Hw10

Peng Zhang

1 b-2-2

1.1 VAR(4) model

The model is

$$z_t = \begin{bmatrix} 0.15 \\ 0.08 \\ 0.24 \end{bmatrix} + \begin{bmatrix} 0.52 & 0.07 & 0.06 \\ 0.38 & 0.32 & 0.41 \\ 0.52 & 0.17 & 0.15 \end{bmatrix} z_{t-1} + \begin{bmatrix} -0.05 & 0.16 & -0 \\ -0.17 & -0.25 & 0.06 \\ -0.22 & -0.16 & 0.23 \end{bmatrix} z_{t-2}$$

$$+ \begin{bmatrix} 0.05 & -0.28 & 0.14 \\ 0.10 & 0.12 & 0.01 \\ 0.05 & -0.08 & 0.07 \end{bmatrix} z_{t-3} + \begin{bmatrix} 0.04 & 0.26 & -0.25 \\ 0.07 & -0.09 & -0.10 \\ 0.15 & -0.15 & -0.05 \end{bmatrix} z_{t-4} + a_t$$

```
> temp=tempfile()
> download.file("http://faculty.chicagobooth.edu/ruey.tsay/teaching/mtsbk/data-ch2.zip",temp)
> da=read.table(unz(temp, "Users/rst/Documents/backup/mts/y2012/data/ch2/q-gdp-ukcaus.txt"),header=T)
> gdp=log(da[,3:5])
> dim(gdp)
```

```
[1] 126   3
```

```
> z=100*(gdp[2:126,]-gdp[1:125,])
> library(MTS)
> m3=VAR(z,4)
```

```
Constant term:
Estimates:  0.1479567 0.07757439 0.2386772
Std.Error:  0.07478564 0.08003665 0.08583514
AR coefficient matrix
AR( 1 )-matrix
      [,1]   [,2]   [,3]
[1,] 0.516 0.0719 0.0639
[2,] 0.378 0.3160 0.4096
[3,] 0.519 0.1730 0.1504
standard error
       [,1]   [,2]   [,3]
[1,] 0.0953 0.0945 0.0887
[2,] 0.1020 0.1011 0.0949
[3,] 0.1094 0.1084 0.1018
```

```
AR( 2 )-matrix
        [,1]   [,2]     [,3]
[1,] -0.0504  0.160 -0.00198
[2,] -0.1740 -0.254  0.06295
[3,] -0.2178 -0.159  0.22561
standard error
      [,1]   [,2]   [,3]
[1,] 0.101 0.0986 0.0955
[2,] 0.108 0.1055 0.1022
[3,] 0.116 0.1132 0.1096
AR( 3 )-matrix
       [,1]    [,2]   [,3]
[1,] 0.0524 -0.2788 0.1411
[2,] 0.0962  0.1203 0.0137
[3,] 0.0478 -0.0786 0.0738
standard error
      [,1]   [,2]   [,3]
[1,] 0.103 0.0983 0.0937
[2,] 0.110 0.1052 0.1003
[3,] 0.118 0.1129 0.1076
AR( 4 )-matrix
       [,1]    [,2]    [,3]
[1,] 0.0401  0.2617 -0.2465
[2,] 0.0747 -0.0903 -0.0978
[3,] 0.1541 -0.1518 -0.0535
standard error
       [,1]   [,2]   [,3]
[1,] 0.0910 0.0869 0.0882
[2,] 0.0974 0.0931 0.0944
[3,] 0.1045 0.0998 0.1013

Residuals cov-mtx:
           [,1]       [,2]       [,3]
[1,] 0.22430413 0.04383870 0.08933612
[2,] 0.04383870 0.25690861 0.09675468
[3,] 0.08933612 0.09675468 0.29548204

det(SSE) =  0.01306715
AIC =  -3.761654
BIC =  -2.9471
HQ  =  -3.430743
```

1.2 Simplify VAR(4) model

The simplified VAR(4) model can be written as

$$z_t = \begin{bmatrix} 0.2 \\ 0 \\ 0.32 \end{bmatrix} + \begin{bmatrix} 0.57 & 0 & 0 \\ 0.38 & 0.30 & 0.41 \\ 0.51 & 0.27 & 0 \end{bmatrix} z_{t-1} + \begin{bmatrix} 0 & 0.28 & 0 \\ 0 & -0.15 & 0 \\ 0 & 0 & 0 \end{bmatrix} z_{t-2}$$

