2022 秋季本科时间序列

第 8 次作业答案

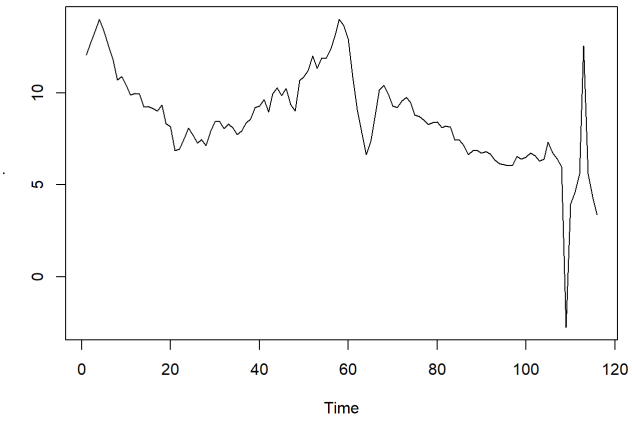
12 月 2 日

1.

```
data<- read.csv("./hw8_data.csv")
library(forecast)
library(tseries)
```

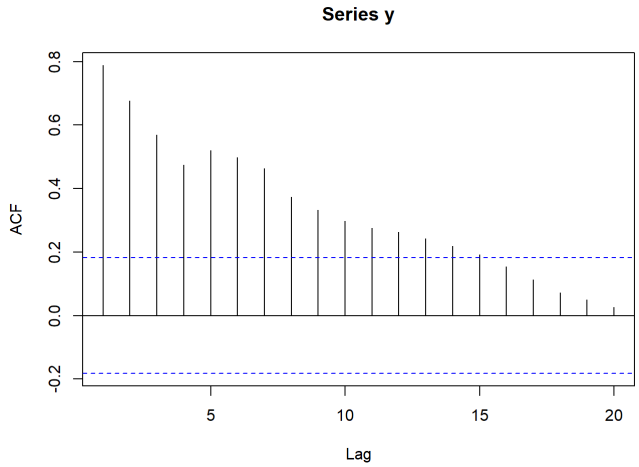
(a) 构造 GDP 季节同比增速序列 y

```
y<-vector()
for (i in 1:100)
{
 y[i]=(data$rGDP[i+4]/data$rGDP[i]-1)*100
}
ts(y)%>%plot()
```

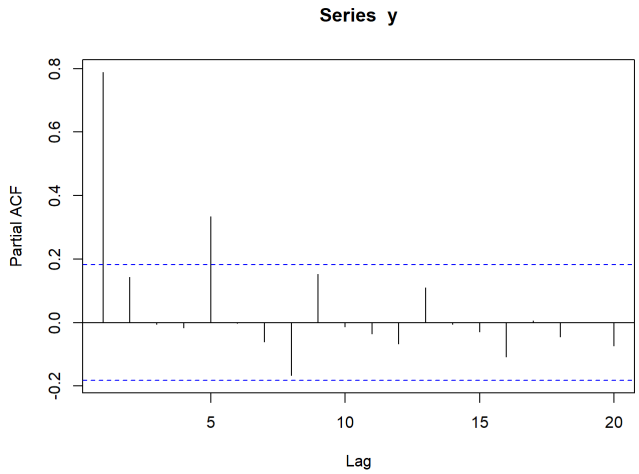


进行建模估计

```
        acf(y)#由图知，max.q=14
```




```
pacf(y)#由图知，max.p=1
```



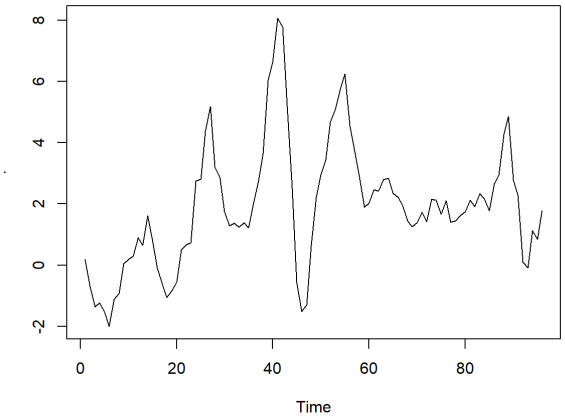
最优 ARMA 滞后阶数，并汇报估计结果

```
      y_best<-auto.arima(y,d=0,D=0,seasonal=F,trace=TRUE,
         method="ML")
      y_best#最优：ARIMA(5,0,0)
```

```
Series: y
ARIMA(5,0,0) with non-zero mean

Coefficients:
         ar1     ar2     ar3      ar4     ar5    mean
      0.8196  0.1297  0.0114  -0.7277  0.7284  8.5808
s.e.  0.0720  0.0872  0.0880   0.0989  0.0816  1.9756

sigma^2 = 1.297:  log likelihood = -179.33
AIC=372.66   AICc=373.7   BIC=391.93
```

