Timeseries HW5

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10/7/2018

Macro Vars

Question (a)

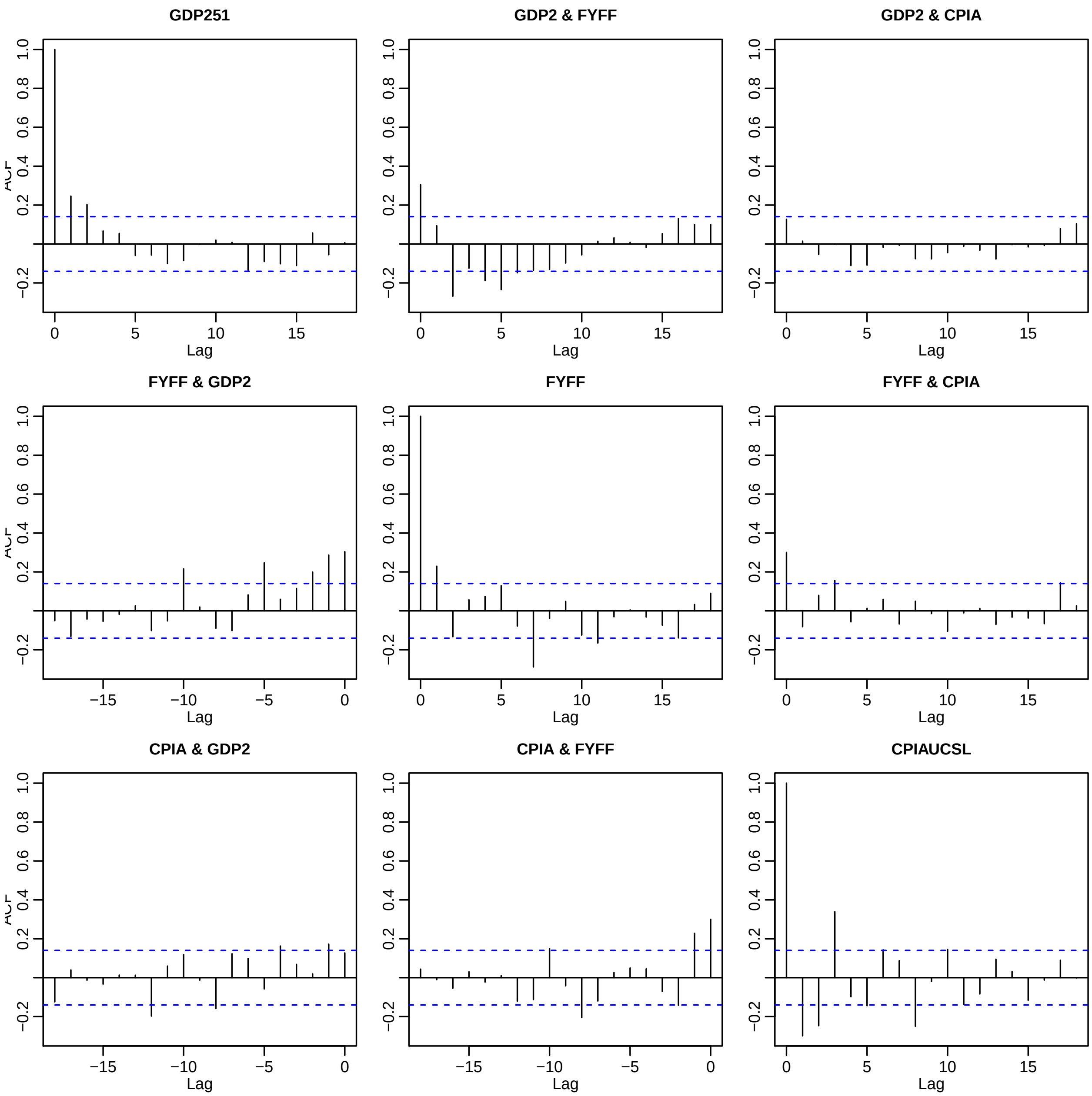
```
library(vars)
```

```
## Loading required package: MASS
## Loading required package: strucchange
## Loading required package: zoo
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
## Loading required package: sandwich
## Loading required package: urca
## Loading required package: lmtest
```