$$+ \begin{bmatrix} 0 & -0.25 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} z_{t-3} + \begin{bmatrix} 0 & 0.30 & -0.24 \\ 0 & 0 & 0 \\ 0 & -0.20 & 0 \end{bmatrix} z_{t-4} + a_t$$

```
> options(digits=2)
> m4=refVAR(m3,thres=1.96)

Constant term:
Estimates:  0.2 0 0.32
Std.Error:  0.069 0 0.081
AR coefficient matrix
AR( 1 )-matrix
      [,1]  [,2]  [,3]
[1,] 0.565 0.000 0.000
[2,] 0.376 0.299 0.408
[3,] 0.508 0.268 0.000
standard error
       [,1]   [,2]   [,3]
[1,] 0.0798 0.0000 0.0000
[2,] 0.0852 0.0899 0.0887
[3,] 0.0882 0.0751 0.0000
AR( 2 )-matrix
     [,1]   [,2] [,3]
[1,]    0  0.284    0
[2,]    0 -0.153    0
[3,]    0  0.000    0
standard error
     [,1]   [,2] [,3]
[1,]    0 0.0728    0
[2,]    0 0.0769    0
[3,]    0 0.0000    0
AR( 3 )-matrix
     [,1]   [,2] [,3]
[1,]    0 -0.249    0
[2,]    0  0.000    0
[3,]    0  0.000    0
standard error
     [,1] [,2] [,3]
[1,]    0 0.09    0
```

```
[2,]    0 0.00    0
[3,]    0 0.00    0
AR( 4 )-matrix
     [,1]   [,2]   [,3]
[1,]    0  0.296 -0.243
[2,]    0  0.000  0.000
[3,]    0 -0.199  0.000
standard error
     [,1]   [,2]   [,3]
[1,]    0 0.0797 0.0849
[2,]    0 0.0000 0.0000
[3,]    0 0.0686 0.0000

Residuals cov-mtx:
      [,1]  [,2] [,3]
[1,] 0.237 0.048 0.10
[2,] 0.048 0.278 0.11
[3,] 0.101 0.110 0.33

det(SSE) =  0.016
AIC =  -3.9
BIC =  -3.7
HQ  =  -3.8
```

1.3 Model check

We can see all the p-valuse are more than 0.05. So the model is adequate.

```
> MTSdiag(m4,adj=12)

[1] "Covariance matrix:"
       uk     ca    us
uk 0.2388 0.0487 0.102
ca 0.0487 0.2790 0.111
us 0.1019 0.1109 0.331
CCM at lag:  0
      [,1]  [,2]  [,3]
[1,] 1.000 0.189 0.362
[2,] 0.189 1.000 0.365
[3,] 0.362 0.365 1.000
Simplified matrix:
CCM at lag:  1
. . .
. . .
. . +
CCM at lag:  2
```

```
. . .
. . .
. . .
CCM at lag:  3
. . .
. . .
. . .
CCM at lag:  4
. . .
. . .
. . .
CCM at lag:  5
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. . .
. . .
CCM at lag:  6
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. . .
. . .
CCM at lag:  7
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. . .
. . .
CCM at lag:  8
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. . .
. - .
CCM at lag:  9
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. . .
CCM at lag:  10
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. . .
. . .
CCM at lag:  11
. . .
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. . .
CCM at lag:  12
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. . .
. . .
CCM at lag:  13
```

```
. . .
. . .
. . .
CCM at lag:  14
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. . .
. . .
CCM at lag:  15
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. . .
. . .
CCM at lag:  16
. . .
. . .
. . .
CCM at lag:  17
. . .
. . .
. . .
CCM at lag:  18
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. . .
. . .
CCM at lag:  19
. . .
. . .
. . .
CCM at lag:  20
. . .
. . .
. . .
CCM at lag:  21
. . .
. . .
. . .
CCM at lag:  22
. . .
. . .
. . .
CCM at lag:  23
. . .
. . .
. . .
CCM at lag:  24
```
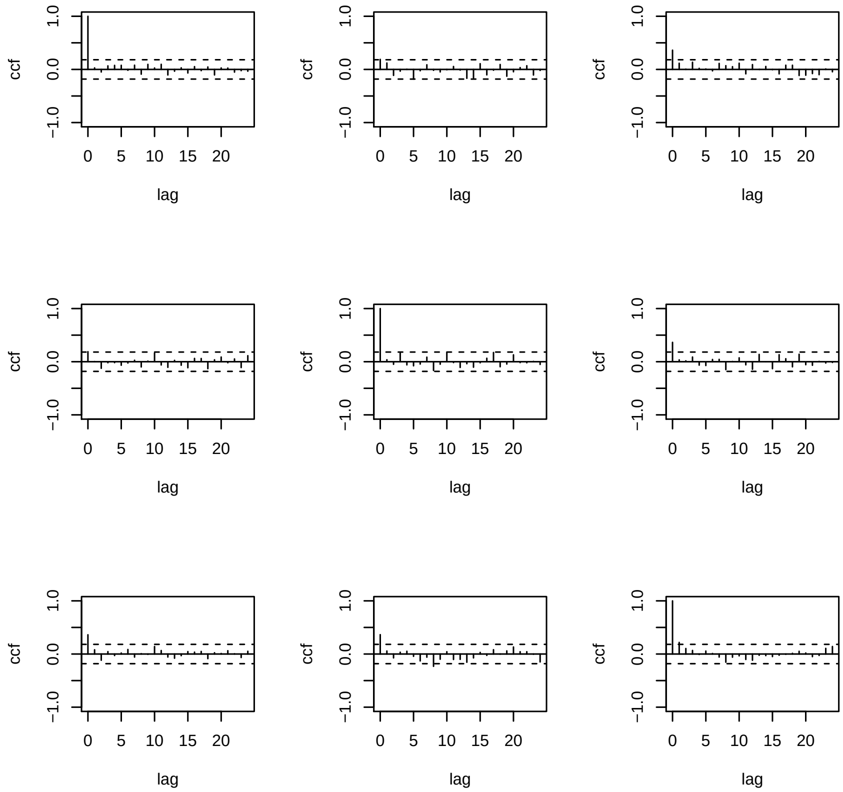

```
. . .
. . .
. . .
Hit Enter for p-value plot of individual ccm:

Hit Enter to compute MQ-statistics:

Ljung-Box Statistics:
         m       Q(m)     df    p-value
 [1,]   1.00      7.93   -3.00     1.00
 [2,]   2.00     16.26    6.00     1.00
 [3,]   3.00     24.71   15.00     0.05
 [4,]   4.00     27.71   24.00     0.27
 [5,]   5.00     36.06   33.00     0.33
 [6,]   6.00     41.54   42.00     0.49
 [7,]   7.00     47.78   51.00     0.60
 [8,]   8.00     64.66   60.00     0.32
 [9,]   9.00     68.22   69.00     0.50
[10,]  10.00     81.99   78.00     0.36
[11,]  11.00     91.03   87.00     0.36
[12,]  12.00    101.83   96.00     0.32
[13,]  13.00    111.75  105.00     0.31
[14,]  14.00    119.75  114.00     0.34
[15,]  15.00    127.84  123.00     0.36
[16,]  16.00    134.71  132.00     0.42
[17,]  17.00    142.92  141.00     0.44
[18,]  18.00    150.03  150.00     0.48
[19,]  19.00    161.08  159.00     0.44
[20,]  20.00    172.29  168.00     0.39
[21,]  21.00    175.93  177.00     0.51
[22,]  22.00    180.17  186.00     0.61
[23,]  23.00    188.40  195.00     0.62
[24,]  24.00    204.69  204.00     0.47
Hit Enter to obtain residual plots:
```


