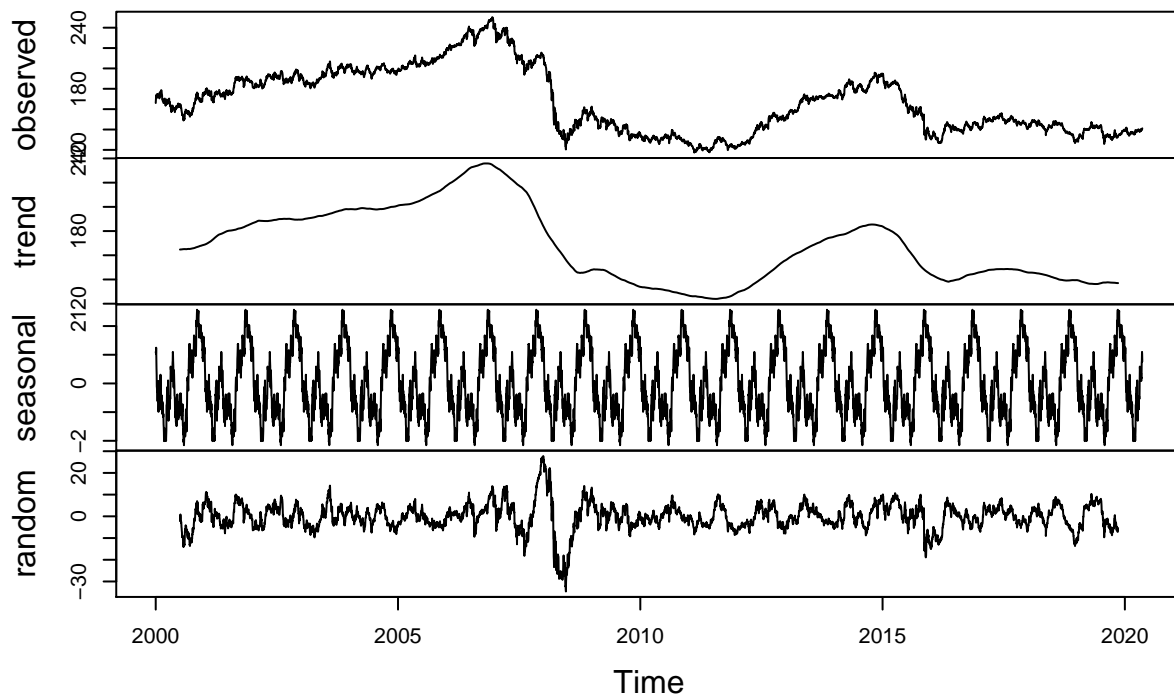
Time Series plot of GBPJPYTimeseries



Finding the component of the Time Series

```
ComponentGBPJPY <- decompose(GBPJPYARIMATS)
plot(ComponentGBPJPY)
```

Decomposition of additive time series



To achieve stationarity by differencing the data – compute the differences between consecutive observations

```
library("fUnitRoots")
```

```
## Warning: package 'fUnitRoots' was built under R version 4.0.5
```

```
## Loading required package: timeDate
```

```
## Warning: package 'timeDate' was built under R version 4.0.4
```

```
## Loading required package: timeSeries
```

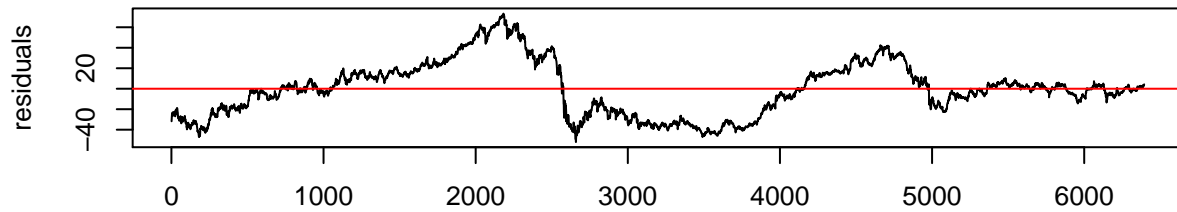
```
## Warning: package 'timeSeries' was built under R version 4.0.5
```

```
## Loading required package: fBasics
```

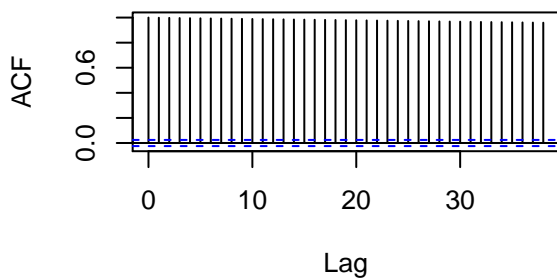
```
## Warning: package 'fBasics' was built under R version 4.0.5
```

```
urkpssTest(GBPJPYARIMATS, type = c("tau"), lags = c("short"), use.lag = NULL, doplot = TRUE)
```