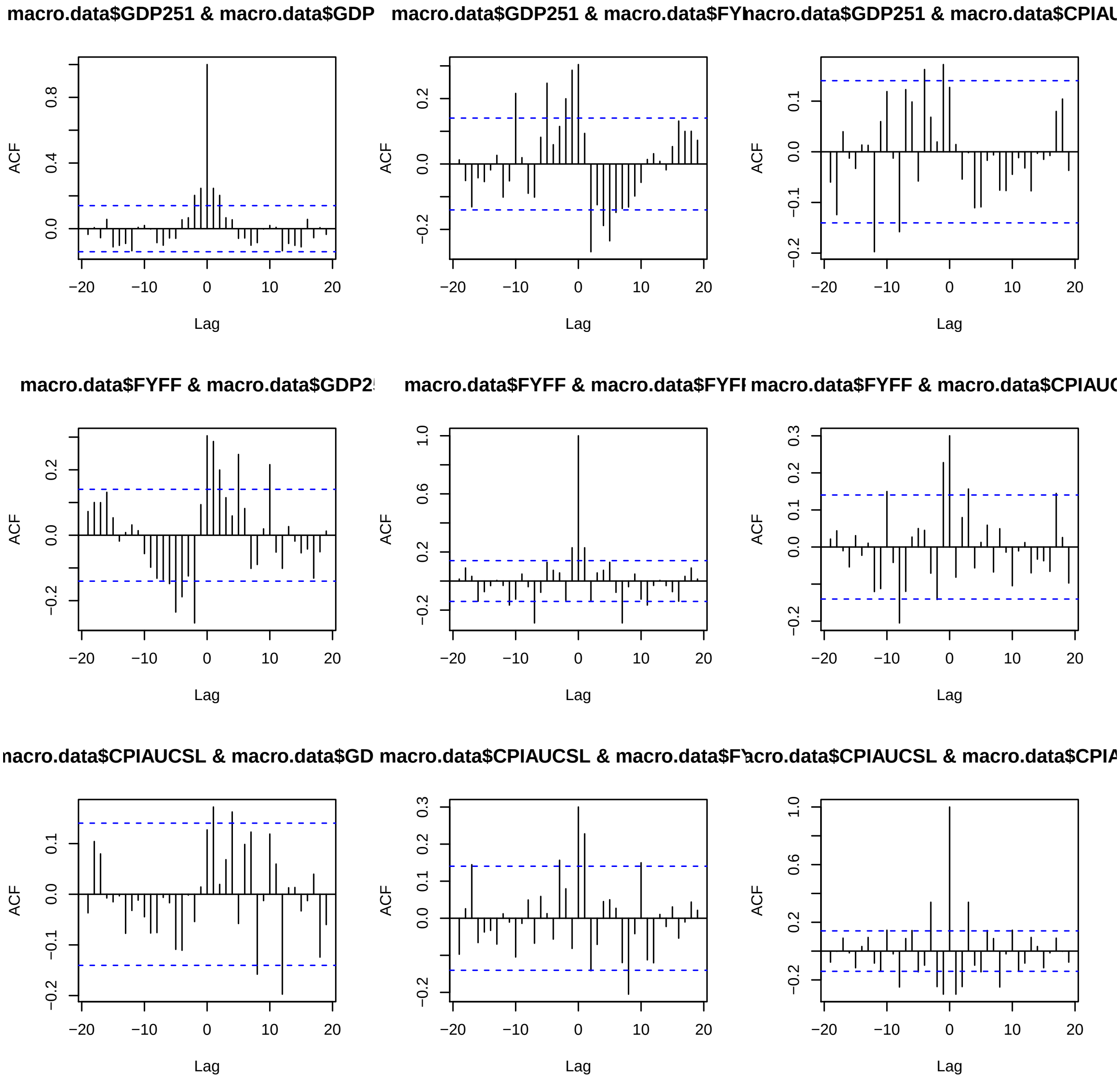
```
source("https://people.orie.cornell.edu/davidr/SDAFE2/Rscripts/SDAFE2.R")
```

```
## Loading required package: fGarch
## Loading required package: timeDate
## Warning in as.POSIXlt.POSIXct(Sys.time()): unknown timezone 'default/
## America/New_York'
## Loading required package: timeSeries
##
## Attaching package: 'timeSeries'
## The following object is masked from 'package:zoo':
##
##     time<-
## Loading required package: fBasics
```

```
macro.data = read.csv('MacroVars.csv')
acf(macro.data)
```




```r
par(mfrow = c(3,3))
ccf(macro.data$GDP251, macro.data$GDP251)
ccf(macro.data$GDP251, macro.data$FYFF)
ccf(macro.data$GDP251, macro.data$CPIAUCSL)
ccf(macro.data$FYFF, macro.data$GDP251)
ccf(macro.data$FYFF, macro.data$FYFF)
ccf(macro.data$FYFF, macro.data$CPIAUCSL)
ccf(macro.data$CPIAUCSL, macro.data$GDP251)
ccf(macro.data$CPIAUCSL, macro.data$FYFF)
ccf(macro.data$CPIAUCSL, macro.data$CPIAUCSL)
```



Interesting Observations

- All the three series have autocorrelation on their own.
- Some pairs of series also have cross serial correlation. The most significant one is the cross-serial correlation between `GDP251` and `FYFF`. The second ccf plot suggests there is positive correlations on negative lags, and negative correlations on positive lags for this pair.
- That is: An above-average change in GDP predicts an above-average change in federal funds rate. But an above-average change in Federal funds rate redicts a below-average change in GDP. This is kinda consistant to the debt-GDP cycle in the real life.