ccf
1.0
0.0
−1.0
0
5
10
15
20
lag

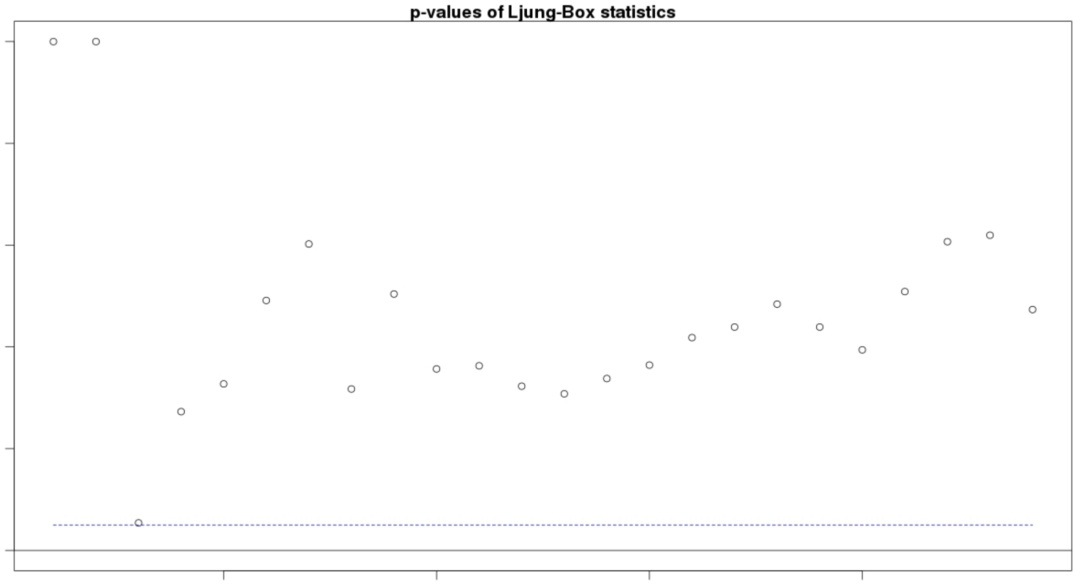


Figure 1: p-values of the $Q_k(m)$ atatistics appllied to the residuals of the simplied VAR(4) model