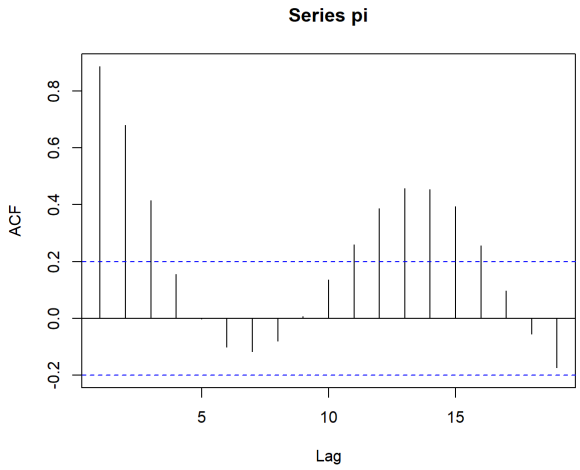
(b) 构造 CPI 季度同比增速序列 π，考虑 97 后的数据

```
pi<-vector()
for (i in 21:116)
{
 pi[i-20]=(data$CPI[i+4]/data$CPI[i]-1)*100
}
ts(pi)%>%plot()
```

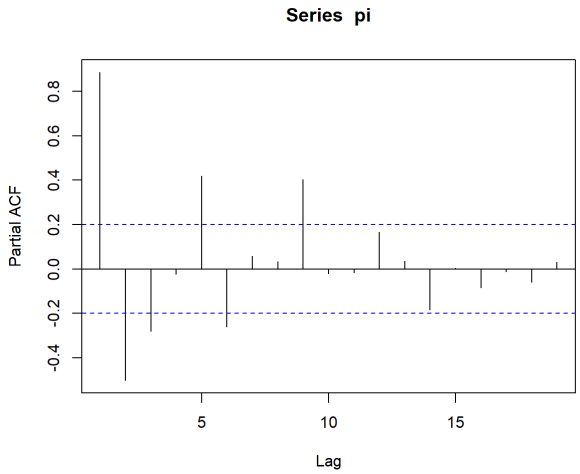


进行建模估计

```
acf(pi)
```




```
pacf(pi)#由图知，max.p=6
```



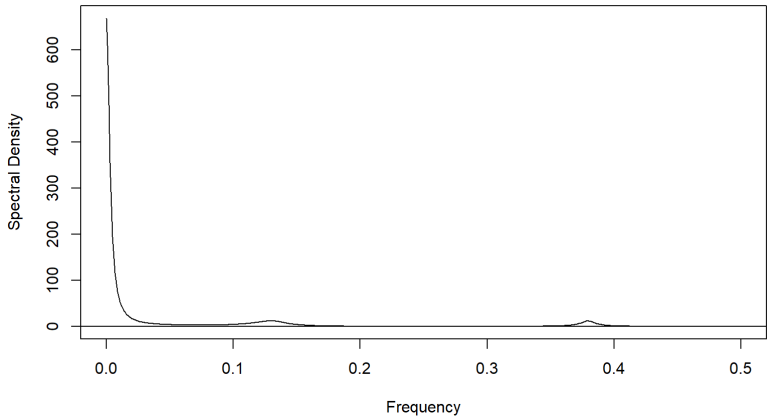
最优 ARMA 滞后阶数，并汇报估计结果

```
pi_best=auto.arima(pi,d=0,D=0,seasonal=F,method="ML")
pi_best #ARIMA(3,0,0)
```

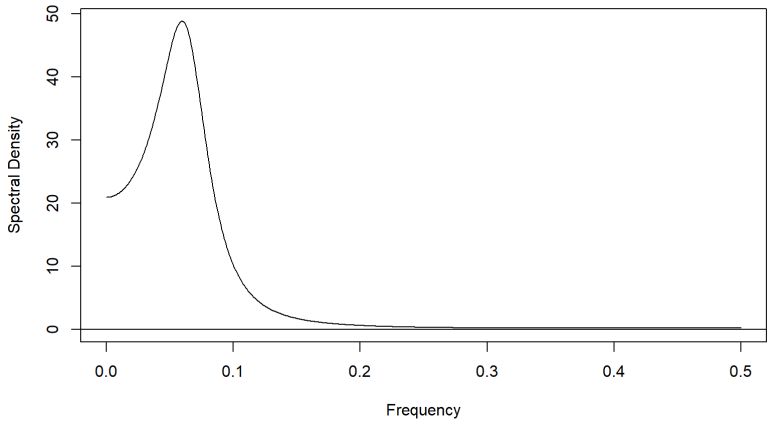
```
ARIMA(3,0,0) with non-zero mean

Coefficients:
         ar1      ar2      ar3    mean
      1.1870  -0.1207  -0.2850  1.9694
s.e.  0.0972   0.1562   0.0983  0.3592

sigma^2 = 0.6216:  log likelihood = -112.54
AIC=235.07   AICc=235.74   BIC=247.89
```