Question (b)

```
var.fit = VAR(macro.data, lag.max=8)
var.fit$p
```

```
## AIC(n)
##      7
```

```r
summary(var.fit)
```

```
##
## VAR Estimation Results:
## =========================
## Endogenous variables: GDP251, FYFF, CPIAUCSL
## Deterministic variables: const
## Sample size: 188
## Log Likelihood: 1276.466
## Roots of the characteristic polynomial:
## 0.8759 0.8759 0.8506 0.8506 0.8371 0.8371 0.8325 0.8325 0.809 0.809 0.7795 0.7795 0.7765 0.7765 0.73
## Call:
## VAR(y = macro.data, lag.max = 8)
##
##
## Estimation results for equation GDP251:
## =======================================
## GDP251 = GDP251.l1 + FYFF.l1 + CPIAUCSL.l1 + GDP251.l2 + FYFF.l2 + CPIAUCSL.l2 + GDP251.l3 + FYFF.l3
##
##               Estimate Std. Error t value Pr(>|t|)
## GDP251.l1    1.696e-01  7.830e-02   2.166   0.0317 *
## FYFF.l1      8.688e-04  7.245e-04   1.199   0.2322
## CPIAUCSL.l1 -5.543e-02  1.630e-01  -0.340   0.7343
## GDP251.l2    1.504e-01  8.263e-02   1.821   0.0704 .
## FYFF.l2     -3.647e-03  7.420e-04  -4.914 2.12e-06 ***
## CPIAUCSL.l2 -4.326e-02  1.807e-01  -0.239   0.8111
## GDP251.l3    2.593e-02  8.260e-02   0.314   0.7540
## FYFF.l3      3.601e-05  7.687e-04   0.047   0.9627
## CPIAUCSL.l3 -2.167e-01  1.950e-01  -1.111   0.2681
## GDP251.l4    1.681e-01  7.858e-02   2.139   0.0339 *
## FYFF.l4     -1.648e-03  7.656e-04  -2.153   0.0328 *
## CPIAUCSL.l4 -1.431e-01  1.937e-01  -0.739   0.4612
## GDP251.l5    2.192e-03  8.319e-02   0.026   0.9790
## FYFF.l5     -1.355e-03  7.600e-04  -1.783   0.0765 .
## CPIAUCSL.l5  4.781e-02  1.927e-01   0.248   0.8043
## GDP251.l6    1.269e-02  7.916e-02   0.160   0.8728
## FYFF.l6     -3.983e-04  7.810e-04  -0.510   0.6108
## CPIAUCSL.l6  1.197e-01  1.804e-01   0.664   0.5079
## GDP251.l7    7.850e-02  7.697e-02   1.020   0.3092
## FYFF.l7     -4.765e-04  7.705e-04  -0.618   0.5372
## CPIAUCSL.l7  1.954e-01  1.624e-01   1.203   0.2306
## const        3.331e-03  1.358e-03   2.453   0.0152 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.007268 on 166 degrees of freedom
## Multiple R-Squared: 0.313,   Adjusted R-squared: 0.2261
## F-statistic: 3.602 on 21 and 166 DF,  p-value: 1.66e-06
##
##
## Estimation results for equation FYFF:
```