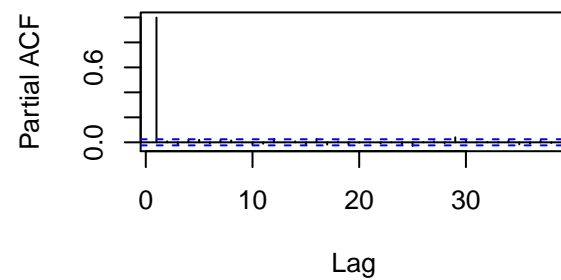
Residuals from test regression of type: tau with 11 lags



Autocorrelations of Residuals

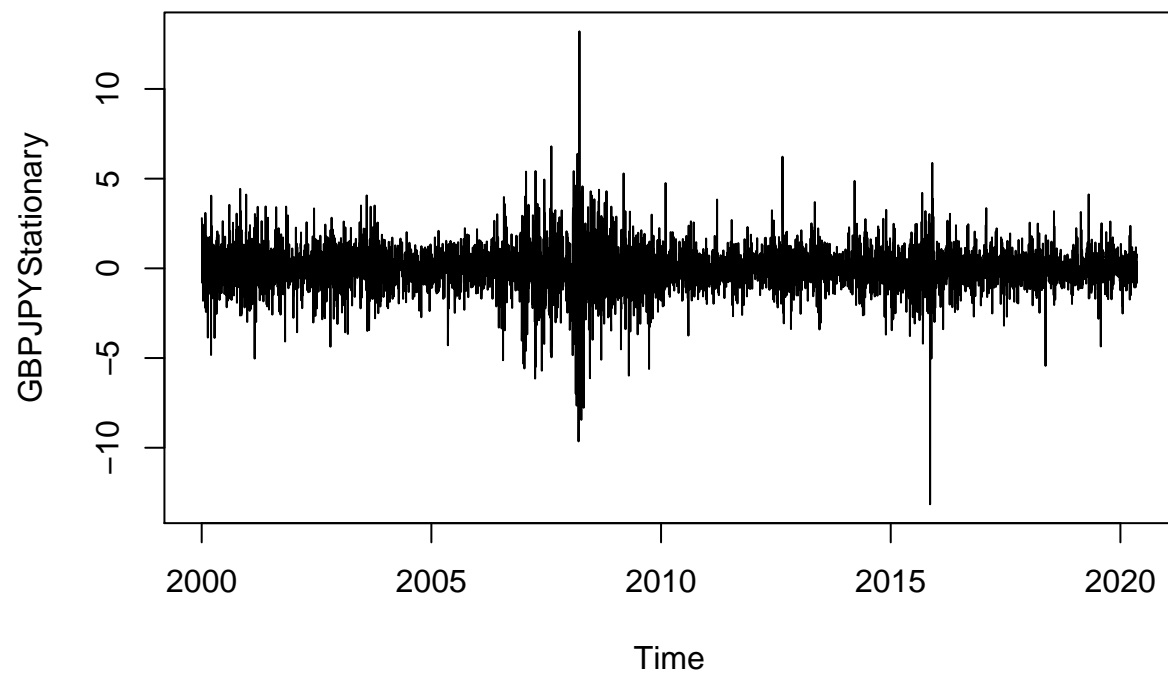


Partial Autocorrelations of Residuals



```
##
## Title:
## KPSS Unit Root Test
##
## Test Results:
## NA
##
## Description:
## Tue May 04 00:13:38 2021 by user: janeo
```