1.4 Comparing

Let's comparing the model VAR(2). Here we could compare the p-value,the VAR(2) model have a point below the 0.05 line,but VAR(4) are not. We also could compare through AIC,BIC and HQ values.All of values in VAR(4) are smaller than VAR(2). So we can say, simplified VAR(4) is better than simplified VAR(2).

```
> m1=VAR(z,2)

Constant term:
Estimates:  0.13 0.12 0.29
Std.Error:  0.073 0.074 0.082
AR coefficient matrix
AR( 1 )-matrix
      [,1]  [,2]   [,3]
[1,] 0.393 0.103 0.0521
[2,] 0.351 0.338 0.4691
[3,] 0.491 0.240 0.2356
standard error
       [,1]   [,2]   [,3]
[1,] 0.0934 0.0984 0.0911
[2,] 0.0949 0.1000 0.0926
[3,] 0.1050 0.1106 0.1024
AR( 2 )-matrix
        [,1]   [,2]     [,3]
```

```
[1,]  0.0566  0.106  0.01889
[2,] -0.1914 -0.175 -0.00868
[3,] -0.3120 -0.131  0.08531
standard error
       [,1]   [,2]   [,3]
[1,] 0.0924 0.0876 0.0938
[2,] 0.0939 0.0890 0.0953
[3,] 0.1038 0.0984 0.1055

Residuals cov-mtx:
      [,1]  [,2]  [,3]
[1,] 0.282 0.027 0.074
[2,] 0.027 0.292 0.139
[3,] 0.074 0.139 0.357

det(SSE) =  0.023
AIC =  -3.5
BIC =  -3.1
HQ  =  -3.3
```

```
> m2=refVAR(m1,thres=1.96)
```

```
Constant term:
Estimates:  0.16 0 0.28
Std.Error:  0.068 0 0.08
AR coefficient matrix
AR( 1 )-matrix
      [,1]  [,2]  [,3]
[1,] 0.467 0.207 0.000
[2,] 0.334 0.270 0.496
[3,] 0.468 0.225 0.232
standard error
       [,1]   [,2]   [,3]
[1,] 0.0790 0.0686 0.0000
[2,] 0.0921 0.0875 0.0913
[3,] 0.1027 0.0963 0.1023
AR( 2 )-matrix
       [,1] [,2] [,3]
[1,]  0.000    0    0
[2,] -0.197    0    0
[3,] -0.301    0    0
standard error
       [,1] [,2] [,3]
[1,] 0.0000    0    0
[2,] 0.0921    0    0
```

```
[3,] 0.1008    0    0

Residuals cov-mtx:
      [,1]  [,2]  [,3]
[1,] 0.290 0.018 0.071
[2,] 0.018 0.308 0.146
[3,] 0.071 0.146 0.363

det(SSE) =  0.025
AIC =  -3.5
BIC =  -3.3
HQ  =  -3.4
```

```
> MTSdiag(m2,adj=12)
```

```
[1] "Covariance matrix:"
       uk     ca     us
uk 0.2924 0.0182 0.0711
ca 0.0182 0.3084 0.1472
us 0.0711 0.1472 0.3657
CCM at lag:  0
       [,1]   [,2]  [,3]
[1,] 1.0000 0.0605 0.218
[2,] 0.0605 1.0000 0.438
[3,] 0.2175 0.4382 1.000
Simplified matrix:
CCM at lag:  1
. . .
. . .
. . .
CCM at lag:  2
. . .
. . .
. . .
CCM at lag:  3
. . .
. . .
. . .
CCM at lag:  4
. . -
. . .
. . .
CCM at lag:  5
. . .
. . .
```

```
. . .
CCM at lag:  6
. . .
. . .
. . .
CCM at lag:  7
. . .
. . .
. . .
CCM at lag:  8
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. . .
. . .
CCM at lag:  9
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CCM at lag:  10
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. . .
CCM at lag:  11
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. . .
. . .
CCM at lag:  12
. . .
. . .
. . .
CCM at lag:  13
. - .
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. . .
CCM at lag:  14
. - .
. . .
. . .
CCM at lag:  15
. + .
. . .
. . .
CCM at lag:  16
. . .
. . .
```

```
. . .
CCM at lag:  17
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. . .
. . .
CCM at lag:  18
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. . .
. . .
CCM at lag:  19
. . .
. . +
. . .
CCM at lag:  20
. . .
. . .
. . .
CCM at lag:  21
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. . .
CCM at lag:  22
. . .
. . .
. . .
CCM at lag:  23
. . .
. . .
. . .
CCM at lag:  24
. . .
. . .
. . .
Hit Enter for p-value plot of individual ccm:

Hit Enter to compute MQ-statistics:

Ljung-Box Statistics:
        m       Q(m)     df    p-value
 [1,]   1.00      1.78   -3.00     1.00
 [2,]   2.00     12.41    6.00     1.00
 [3,]   3.00     22.60   15.00     0.09
 [4,]   4.00     37.71   24.00     0.04
 [5,]   5.00     41.65   33.00     0.14
```

```
 [6,]   6.00     44.95   42.00     0.35
 [7,]   7.00     51.50   51.00     0.45
 [8,]   8.00     64.87   60.00     0.31
 [9,]   9.00     72.50   69.00     0.36
[10,]  10.00     81.58   78.00     0.37
[11,]  11.00     86.12   87.00     0.51
[12,]  12.00     98.08   96.00     0.42
[13,]  13.00    112.31  105.00     0.30
[14,]  14.00    121.89  114.00     0.29
[15,]  15.00    134.58  123.00     0.22
[16,]  16.00    139.16  132.00     0.32
[17,]  17.00    145.85  141.00     0.37
[18,]  18.00    152.56  150.00     0.43
[19,]  19.00    165.91  159.00     0.34
[20,]  20.00    175.22  168.00     0.34
[21,]  21.00    180.56  177.00     0.41
[22,]  22.00    187.40  186.00     0.46
[23,]  23.00    193.78  195.00     0.51
[24,]  24.00    204.65  204.00     0.47
Hit Enter to obtain residual plots:
```

