GBP/USD Exchange Rate

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Summary Statistics

```
> summary(GBPUSD)
      Date                         Adj_Close          I_UK            I_USA
 Min.   :2012-01-01 00:00:00   Min.   :1.198   Min.   :0.2094   Min.   :0.0500
 1st Qu.:2014-08-24 06:00:00   1st Qu.:1.295   1st Qu.:0.9525   1st Qu.:0.0900
 Median :2017-04-16 00:00:00   Median :1.380   Median :1.5019   Median :0.1550
 Mean   :2017-04-16 11:37:30   Mean   :1.415   Mean   :1.5107   Mean   :0.6439
 3rd Qu.:2019-12-08 18:00:00   3rd Qu.:1.551   3rd Qu.:1.9771   3rd Qu.:1.1525
 Max.   :2022-08-01 00:00:00   Max.   :1.707   Max.   :2.9458   Max.   :2.4200
```

Checking Stationarity

1) adf.test(GBPUSD$Adj_Close)

Augmented Dickey-Fuller Test

data: GBPUSD$Adj_Close

Dickey-Fuller = -2.2814, Lag order = 5, p-value = 0.4595

alternative hypothesis: stationary

2) pp.test(GBPUSD$Adj_Close)

Phillips-Perron Unit Root Test

data: GBPUSD$Adj_Close

Dickey-Fuller Z(alpha) = -8.9411, Truncation lag parameter = 4, p-value = 0.5996

alternative hypothesis: stationary

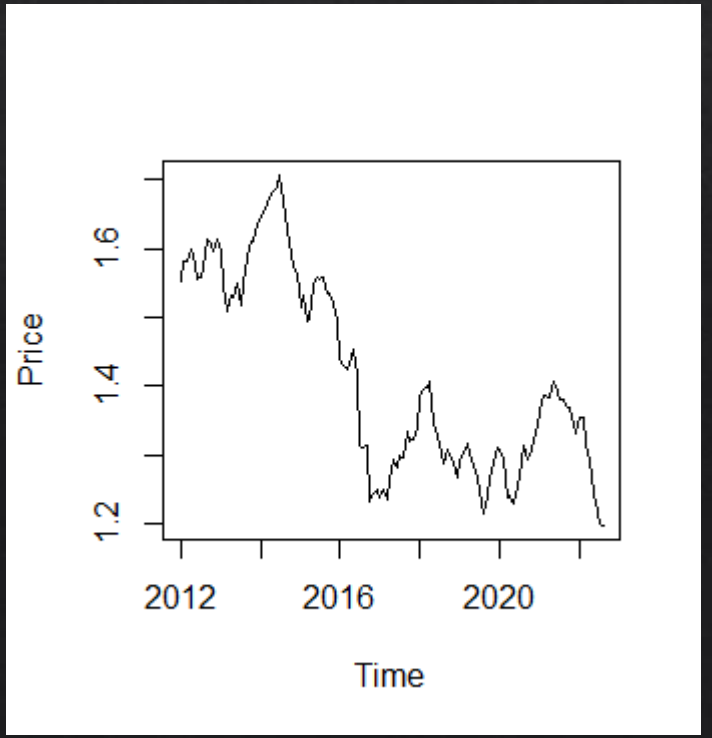
3)kpss.test(GBPUSD$Adj_Close)

KPSS Test for Level Stationarity

data: GBPUSD$Adj_Close

KPSS Level = 1.9266, Truncation lag parameter = 4, p-value = 0.01

4)



Making Stationary

Adj_Close1=diff(log(GBPUSD$Adj_Close))

1) adf.test(Adj_Close1)

Augmented Dickey-Fuller Test

data: Adj_Close1
Dickey-Fuller = -4.1661, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary

2) pp.test(Adj_Close1)

Phillips-Perron Unit Root Test

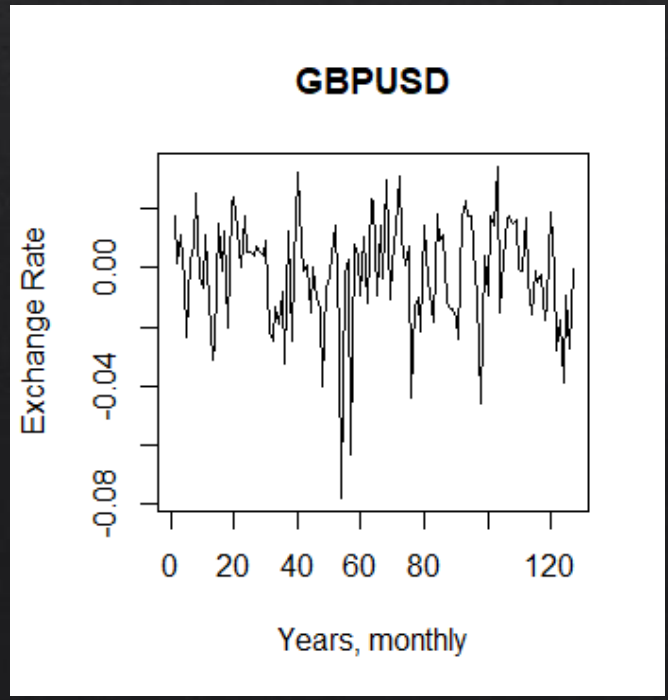
data: Adj_Close1
Dickey-Fuller Z(alpha) = -107.47, Truncation lag parameter = 4, p-value = 0.01
alternative hypothesis: stationary