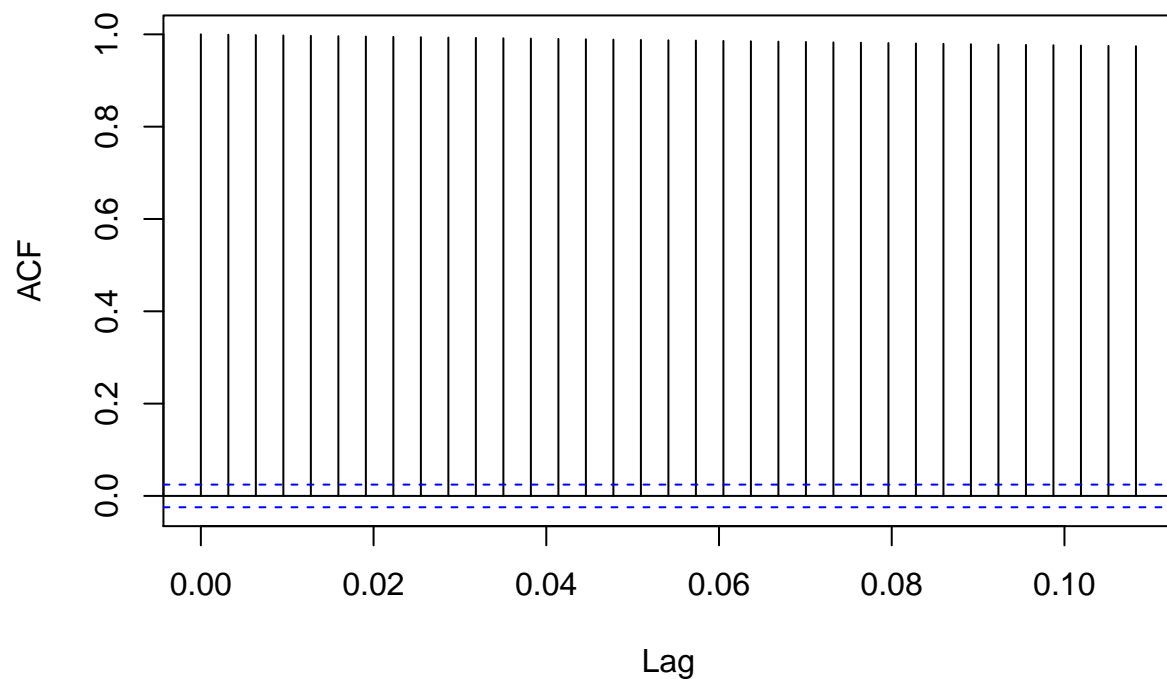
```
GBPJPYStationary= diff(GBPJPYARIMATS, differences=1)
plot(GBPJPYStationary)
```