(c) 计算理论谱密度

```
library(TSA)
ARMAspec(list(ar=c(y_best$coef[[1]],y_best$coef[[2]],y
    _best$coef[[3]],y_best$coef[[4]],y_best$coef[[5]]))
    )
```

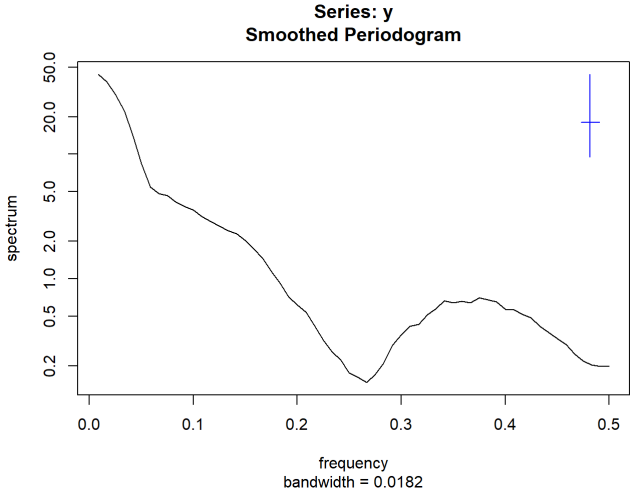



```
ARMAspec(list(ar=c(pi_best$coef[[1]],pi_best$coef[[2]],
   pi_best$coef[[3]])))
```

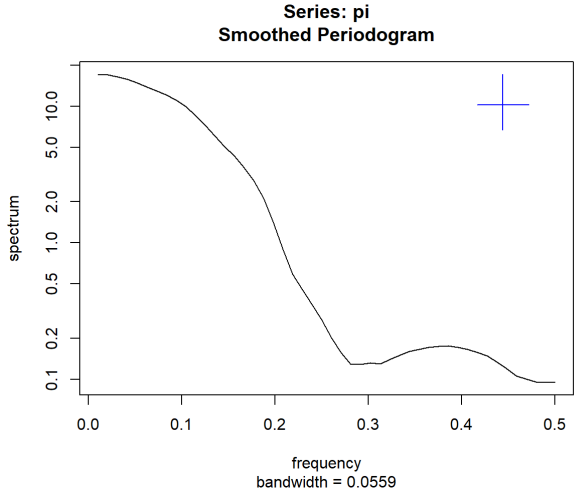


估计样本谱密度

```
spec.pgram(y, kernel("daniell", c(1,3)),taper = 0.1)
```




```
spec.pgram(pi, kernel("daniell", c(5,7)),taper = 0.1)
```



理论谱密度和样本谱密度差别较大，估计得到的 ARMA 不能很好反映出序列的波动

(d)

```
y_OLS<-auto.arima(y,max.p=5,max.q=0,d=0,D=0,seasonal=F,
   method="CSS")
y_OLS #ARIMA(2,0,0)

y_ML<-arima(y,c(2,0,0),method = "ML")
y_ML
```

```
ARIMA(2,0,0) with non-zero mean

Coefficients:
         ar1     ar2     mean
      0.6664  0.185  8.0276
s.e.  0.0915  0.092  0.9241

sigma^2 = 2.029:  log likelihood = -205.14
```

```
arima(x = y, order = c(2, 0, 0), method = "ML")

Coefficients:
         ar1     ar2  intercept
      0.6815  0.1840     8.5584
s.e.  0.0910  0.0932     0.9237

sigma^2 estimated as 2.029:  log likelihood = -206.26,  aic = 418.52
```

```r
pi_OLS<-auto.arima(pi,max.p=2,max.q=0,d=0,D=0,seasonal=F,
    method="CSS")
pi_OLS #ARIMA(2,0,0)

pi_ML<-arima(pi,c(2,0,0),method = "ML")
pi_ML
```

```
ARIMA(2,0,0) with non-zero mean

Coefficients:
         ar1      ar2    mean
      1.3290  -0.5002  2.0657
s.e.  0.0879   0.0877  0.4811

sigma^2 = 0.6551:  log likelihood = -115.4
```

```
arima(x = pi, order = c(2, 0, 0), method = "ML")

Coefficients:
         ar1      ar2  intercept
      1.3308  -0.5008     1.9302
s.e.  0.0876   0.0882     0.4747

sigma^2 estimated as 0.6492:  log likelihood = -116.54,  aic = 239.09
```