3) kpss.test(Adj_Close1)

KPSS Test for Level Stationarity

data: Adj_Close1
KPSS Level = 0.073198, Truncation lag parameter = 4, p-value = 0.1

4)



Creating Model

1) Creating the data with the 1st difference

```
GBPUSD$Adj_Close1 <- c(NA,Adj_Close1)
GBPUSD$I_UK1 <- c(NA,I_UK1)
GBPUSD$I_USA1 <- c(NA,I_USA1)
```

2) Creating the lags

```
GBPUSD$Adj_Close.1_lag_1<- .Lag(GBPUSD$Adj_Close1, 1)
GBPUSD$Adj_Close.1_lag_2<- .Lag(GBPUSD$Adj_Close1, 2)
GBPUSD$I_USA.1_lag_1 <- .Lag(GBPUSD$I_USA1, 1)
GBPUSD$I_USA.1_lag_2 <- .Lag(GBPUSD$I_USA1, 2)
GBPUSD$I_UK.1_lag_1 <- .Lag(GBPUSD$I_UK1, 1)
GBPUSD$I_UK.1_lag_2 <- .Lag(GBPUSD$I_UK1, 2)
```

3) We estimate the model

```
m1 <- lm(formula = Adj_Close1 ~ Adj_Close.1_lag_1, data = GBPUSD)
m2 <- lm(formula = Adj_Close1 ~ Adj_Close.1_lag_1+Adj_Close.1_lag_2, data = GBPUSD)
m3 = lm(formula = Adj_Close1 ~
Adj_Close.1_lag_1+Adj_Close.1_lag_2+I_USA.1_lag_1+I_USA.1_lag_2+I_UK.1_lag_1+I_UK.1_lag_2  , data =
GBPUSD)
```

Deciding Appropriate Model

1) Checking by summary

```
> summary(m1)

Call:
lm(formula = Adj_Close1 ~ Adj_Close.1_lag_1, data = GBPUSD)

Residuals:
      Min        1Q    Median        3Q       Max
-0.071783 -0.010735  0.000787  0.013845  0.033809

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.001814   0.001658  -1.094   0.2761
Adj_Close.1_lag_1  0.186512   0.087817   2.124   0.0357 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0185 on 124 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared:  0.0351,    Adjusted R-squared:  0.02732
F-statistic: 4.511 on 1 and 124 DF,  p-value: 0.03567
```

```
> summary(m2)

Call:
lm(formula = Adj_Close1 ~ Adj_Close.1_lag_1 + Adj_Close.1_lag_2,
    data = GBPUSD)

Residuals:
      Min        1Q    Median        3Q       Max
-0.072790 -0.011060  0.002158  0.013856  0.034974

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.001739   0.001683  -1.034   0.3034
Adj_Close.1_lag_1  0.177110   0.090470   1.958   0.0526 .
Adj_Close.1_lag_2  0.050344   0.090728   0.555   0.5800
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.01863 on 122 degrees of freedom
  (3 observations deleted due to missingness)
Multiple R-squared:  0.03727,    Adjusted R-squared:  0.02149
F-statistic: 2.362 on 2 and 122 DF,  p-value: 0.09857
```

```
> summary(m3)

Call:
lm(formula = Adj_Close1 ~ Adj_Close.1_lag_1 + Adj_Close.1_lag_2 +
    I_USA.1_lag_1 + I_USA.1_lag_2 + I_UK.1_lag_1 + I_UK.1_lag_2,
    data = GBPUSD)

Residuals:
      Min        1Q    Median        3Q       Max
-0.074842 -0.011262  0.002611  0.013379  0.033832

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.001490   0.001686  -0.883   0.3788
Adj_Close.1_lag_1  0.234085   0.099571   2.351   0.0204 *
Adj_Close.1_lag_2  0.040076   0.098216   0.408   0.6840
I_USA.1_lag_1     -0.004219   0.006059  -0.696   0.4876
I_USA.1_lag_2     -0.003100   0.006018  -0.515   0.6074
I_UK.1_lag_1      -0.022962   0.013927  -1.649   0.1019
I_UK.1_lag_2       0.014261   0.014011   1.018   0.3109
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0186 on 118 degrees of freedom
  (3 observations deleted due to missingness)
Multiple R-squared:  0.07216,    Adjusted R-squared:  0.02499
F-statistic:  1.53 on 6 and 118 DF,  p-value: 0.1743
```