Calculating Autocorrelation function and partil autocorlation function

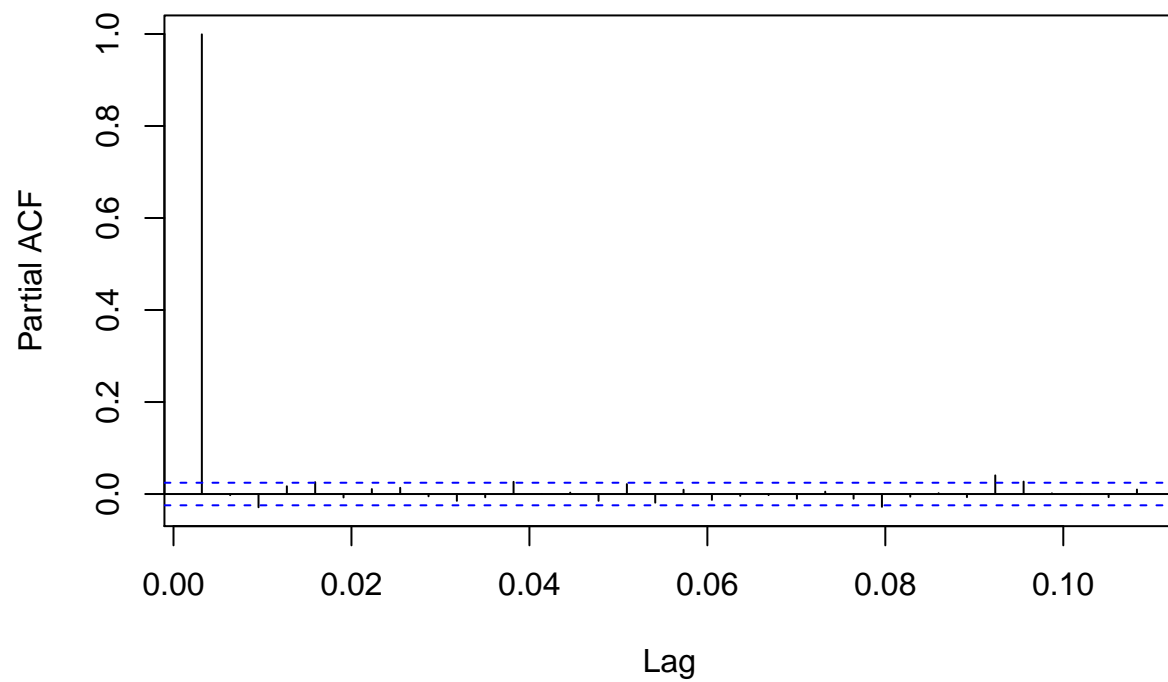
```
acf(GBPJPYARIMATS, lag.max=34)
```

Series GBPJPYARIMATS



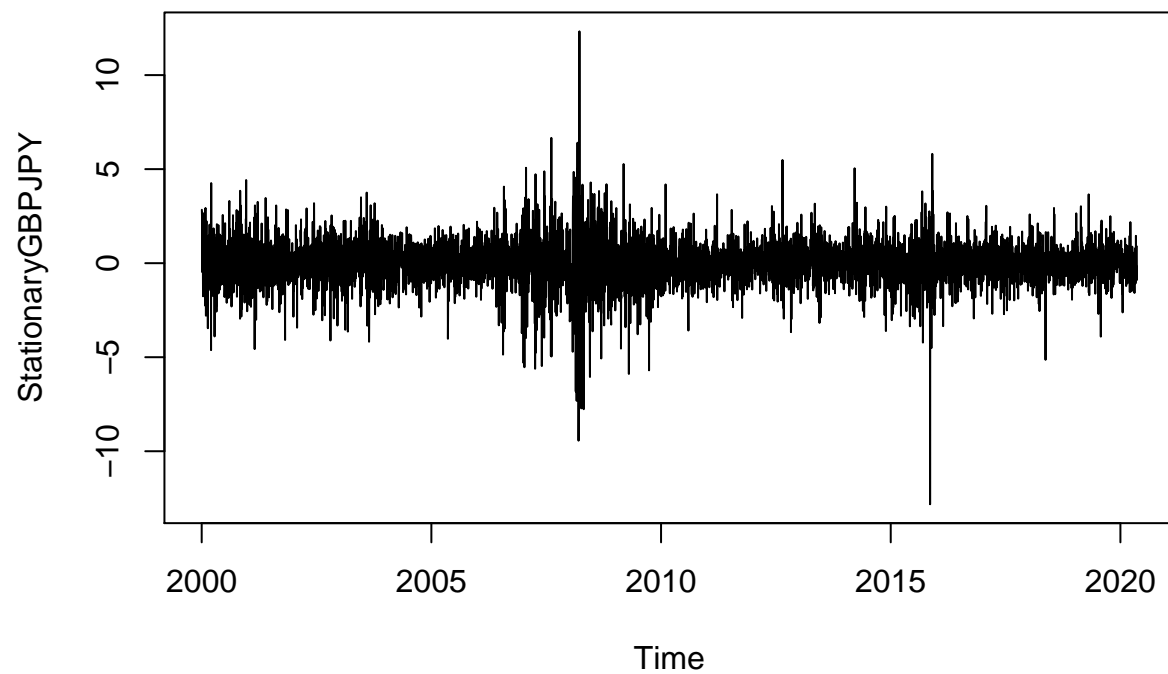
```
pacf(GBPJPYARIMATS, lag.max = 34)
```

Series GBPJPYARIMATS



Adjusting and ensuring there are no seasonality

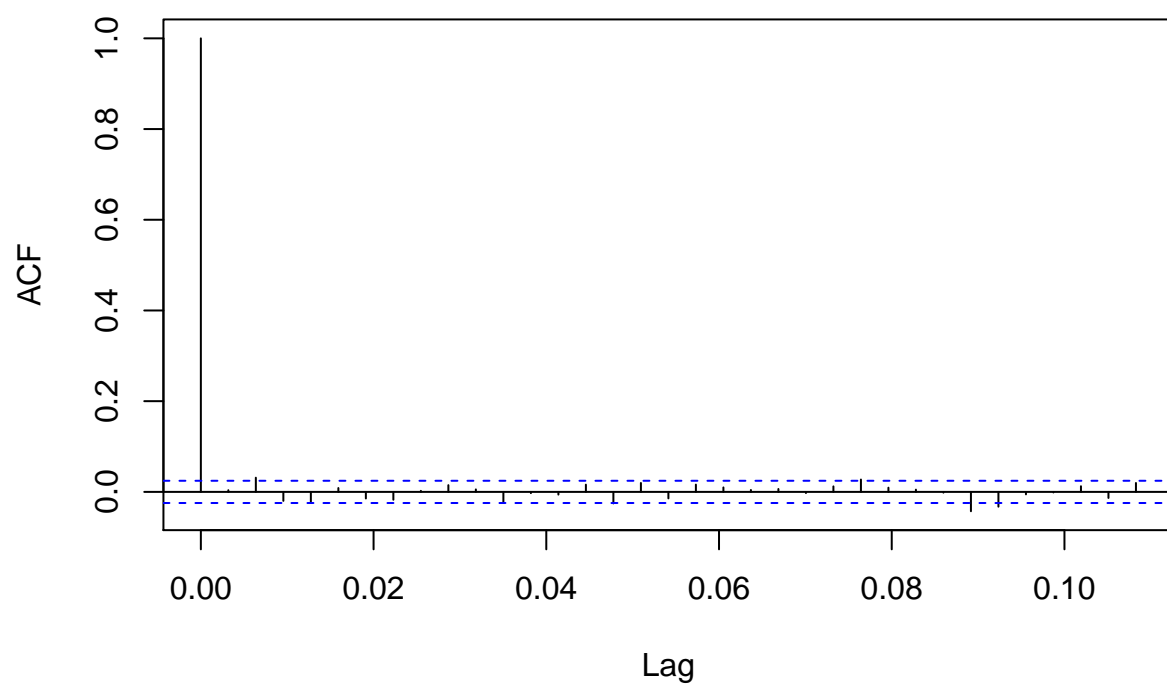
```
TSseasonallyadjustedGBPJPY <- GBPJPYARIMATS - ComponentGBPJPY$seasonal  
StationaryGBPJPY <- diff(TSseasonallyadjustedGBPJPY, differences=1)  
plot(StationaryGBPJPY)
```