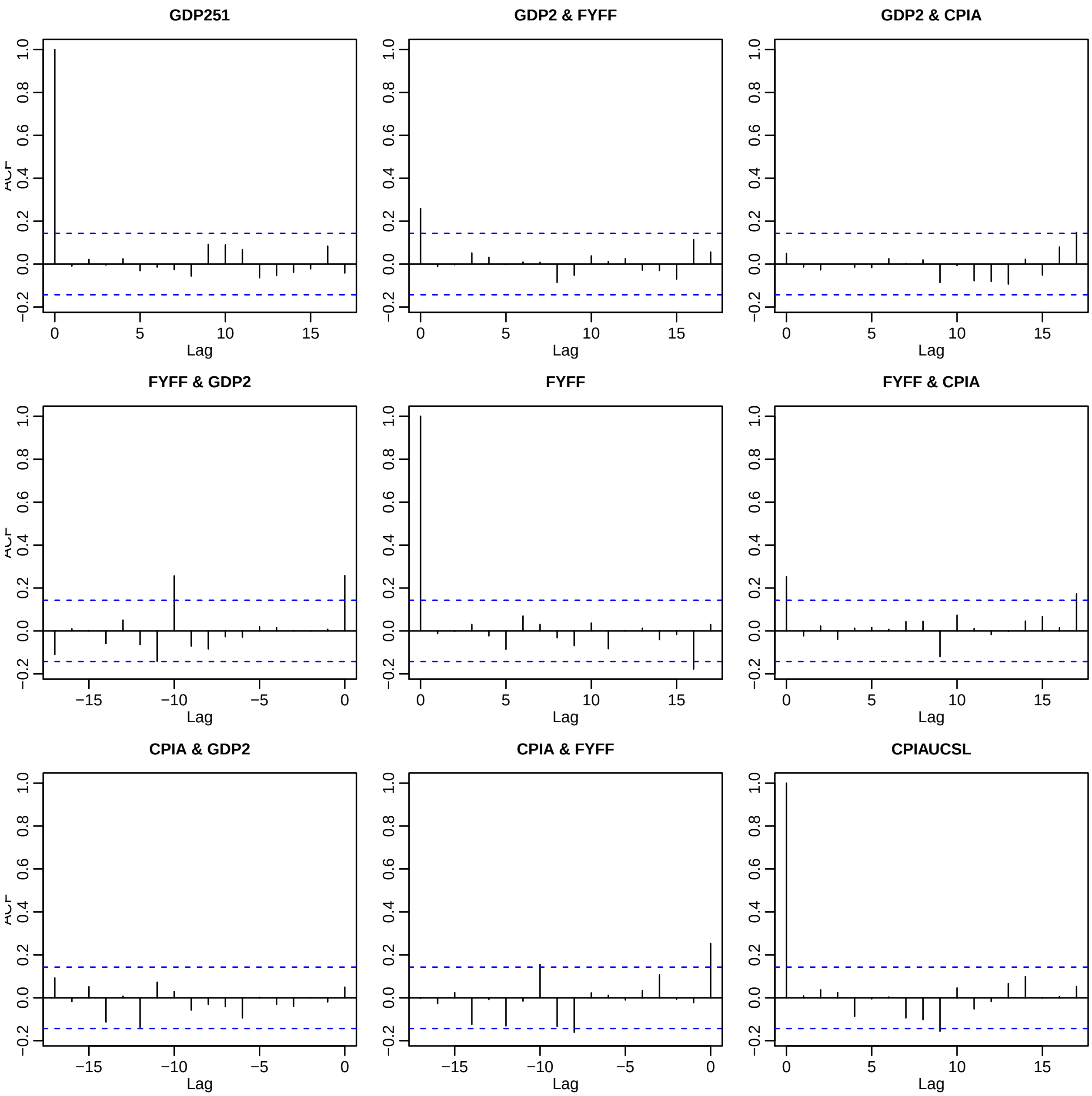
```
## ========================================
## FYFF = GDP251.l1 + FYFF.l1 + CPIAUCSL.l1 + GDP251.l2 + FYFF.l2 + CPIAUCSL.l2 + GDP251.l3 + FYFF.l3 +
##
##               Estimate Std. Error t value Pr(>|t|)
## GDP251.l1    34.30826    8.86489   3.870 0.000156 ***
## FYFF.l1       0.18695    0.08203   2.279 0.023938 *
## CPIAUCSL.l1  -2.65512   18.45806  -0.144 0.885797
## GDP251.l2    15.71441    9.35559   1.680 0.094900 .
## FYFF.l2      -0.30204    0.08401  -3.595 0.000427 ***
## CPIAUCSL.l2  49.85484   20.45589   2.437 0.015858 *
## GDP251.l3     0.46597    9.35279   0.050 0.960324
## FYFF.l3       0.13653    0.08703   1.569 0.118601
## CPIAUCSL.l3  49.07421   22.07643   2.223 0.027572 *
## GDP251.l4   -10.30967    8.89737  -1.159 0.248230
## FYFF.l4      -0.04571    0.08668  -0.527 0.598698
## CPIAUCSL.l4   8.82019   21.93601   0.402 0.688137
## GDP251.l5    19.43478    9.41881   2.063 0.040631 *
## FYFF.l5       0.26031    0.08605   3.025 0.002881 **
## CPIAUCSL.l5  16.17587   21.81501   0.742 0.459437
## GDP251.l6    -8.96569    8.96301  -1.000 0.318622
## FYFF.l6      -0.06717    0.08843  -0.760 0.448616
## CPIAUCSL.l6  41.01915   20.42969   2.008 0.046284 *
## GDP251.l7   -11.50636    8.71454  -1.320 0.188532
## FYFF.l7      -0.12959    0.08724  -1.485 0.139353
## CPIAUCSL.l7  24.36437   18.38352   1.325 0.186880
## const        -0.31173    0.15374  -2.028 0.044194 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.8229 on 166 degrees of freedom
## Multiple R-Squared: 0.376,   Adjusted R-squared: 0.297
## F-statistic: 4.763 on 21 and 166 DF,  p-value: 3.032e-09
##
##
## Estimation results for equation CPIAUCSL:
## ============================================
## CPIAUCSL = GDP251.l1 + FYFF.l1 + CPIAUCSL.l1 + GDP251.l2 + FYFF.l2 + CPIAUCSL.l2 + GDP251.l3 + FYFF.l
##
##                Estimate Std. Error t value Pr(>|t|)
## GDP251.l1    0.0824823  0.0370374   2.227 0.027292 *
## FYFF.l1      0.0011813  0.0003427   3.447 0.000718 ***
## CPIAUCSL.l1 -0.4922660  0.0771175  -6.383 1.67e-09 ***
## GDP251.l2   -0.0045119  0.0390875  -0.115 0.908244
## FYFF.l2     -0.0002448  0.0003510  -0.697 0.486581
## CPIAUCSL.l2 -0.3248935  0.0854644  -3.802 0.000202 ***
## GDP251.l3    0.0179658  0.0390758   0.460 0.646284
## FYFF.l3     -0.0001194  0.0003636  -0.328 0.743027
## CPIAUCSL.l3  0.0481986  0.0922350   0.523 0.601975
## GDP251.l4    0.1235843  0.0371731   3.325 0.001090 **
## FYFF.l4     -0.0005334  0.0003621  -1.473 0.142648
## CPIAUCSL.l4 -0.1369755  0.0916483  -1.495 0.136923
## GDP251.l5   -0.0178514  0.0393517  -0.454 0.650682
## FYFF.l5      0.0002736  0.0003595   0.761 0.447654
```

```
## CPIAUCSL.l5 -0.0793641  0.0911428  -0.871 0.385139
## GDP251.l6   -0.0109323  0.0374473  -0.292 0.770698
## FYFF.l6      0.0005305  0.0003695   1.436 0.152946
## CPIAUCSL.l6  0.0643632  0.0853549   0.754 0.451878
## GDP251.l7    0.0718766  0.0364092   1.974 0.050026 .
## FYFF.l7     -0.0007839  0.0003645  -2.151 0.032961 *
## CPIAUCSL.l7  0.2073577  0.0768060   2.700 0.007658 **
## const       -0.0020991  0.0006423  -3.268 0.001317 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## Residual standard error: 0.003438 on 166 degrees of freedom
## Multiple R-Squared: 0.4711,  Adjusted R-squared: 0.4042
## F-statistic: 7.041 on 21 and 166 DF,  p-value: 2.636e-14
##
##
##
## Covariance matrix of residuals:
##             GDP251      FYFF  CPIAUCSL
## GDP251   5.282e-05 0.0015424 1.236e-06
## FYFF     1.542e-03 0.6771124 7.162e-04
## CPIAUCSL 1.236e-06 0.0007162 1.182e-05
##
## Correlation matrix of residuals:
##           GDP251   FYFF CPIAUCSL
## GDP251   1.00000 0.2579  0.04945
## FYFF     0.25791 1.0000  0.25316
## CPIAUCSL 0.04945 0.2532  1.00000
```