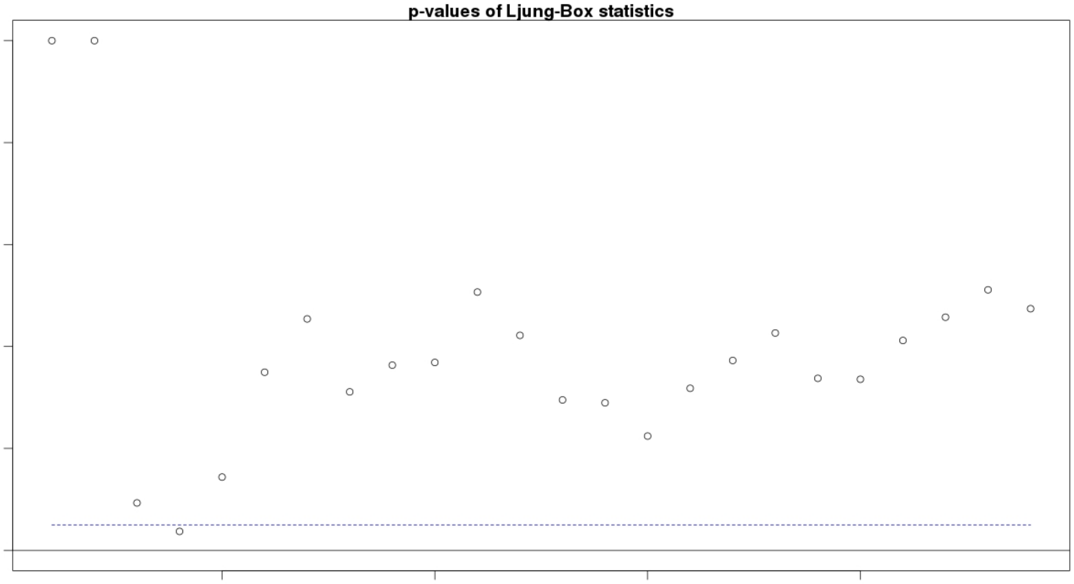

Figure 2: p-values of the $Q_k(m)$ atatistics appllied to the residuals of the simplied VAR(2) model

2 b-2-3

2.1 z_t graph

```
> temp=tempfile()
> download.file("http://faculty.chicagobooth.edu/ruey.tsay/teaching/mtsbk/data-ch2.zip",temp)
> da=read.table(unz(temp, "Users/rst/Documents/backup/mts/y2012/data/ch2/m-cpitb3m.txt"),header=T)
> dim(da)
```

```
[1] 792   4
```

```
> z1=da$tb3m[1:791]
> z2=100*(log(da$cpiaucsl[2:792])-log(da$cpiaucsl[1:791]))
> Z=cbind(z1,z2)
> t=1:791/12+1947
```

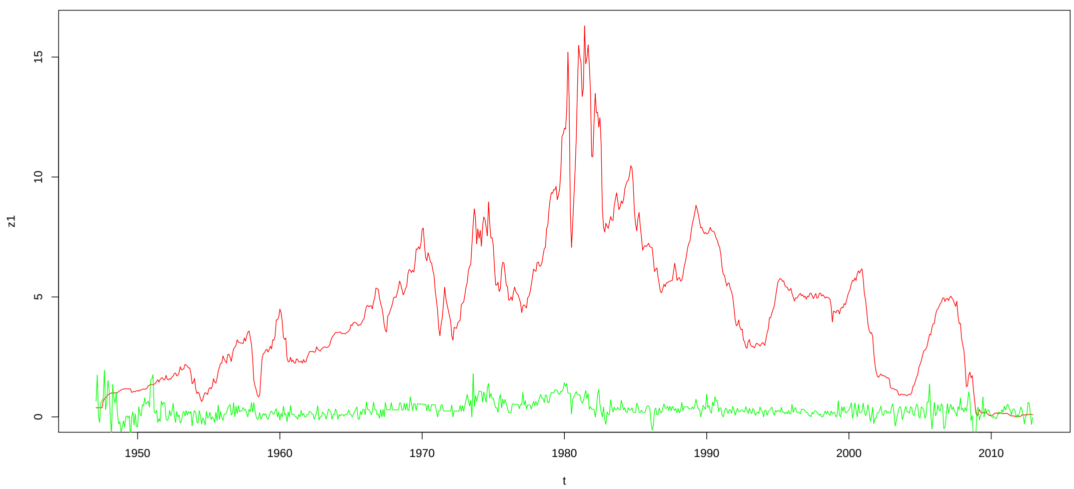

Figure 3: Time series of z_t, change in monthly US treasury bills line is red, the line of inflation rate of CPI is green

2.2 Choose the order by BIC criterion

We can see the best oder choosing throgh BIC criterion is 3. So we are using VAR(3) model.

```
> library(MTS)
> m1=VARorder(Z)

selected order: aic =  13
selected order: bic =  3
selected order: hq =  12
Summary table:
       p   AIC   BIC    HQ   M(p) p-value
 [1,]  0 -0.22 -0.22 -0.22    0.0  0.0000
 [2,]  1 -4.46 -4.44 -4.45 3291.5  0.0000
 [3,]  2 -4.58 -4.53 -4.56   99.5  0.0000
 [4,]  3 -4.62 -4.55 -4.60   42.9  0.0000
 [5,]  4 -4.63 -4.53 -4.59    8.2  0.0850
 [6,]  5 -4.63 -4.51 -4.58    9.1  0.0580
 [7,]  6 -4.64 -4.50 -4.58   16.5  0.0024
 [8,]  7 -4.70 -4.54 -4.64   56.9  0.0000
 [9,]  8 -4.71 -4.52 -4.63   10.7  0.0303
[10,]  9 -4.72 -4.51 -4.64   19.6  0.0006
[11,] 10 -4.73 -4.50 -4.64   14.4  0.0060
[12,] 11 -4.73 -4.47 -4.63    3.4  0.4971
[13,] 12 -4.76 -4.48 -4.65   35.1  0.0000
[14,] 13 -4.77 -4.46 -4.65   14.3  0.0063
```

2.3 VAR(3) model and fitted VAR(3) model

Here is the VAR(3) model.

$$z_t = \begin{bmatrix} 0.03 \\ 0.04 \end{bmatrix} + \begin{bmatrix} 1.39 & 0.13 \\ 0.09 & 0.45 \end{bmatrix} z_{t-1} + \begin{bmatrix} -0.61 & 0.06 \\ -0.08 & 0.02 \end{bmatrix} z_{t-2} + \begin{bmatrix} 0.21 & -0.09 \\ 0.01 & 0.11 \end{bmatrix} z_{t-3} + a_t$$