Calculating again for ACF and PACF after finding stationality

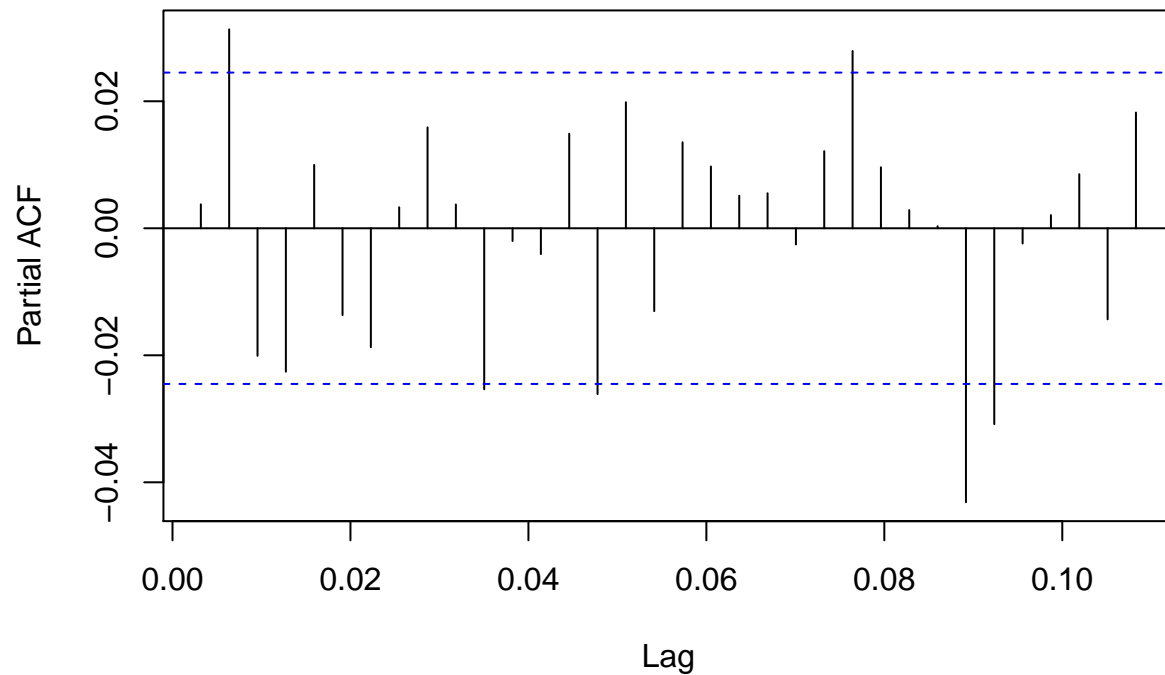
```
acf(StationaryGBPJPY, lag.max=34)
```