A model of $p = 7$ is chosen in this cased based on AIC criterion.

Question (c)

```r
acf(residuals(var.fit))
```




```
mLjungBox(residuals(var.fit), lag=20)
```

```
##    K  Q(K) d.f. p-value
## 1 20 145.7  180   0.971
```

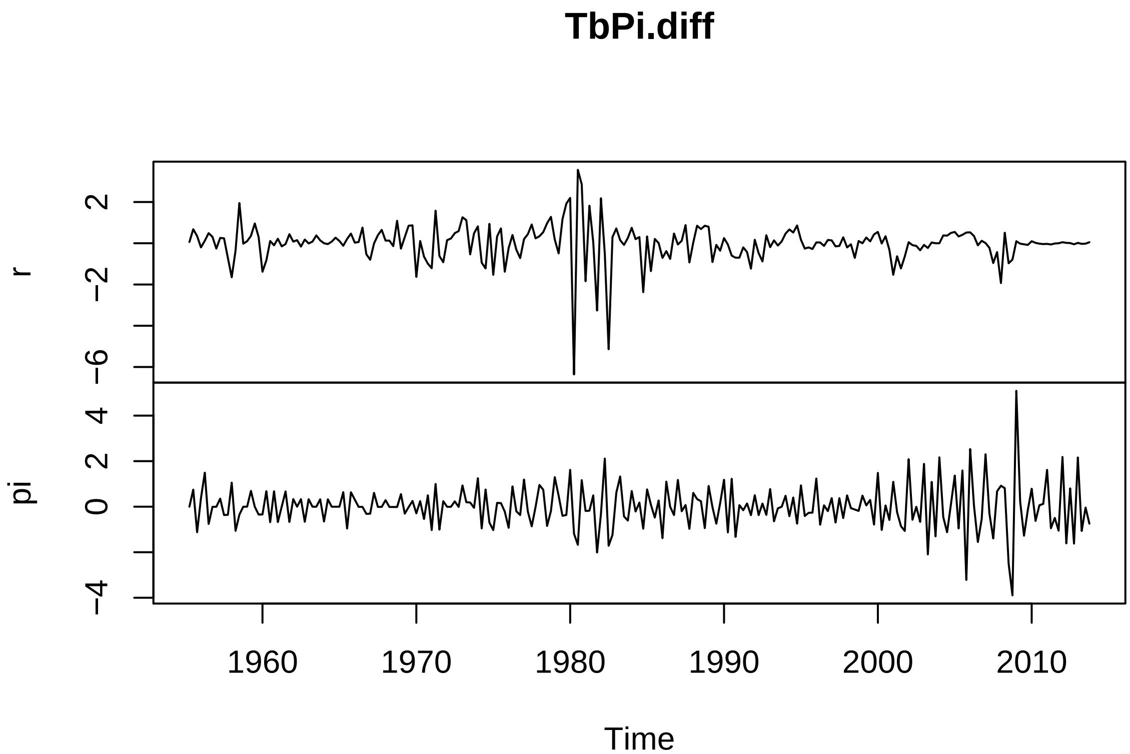
Comments

- The multivariate Ljung-Box test has a p-value $= 0.971$. Meaning that we fail to reject the null hypothesis: the residual series has no serial correlation within or between all variables.
- The ACF plots of residuals also display no significant serial correlation for the residuals. Thus we conclude that the VAR fit is likely to be adequate.