And the fitted VAR(3) model is

$$z_t = \begin{bmatrix} 0 \\ 0.04 \end{bmatrix} + \begin{bmatrix} 1.39 & 0.14 \\ 0.08 & 0.46 \end{bmatrix} z_{t-1} + \begin{bmatrix} -0.61 & 0 \\ -0.07 & 0 \end{bmatrix} z_{t-2} + \begin{bmatrix} 0.21 & 0 \\ 0 & 0.12 \end{bmatrix} z_{t-3} + a_t$$

```
> options(digits=2)
> m2=VAR(Z,3)

Constant term:
Estimates:  0.035 0.042
Std.Error:  0.024 0.018
AR coefficient matrix
AR( 1 )-matrix
       [,1]  [,2]
```

```
[1,] 1.3857 0.128
[2,] 0.0886 0.449
standard error
       [,1]   [,2]
[1,] 0.0350 0.0491
[2,] 0.0253 0.0355
AR( 2 )-matrix
        [,1]   [,2]
[1,] -0.6095 0.0608
[2,] -0.0849 0.0223
standard error
       [,1]   [,2]
[1,] 0.0566 0.0528
[2,] 0.0409 0.0381
AR( 3 )-matrix
       [,1]    [,2]
[1,] 0.2095 -0.0945
[2,] 0.0149  0.1109
standard error
       [,1]   [,2]
[1,] 0.0349 0.0484
[2,] 0.0252 0.0349

Residuals cov-mtx:
       [,1]   [,2]
[1,] 0.1405 0.0099
[2,] 0.0099 0.0732

det(SSE) =  0.01
AIC =  -4.6
BIC =  -4.5
HQ  =  -4.5
```

> m3=refVAR(m2,thres=1.65)

```
Constant term:
Estimates:  0 0.044
Std.Error:  0 0.017
AR coefficient matrix
AR( 1 )-matrix
       [,1]  [,2]
[1,] 1.3887 0.139
[2,] 0.0842 0.456
standard error
       [,1]   [,2]
```

```
[1,] 0.0350 0.0428
[2,] 0.0239 0.0324
AR( 2 )-matrix
        [,1] [,2]
[1,] -0.6137    0
[2,] -0.0654    0
standard error
       [,1] [,2]
[1,] 0.0567    0
[2,] 0.0237    0
AR( 3 )-matrix
      [,1]  [,2]
[1,] 0.213 0.000
[2,] 0.000 0.119
standard error
       [,1]   [,2]
[1,] 0.0348 0.0000
[2,] 0.0000 0.0319

Residuals cov-mtx:
       [,1]   [,2]
[1,] 0.1415 0.0099
[2,] 0.0099 0.0732

det(SSE) =  0.01
AIC =  -4.6
BIC =  -4.5
HQ  =  -4.5
```

2.4 check the model

We can find this model is not adequate.Since most p-value is below the 0.05 line.That means the residuals have great dependent.

> MTSdiag(m3,adj=12)

```
[1] "Covariance matrix:"
        z1      z2
z1 0.14161 0.00995
z2 0.00995 0.07333
CCM at lag:  0
       [,1]   [,2]
[1,] 1.0000 0.0976
[2,] 0.0976 1.0000
Simplified matrix:
CCM at lag:  1
```

```
. .
. .
CCM at lag:  2
. .
. .
CCM at lag:  3
. .
. .
CCM at lag:  4
. .
. .
CCM at lag:  5
+ -
. .
CCM at lag:  6
- .
. .
CCM at lag:  7
- .
. +
CCM at lag:  8
+ .
. .
CCM at lag:  9
+ .
. +
CCM at lag:  10
. .
. +
CCM at lag:  11
. .
. +
CCM at lag:  12
- .
. -
CCM at lag:  13
. .
. .
CCM at lag:  14
+ .
. .
CCM at lag:  15
- .
. +
```

```
CCM at lag:  16
. .
. .
CCM at lag:  17
. .
. .
CCM at lag:  18
. .
. .
CCM at lag:  19
. .
. .
CCM at lag:  20
- .
. .
CCM at lag:  21
- .
. .
CCM at lag:  22
. .
. .
CCM at lag:  23
. .
. .
CCM at lag:  24
. .
- .
Hit Enter for p-value plot of individual ccm:

Hit Enter to compute MQ-statistics:

Ljung-Box Statistics:
         m       Q(m)     df    p-value
 [1,]   1.000     0.674  -8.000        1
 [2,]   2.000     3.230  -4.000        1
 [3,]   3.000    11.058   0.000        1
 [4,]   4.000    15.185   4.000        0
 [5,]   5.000    33.410   8.000        0
 [6,]   6.000    60.387  12.000        0
 [7,]   7.000    80.578  16.000        0
 [8,]   8.000    89.132  20.000        0
 [9,]   9.000   114.434  24.000        0
[10,]  10.000   125.633  28.000        0
[11,]  11.000   139.892  32.000        0
```

```
[12,]  12.000   161.040  36.000        0
[13,]  13.000   164.302  40.000        0
[14,]  14.000   186.355  44.000        0
[15,]  15.000   209.769  48.000        0
[16,]  16.000   218.822  52.000        0
[17,]  17.000   223.414  56.000        0
[18,]  18.000   227.421  60.000        0
[19,]  19.000   229.788  64.000        0
[20,]  20.000   262.002  68.000        0
[21,]  21.000   272.053  72.000        0
[22,]  22.000   276.621  76.000        0
[23,]  23.000   281.061  80.000        0
[24,]  24.000   288.536  84.000        0
Hit Enter to obtain residual plots:
```