Series StationaryGBPJPY



```
pacf(StationaryGBPJPY, lag.max=34)
```

Series StationaryGBPJPY



Fitting The ARIMA Model

ARIMA fitting (1,1,0)

```
fitArima1GBPJPY <- arima(GBPJPYARIMATS, order = c(1,1,0), include.mean = TRUE)
fitArima1GBPJPY
```

```
##
## Call:
## arima(x = GBPJPYARIMATS, order = c(1, 1, 0), include.mean = TRUE)
##
## Coefficients:
##          ar1
##          0.0009
## s.e.      0.0125
##
## sigma^2 estimated as 1.416:  log likelihood = -10183.86,  aic = 20371.72
```

```
##Arima Fitting (0,1,0)
```

```
fitArima2GBPJPY <- arima(GBPJPYARIMATS, order = c(0,1,0), include.mean = TRUE)
fitArima2GBPJPY
```

```
##
## Call:
## arima(x = GBPJPYARIMATS, order = c(0, 1, 0), include.mean = TRUE)
##
##
## sigma^2 estimated as 1.416:  log likelihood = -10183.86,  aic = 20369.73
```

Arima Fitting (2,1,1)

```
fitArima3GBPJPY <- arima(GBPJPYARIMATS, order = c(2,1,1), include.mean = TRUE)
fitArima3GBPJPY
```

```
##
## Call:
## arima(x = GBPJPYARIMATS, order = c(2, 1, 1), include.mean = TRUE)
##
## Coefficients:
##          ar1      ar2      ma1
##       -0.2093  0.0301  0.2104
## s.e.    0.2288  0.0126  0.2286
##
## sigma^2 estimated as 1.415:  log likelihood = -10180.87,  aic = 20369.74
```

##Fitting Arima (0,1,3)

```
fitArima4GBPJPY <- arima(GBPJPYARIMATS, order = c(3,1,0), include.mean = TRUE)
fitArima4GBPJPY
```

```
##
## Call:
## arima(x = GBPJPYARIMATS, order = c(3, 1, 0), include.mean = TRUE)
##
## Coefficients:
##          ar1      ar2      ar3
##       0.0014  0.0286 -0.0185
## s.e.  0.0125  0.0125   0.0125
##
## sigma^2 estimated as 1.415:  log likelihood = -10180.15,  aic = 20368.3
```

##Best possible model is selected by AIC scores of the models

```
library(dLagM)
```

```
## Warning: package 'dLagM' was built under R version 4.0.5
```

```
## Loading required package: nardl
```

```
## Warning: package 'nardl' was built under R version 4.0.5
```

```
## Registered S3 method overwritten by 'quantmod':
##   method      from
##   as.zoo.data.frame zoo

## Loading required package: dynlm

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following object is masked from 'package:timeSeries':
##
##   time<-

## The following objects are masked from 'package:base':
##
##   as.Date, as.Date.numeric

ARIMAModelSelectionGBPJPY = AIC(fitArima1GBPJPY,fitArima2GBPJPY,fitArima3GBPJPY,fitArima4GBPJPY)
sortScore(ARIMAModelSelectionGBPJPY, score ="aic")

##           df      AIC
## fitArima4GBPJPY  4 20368.30
## fitArima2GBPJPY  1 20369.73
## fitArima3GBPJPY  4 20369.74
## fitArima1GBPJPY  2 20371.72
```

Base on the above the fitArima1CanJap is selected

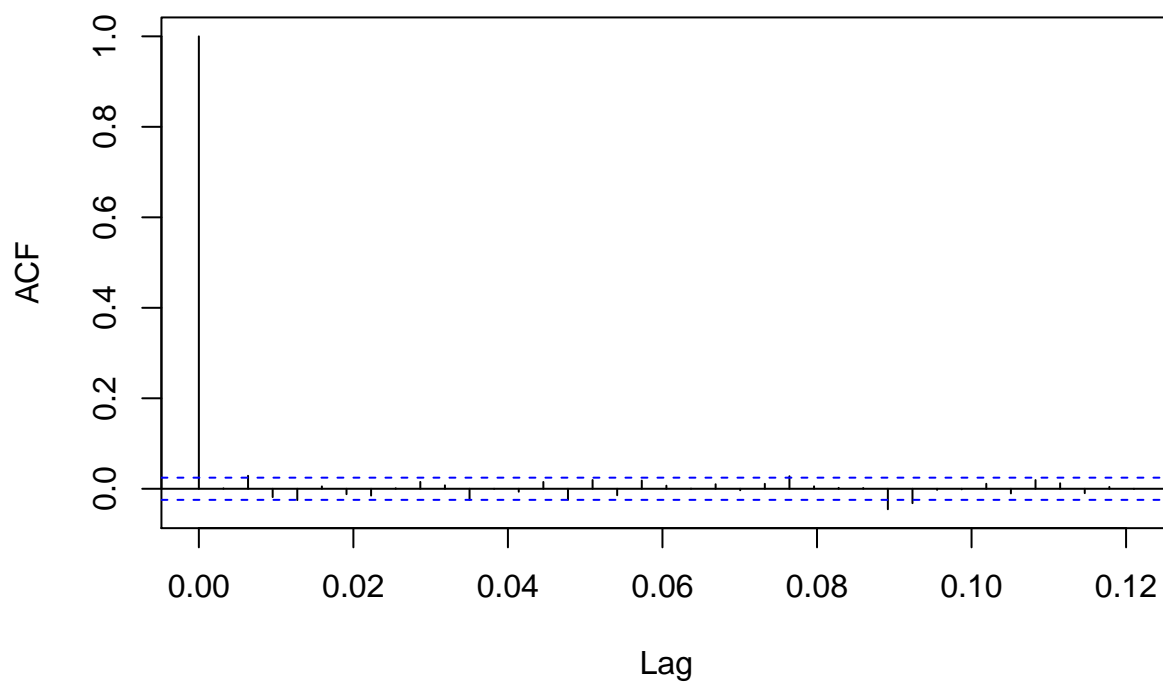
```
confint(fitArima2GBPJPY)
```

```
##      2.5 % 97.5 %
```