OLS 和极大似然法结果在数值上类似

(e) 样本谱密度图像中 y 和 pi 均有明显的高频波动特征，因此需要加入 MA 项加以刻画。

2. (a)

```r
    library(vars)
    library(dplyr)
    pi<-vector()
    m<-vector()
    for (i in 1:116)
    {
     pi[i]=(data$CPI[i+4]/data$CPI[i]-1)*100
     m[i]=(data$M2[i+4]/data$M2[i]-1)*100
    }
    vardata <- tibble(y,pi,m)[17:116,]
    VAR1 <- VAR(vardata, p=1, type='const')
    VAR1
    VAR2 <- VAR(vardata, p=2, type='const')
    VAR2
    VAR3 <- VAR(vardata, p=4, type='const')
    VAR3
```

```
    coef <- tribble(
    ~"p", ~"y_{t-1}",~"pi_{t-1}",
    #---------/---------------/
    "1" , -0.002515041, -0.171294481,
    "2" ,  -0.1138384, -0.6350318,
    "4" , -0.148337868, -0.514526718,
    )
    knitr::kable(coef,digits = 4,
    caption = "方程估计系数")
```

所以该方程得估计系数为

p	y_{t-1}	π_{t-1}
1	-0.0025	-0.1713
2	-0.1138	-0.6350
4	-0.1483	-0.5145

(b)

```
VARselect(vardata, type = "const")
```

```
$selection
AIC(n)  HQ(n)  SC(n) FPE(n)
    10      5      5     10
```