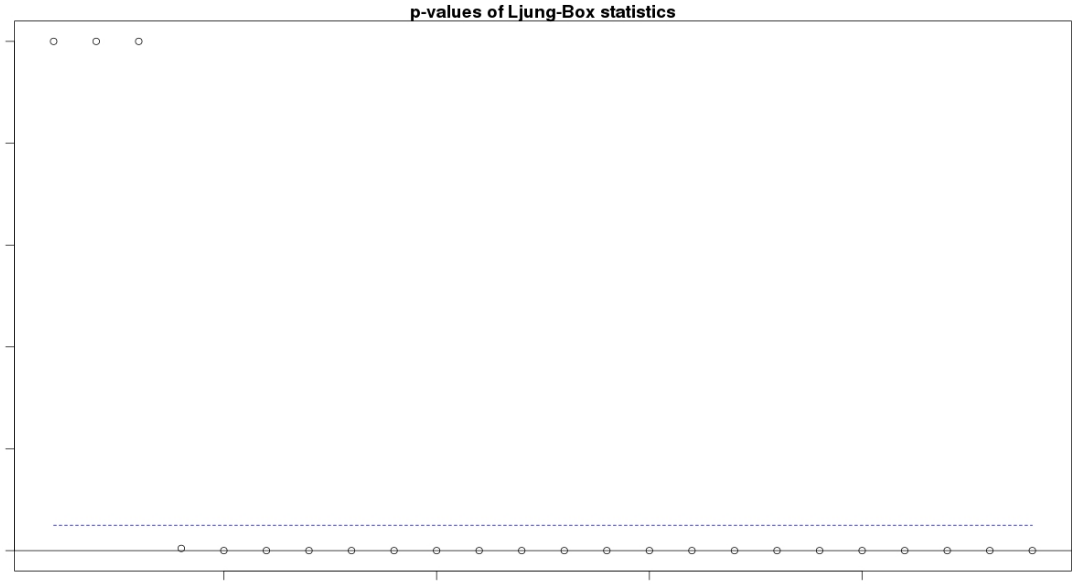

Figure 4: p-values of the $Q_k(m)$ atatistics appllied to the residuals of the simplied VAR(3) model

2.5 Impulse response functions

The upper-left plot shows that there is a delayed effect on the US treasury bill if one changeed the US treasury bill by 1.The upper two plots does not decay to 0 quickly.

```
> Phi=m3$Phi
> Sig=m3$Sigma

> VARirf(Phi,Sig)

Press return to continue
```