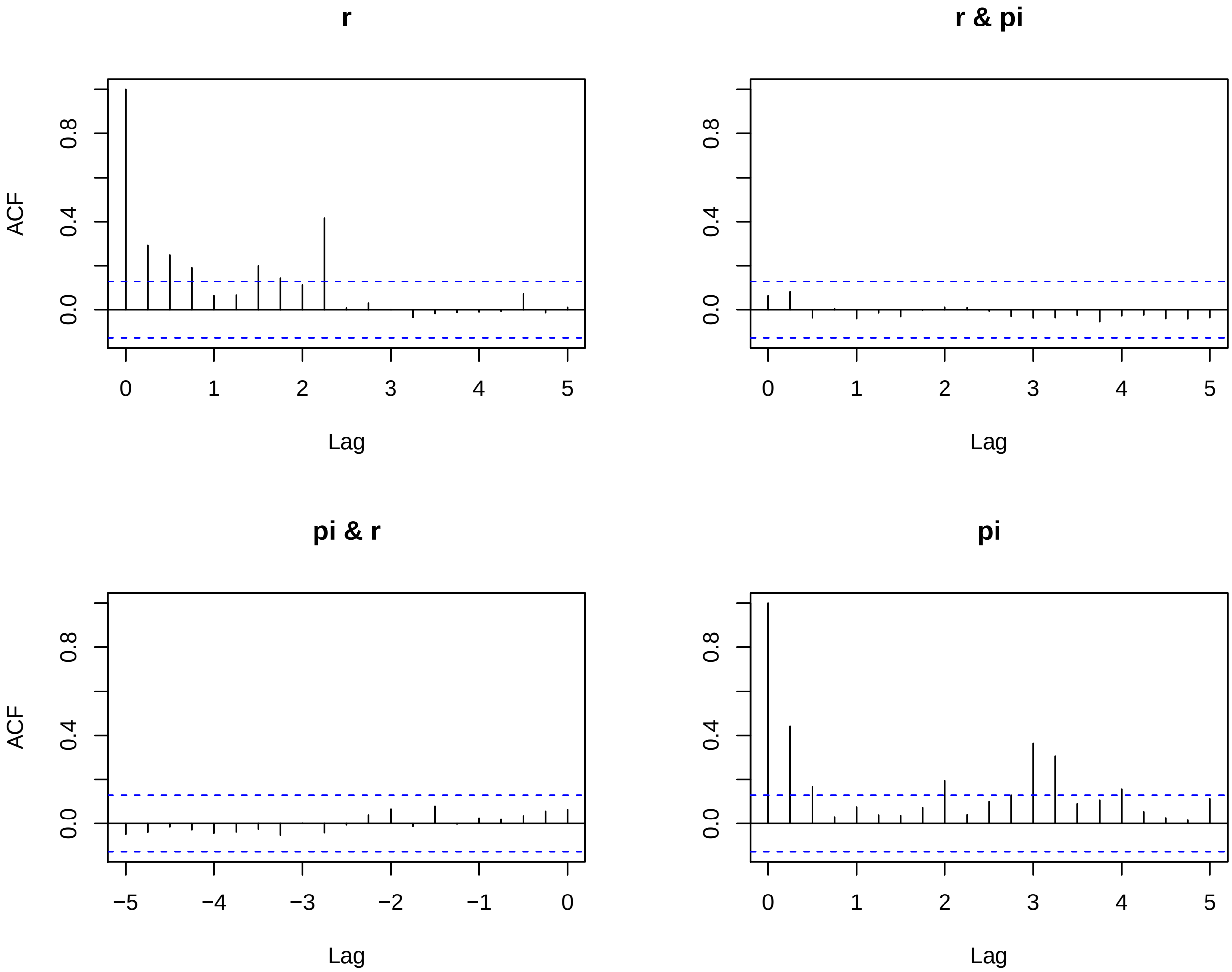
Ruppert & Matteson R Lab

Problem 7

```r
TbGdpPi = read.csv("TbGdpPi.csv", header=TRUE)
TbPi.diff = ts(apply(TbGdpPi[,-2], 2, diff), start=c(1955, 2), freq=4)
plot(TbPi.diff)
```




```r
acf(TbPi.diff^2)
```




```
mLjungBox(TbPi.diff^2, lag=8)
```

```
##   K   Q(K) d.f. p-value
## 1 8 132.57   32       0
```

Answer: Yes, the joint series exhibit conditional heteroskedasticity. Because both series has clear volatility clustering pattern: r_t has high variance in early 1980s, while π_t has high variance during 2000s.