Runing code to obtain Box Test Rest

```
acf(fitArima2GBPJPY$residuals)
```

Series fitArima2GBPJPY\$residuals



```
library(FitAR)
```

```
## Warning: package 'FitAR' was built under R version 4.0.5
```

```
## Loading required package: lattice
```

```
## Loading required package: leaps
```

```
## Loading required package: ltsa
```

```
## Loading required package: bestglm
```

```
## Warning: package 'bestglm' was built under R version 4.0.5
```

```
library(bestglm)
```

```
Box.test(resid(fitArima2GBPJPY),type="Ljung",lag=20,fitdf=1)
```

```
##
```

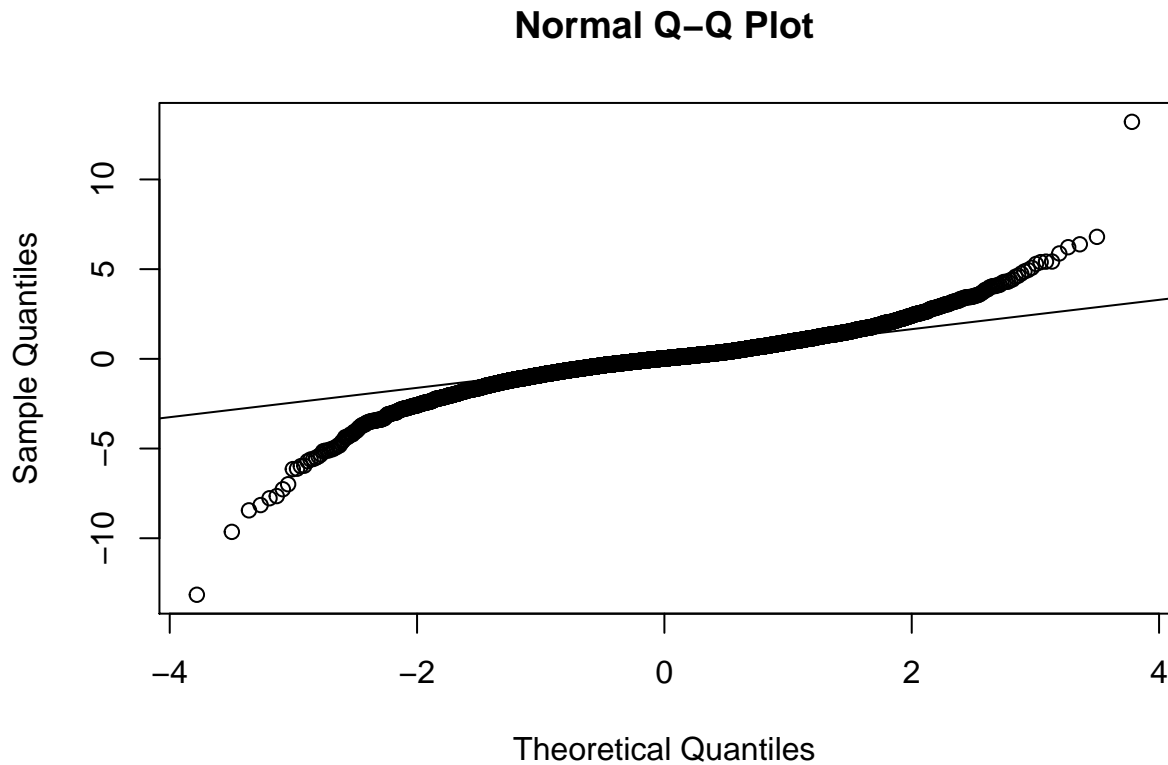
```
## Box-Ljung test
```

```
##
```

```
## data: resid(fitArima2GBPJPY)
```

```
## X-squared = 31.293, df = 19, p-value = 0.03748
```

```
qqnorm(fitArima2GBPJPY$residuals)
qqline(fitArima2GBPJPY$residuals)
```