Deciding Appropriate Model

2) Akaike Information Criteria

AIC(m1) = -643.8825
AIC(m2) = -636.044
AIC(m3) = -632.6586

3) Bayesian Information Criteria

BIC(m1) = -635.737
BIC(m2) = -624.7307
BIC(m3) = -610.0321

Checking the autocorrelation in residuals

1) Durbin-Watson test

data: m1
DW = 2.0174, p-value = 0.5319
alternative hypothesis: true autocorrelation is greater than 0

2) Breusch-Godfrey test for serial correlation of order up to 1

data: m1
LM test = 0.24671, df = 1, p-value = 0.6194

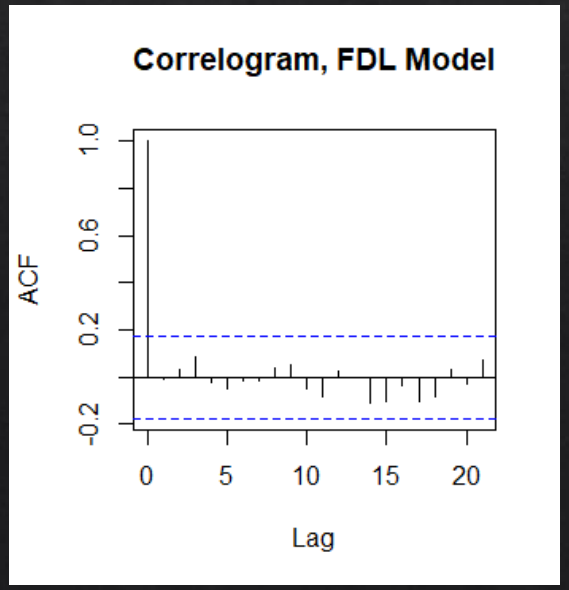
3) Box-Pierce test

data: m1$residuals
X-squared = 0.010659, df = 1, p-value = 0.9178

4) Box-Ljung Test

data: m1$residuals
X-squared = 0.010915, df = 1, p-value = 0.9168

5)



Checking Heteroskedasticity

1) studentized Breusch-Pagan test

data: m1
BP = 1.1086, df = 1, p-value = 0.2924

2) White test

data: m1
statistic = 2.39, p-value = 0.303

FORECASTING

```
> fcast_m1 <- predict(m1, h=9, newdata = GBPUSD[120:128,], interval = "confidence", level = 0.95)
> fcast_m1
              fit          lwr           upr
120 -0.005086468 -0.009316914 -0.0008560216
121 -0.004038910 -0.007725590 -0.0003522300
122  0.001690248 -0.003184770  0.0065652668
123 -0.002020971 -0.005287633  0.0012456920
124 -0.007010936 -0.012558266 -0.0014636053
125 -0.005168192 -0.009447524 -0.0008888601
126 -0.009093177 -0.016300841 -0.0018855126
127 -0.003591041 -0.007102837 -0.0000792452
128 -0.006936508 -0.012427893 -0.0014451229
> f_multi.stp.ahead <- forecast(m1, h=9, newdata = GBPUSD[120:128,], level = 95)
> f_multi.stp.ahead
  Point Forecast       Lo 95      Hi 95
1   -0.005086468 -0.04195208 0.03177914
2   -0.004038910 -0.04084609 0.03276827
3    0.001690248 -0.03525488 0.03863538
4   -0.002020971 -0.03878845 0.03474651
5   -0.007010936 -0.04405077 0.03002890
6   -0.005168192 -0.04203945 0.03170306
7   -0.009093177 -0.04641779 0.02823144
8   -0.003591041 -0.04038111 0.03319903
9   -0.006936508 -0.04396801 0.03009499
```

FORECASTING

```
# Actual
plot(GBPUSD$Date[120:128], GBPUSD$Adj_Close1[120:128], type ="l",
     ylab = "log diff", xlab = "years,quarterly", main = "Exchange Rate")

# Model 2 prediction with red color
lines(GBPUSD$Date[120:128],fcast_m1[,1], type = "l",  lty =1, col = 2)

# confidence bands
lines(GBPUSD$Date[120:128],fcast_m1[,2], type = "l",  lty =2, col = 4)
lines(GBPUSD$Date[120:128],fcast_m1[,3], type = "l",  lty =2, col = 4)
```