Problem 8

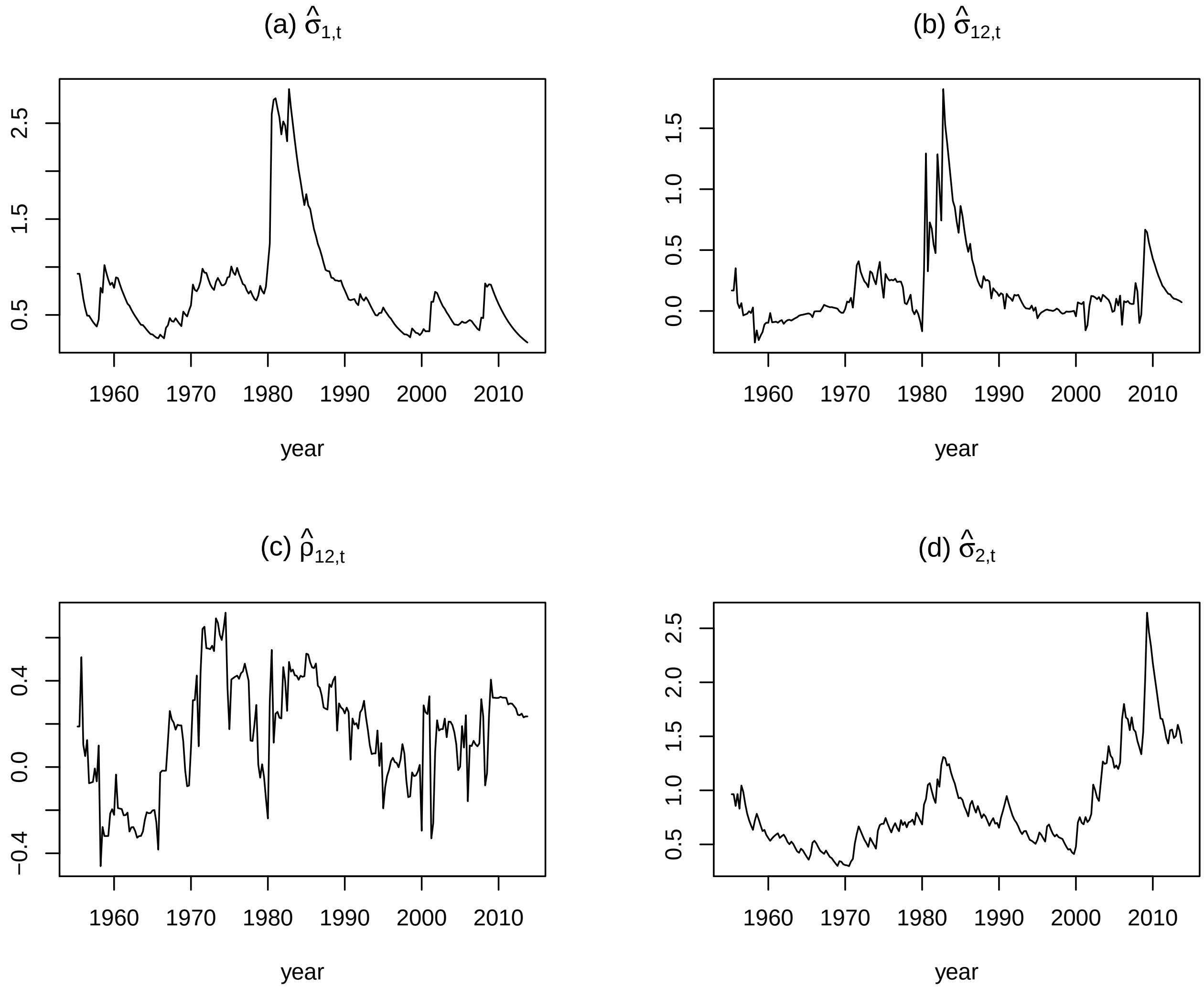
```
EWMA.param = est.ewma(lambda.0 = 0.95, innov=TbPi.diff)
EWMA.param$lambda.hat
```

```
## [1] 0.8665812
```

```
EWMA.Sigma = sigma.ewma(lambda = EWMA.param$lambda.hat, innov=TbPi.diff)

par(mfrow = c(2,2))
plot(ts(EWMA.Sigma[1,1,]^.5, start = c(1955, 2), frequency = 4),
     type = 'l', xlab = "year", ylab = NULL,
     main = expression(paste("(a) ", {hat(sigma)[{"1,t"}]})))
plot(ts(EWMA.Sigma[1,2,], start = c(1955, 2), frequency = 4),
```

```
     type = 'l', xlab = "year", ylab = NULL,
     main = expression(paste("(b) ", {hat(sigma)[{"12,t"}]})))
plot(ts(EWMA.Sigma[1,2,]/(sqrt(EWMA.Sigma[1,1,]* EWMA.Sigma[2,2,])),
        start = c(1955, 2), frequency = 4),type = 'l', xlab = "year",
     ylab = NULL,main = expression(paste("(c) ", {hat(rho)[{"12,t"}]})))
plot(ts(EWMA.Sigma[2,2,]^.5, start = c(1955, 2), frequency = 4),
     type = 'l', xlab = "year", ylab = NULL,
     main = expression(paste("(d) ", {hat(sigma)[{"2,t"}]})))
```