Using Auto.arima to find the best model fit

```
library(forecast)
```

```
## Warning: package 'forecast' was built under R version 4.0.5
```

```
##
```

```
## Attaching package: 'forecast'
```

```
## The following object is masked from 'package:FitAR':
```

```
##
```

```
##   BoxCox
```

```
## The following object is masked from 'package:dLagM':
```

```
##
```

```
##   forecast
```

```
auto.arima(GBPJPYARIMATS, trace=TRUE)
```

```
##
## Fitting models using approximations to speed things up...
##
## ARIMA(2,1,2)(1,0,1)[314] with drift : Inf
## ARIMA(0,1,0) with drift : 20371.32
## ARIMA(1,1,0)(1,0,0)[314] with drift : Inf
## ARIMA(0,1,1)(0,0,1)[314] with drift : Inf
## ARIMA(0,1,0) : 20369.38
## ARIMA(0,1,0)(1,0,0)[314] with drift : 20286.36
## ARIMA(0,1,0)(2,0,0)[314] with drift : Inf
## ARIMA(0,1,0)(1,0,1)[314] with drift : Inf
## ARIMA(0,1,0)(0,0,1)[314] with drift : Inf
## ARIMA(0,1,0)(2,0,1)[314] with drift : Inf
## ARIMA(0,1,1)(1,0,0)[314] with drift : 20288.36
## ARIMA(1,1,1)(1,0,0)[314] with drift : Inf
## ARIMA(0,1,0)(1,0,0)[314] : Inf
##
## Now re-fitting the best model(s) without approximations...
##
## ARIMA(0,1,0)(1,0,0)[314] with drift : 20372.69
##
## Best model: ARIMA(0,1,0)(1,0,0)[314] with drift

## Series: GBPJPYARIMATS
## ARIMA(0,1,0)(1,0,0)[314] with drift
##
## Coefficients:
##      sar1      drift
##      0.0125 -0.0041
## s.e. 0.0127 0.0151
##
## sigma^2 estimated as 1.417: log likelihood=-10183.34
## AIC=20372.69 AICc=20372.69 BIC=20392.98
```

forecasting using Best model: ARIMA(1,1,0)

```
forecastarimaGBPJPY<- predict(fitArima2GBPJPY,n.ahead = 100)
forecastarimaGBPJPY
```

```
## $pred
## Time Series:
## Start = c(2020, 115)
## End = c(2020, 214)
## Frequency = 314
## [1] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [10] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [19] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [28] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [37] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
```



```
## [46] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [55] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [64] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [73] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [82] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [91] 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168 141.168
## [100] 141.168
##
## $se
## Time Series:
## Start = c(2020, 115)
## End = c(2020, 214)
## Frequency = 314
## [1] 1.190094 1.683048 2.061304 2.380189 2.661132 2.915124 3.148694
## [8] 3.366095 3.570283 3.763409 3.947097 4.122608 4.290947 4.452926
## [15] 4.609216 4.760378 4.906885 5.049143 5.187501 5.322264 5.453698
## [22] 5.582038 5.707492 5.830248 5.950472 6.068315 6.183912 6.297388
## [29] 6.408855 6.518416 6.626165 6.732191 6.836572 6.939383 7.040694
## [36] 7.140567 7.239062 7.336235 7.432137 7.526818 7.620323 7.712693
## [43] 7.803971 7.894193 7.983396 8.071613 8.158876 8.245216 8.330661
## [50] 8.415238 8.498974 8.581893 8.664018 8.745372 8.825977 8.905851
## [57] 8.985016 9.063489 9.141289 9.218432 9.294935 9.370813 9.446082
## [64] 9.520756 9.594848 9.668373 9.741343 9.813770 9.885667 9.957044
## [71] 10.027914 10.098286 10.168171 10.237579 10.306520 10.375003 10.443036
## [78] 10.510629 10.577791 10.644528 10.710850 10.776764 10.842276 10.907396
## [85] 10.972129 11.036482 11.100462 11.164075 11.227328 11.290227 11.352777
## [92] 11.414985 11.476855 11.538394 11.599606 11.660496 11.721071 11.781334
## [99] 11.841290 11.900944
```

```
par(mfrow = c(1,1))
```