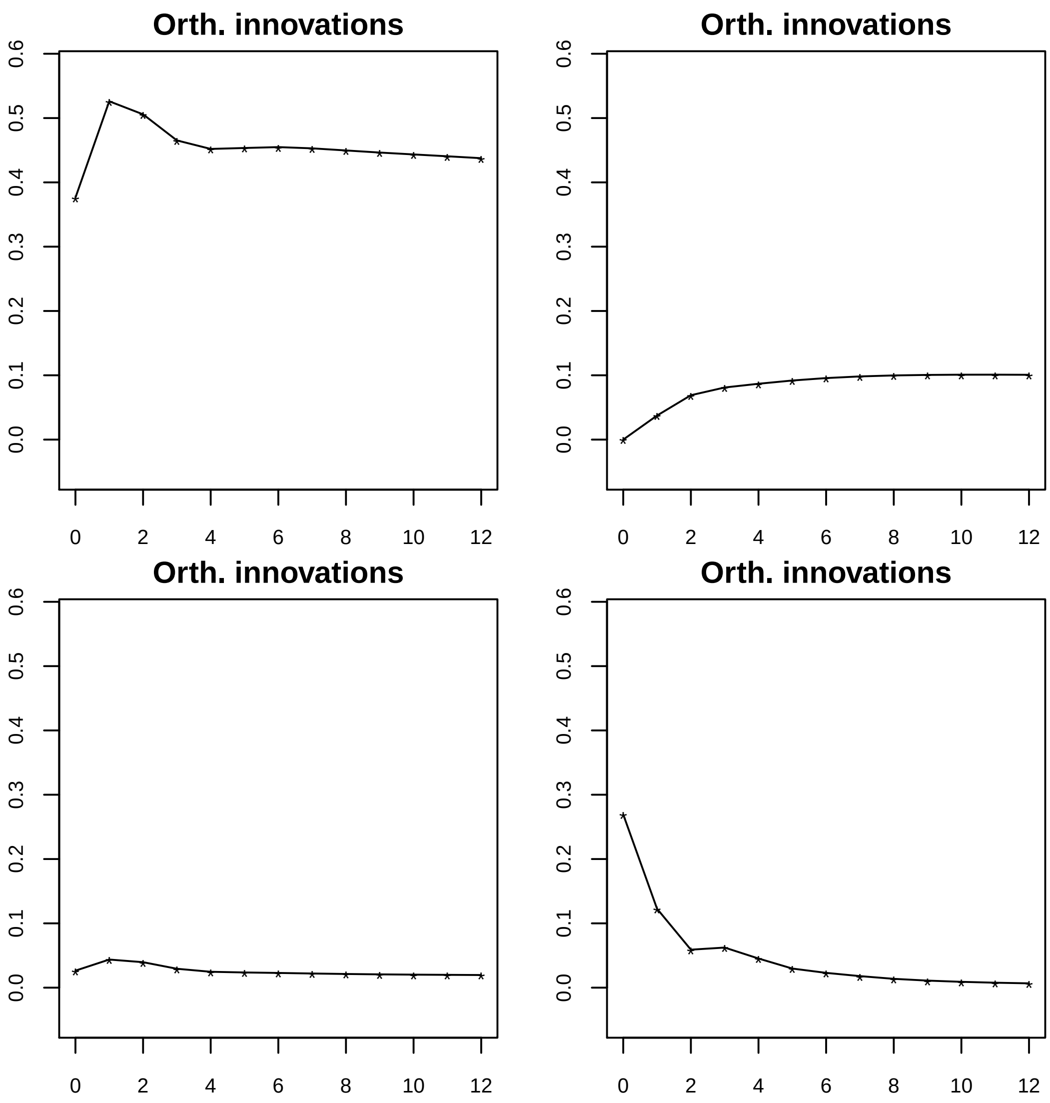

Figure 5: Impulse response function of the simplified VAR(3)

2.6 Cholesky decomposition and transformed innovations

Since a_t is the residual matrix,we find the covariance matrix and the Cholesky decomposition matrix are

$$Cov(a_t) = \begin{bmatrix} 0.14 & 0.01 \\ 0.01 & 0.07 \end{bmatrix}$$

$$U = \begin{bmatrix} 0.4 & 0.03 \\ 0.0 & 0.27 \end{bmatrix}$$

So we could see

$$Cov(a_t) = U^{'}U \tag{2.1}$$

And the transformed innovations are $\eta_t = (U^{'})^{-1}a_t$

```
> Resi=t(m3$residuals)
> Cov=cov(t(Resi))
> Cov

       [,1]   [,2]
[1,] 0.1416 0.0099
[2,] 0.0099 0.0733

> dd=t(chol(Cov))
> dd

      [,1] [,2]
[1,] 0.376 0.00
[2,] 0.026 0.27

> ent=solve(dd)%*%Resi
> t1=4:791/12+1947
```

```
> plot(t1,ent[1,],type='l',col="red")
> lines(t1,ent[2,],lty=2,col="green")
```

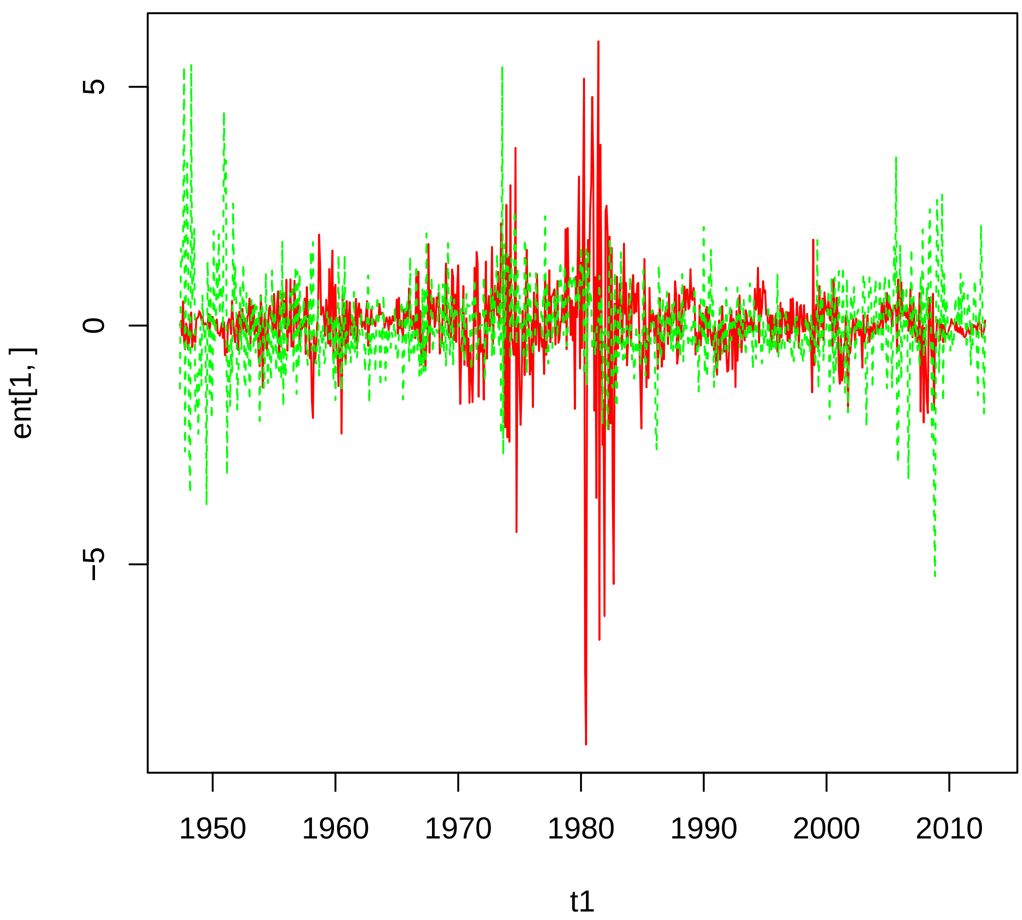

Figure 6: The transformed innovations plot