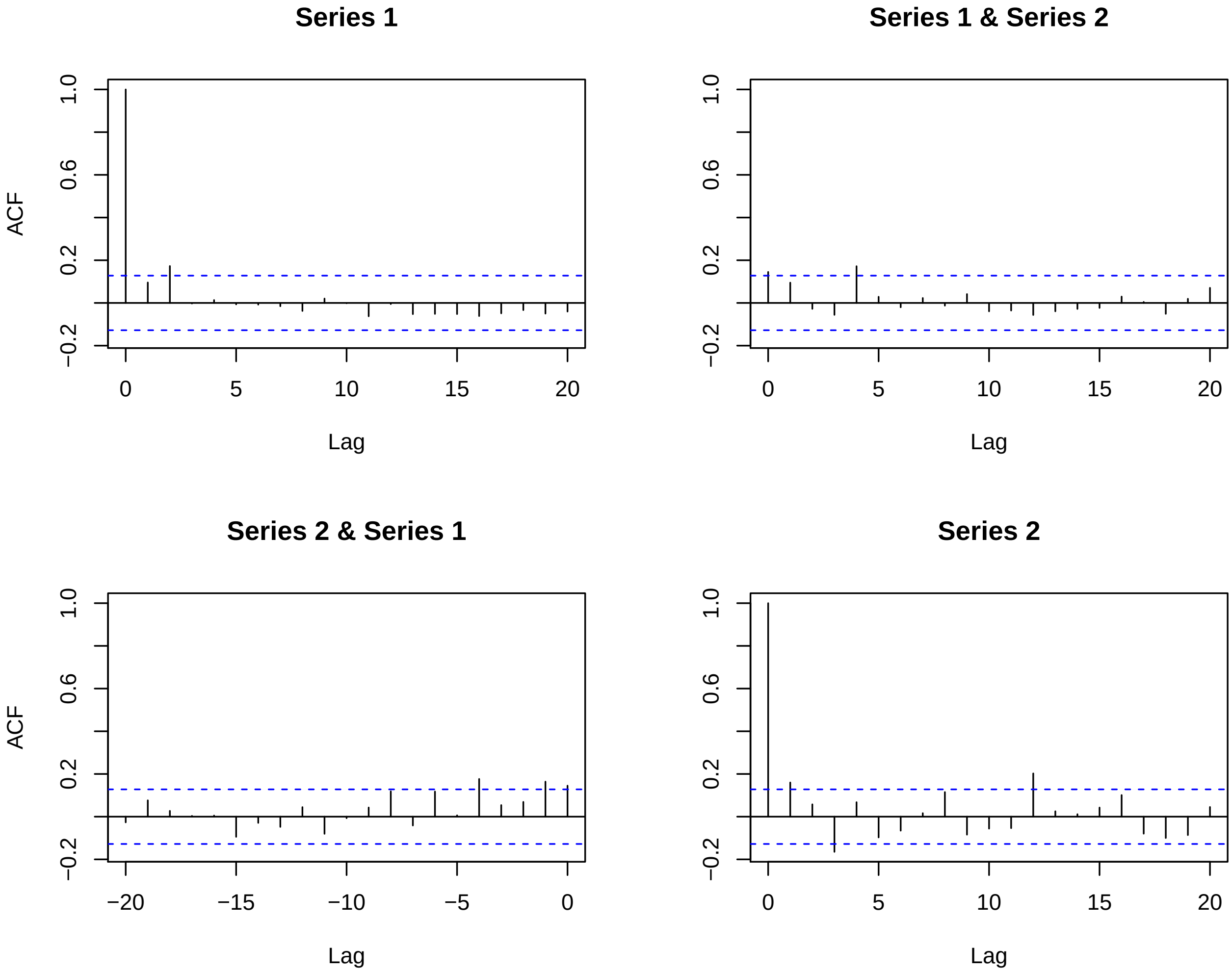
Answer: The estimated persisitence parameter is $\hat{\lambda} = 0.8665812$.

Problem 9

```
n = dim(TbPi.diff)[1]
d = dim(TbPi.diff)[2]
stdResid.EWMA = matrix(0,n,d)
for(t in 1:n){
  stdResid.EWMA[t,] = TbPi.diff[t,] %*% matrix.sqrt.inv(EWMA.Sigma[,,t])}
mLjungBox(stdResid.EWMA^2, lag=8)
```

```
##   K  Q(K) d.f. p-value
## 1 8 60.22   32   0.002
```

```r
acf(stdResid.EWMA^2)
```



Answer: It is likely that the EWMA model is not very adequate based on the results of multivariate Ljung-Box test. Because:

- The p-value of the test is 0.002, small. Therefore we can reject the null hypothesis H_0 : {The standardized residual series have neither serial correlation within series nor between series up to lag 8}.
- The ACF plots of the standardized residual series also suggests that there are significant amount of remaining serial correlations (the parts beyond the dashed blue line thresholds).