优先考虑 AIC 准则，滞后阶数取 10 阶

(c)

```
    plot(irf(VAR1))
    plot(irf(VAR2))
    plot(irf(VAR3))
```

三种估计结果分别如下图所示：

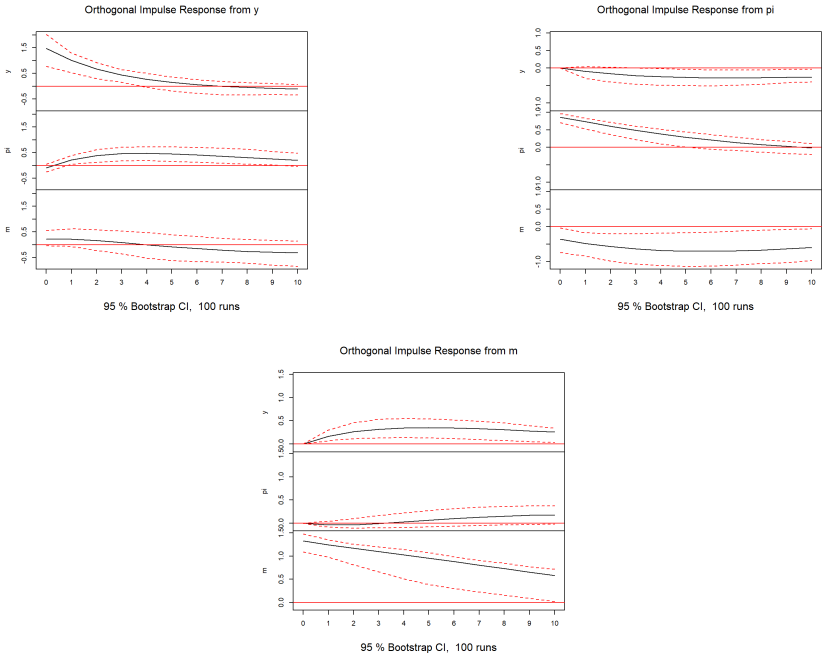


图 1: p=1 估计结果

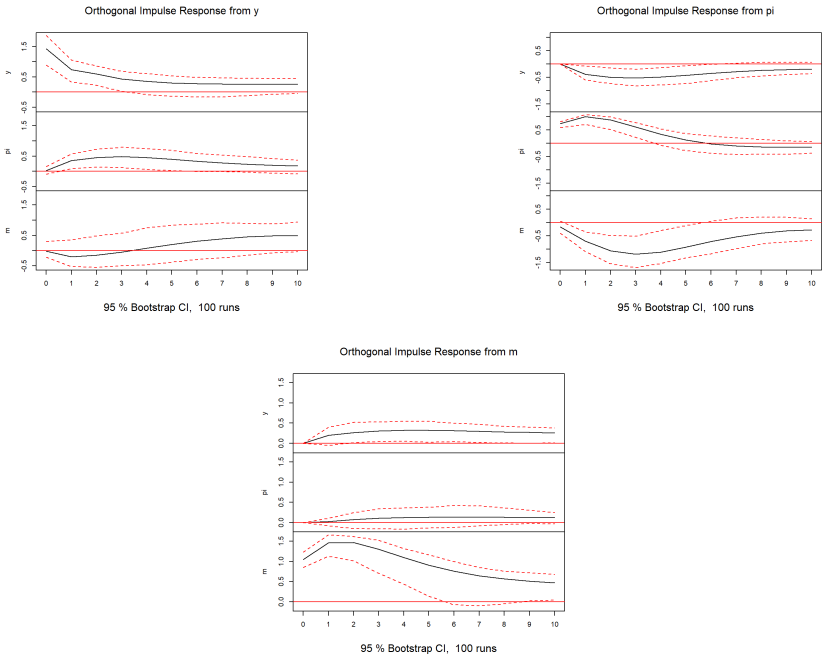


图 2: p=2 估计结果

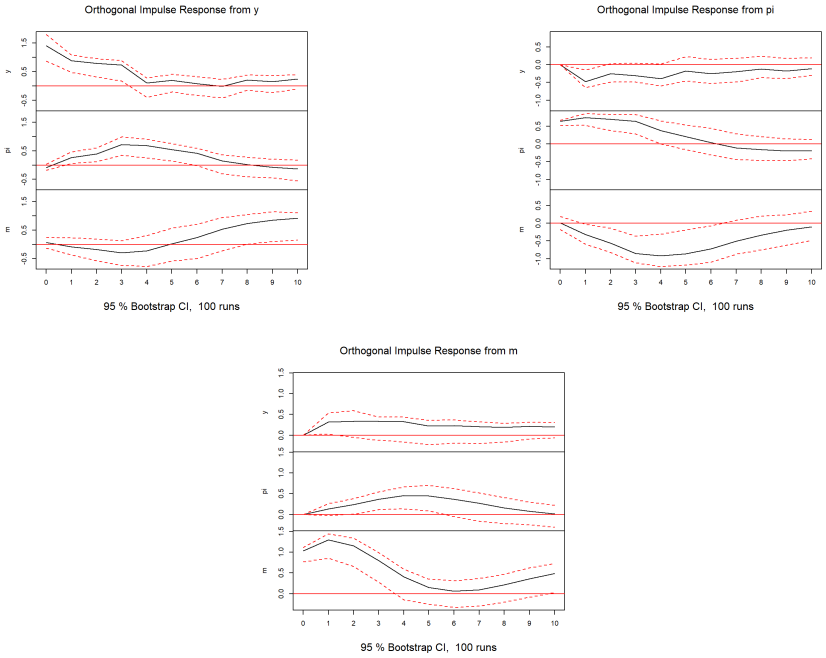


图 3: p=4 估计结果

(d) 当经济体面临一个外生的货币政策冲击时，将在今后 10 期，即 2.5 年的时间内受其影响，短期 GDP 增速和 CPI 增速均小幅上升，然后回落，长期来看会恢复到经济的长期均衡。因此 M2 同比增速作为中国货币政策中介变量能捕捉货币政策松紧变化的效果。

(e) 取 $p = 10$, 计算出 $j = 4, 8, 12, 36$ 期的预测方差分解, 结果如图 5 所示
代码如下:

```
VAR4 <- VAR(vardata, p=10, type='const')
fe = fevd(VAR4, n.ahead=36)
fe$y[c(4,8,12,36),]
fe$pi[c(4,8,12,36),]
fe$m[c(4,8,12,36),]
```

```
             y         pi          m
[1,] 0.8111552 0.1555935 0.03325139
[2,] 0.6831798 0.2881972 0.02862300
[3,] 0.6560383 0.2513870 0.09257474
[4,] 0.7882577 0.1575160 0.05422634
             y         pi          m
[1,] 0.2213989 0.7428096 0.03579146
[2,] 0.3487794 0.6048123 0.04640823
[3,] 0.3231262 0.6046381 0.07223567
[4,] 0.6047232 0.3377719 0.05750496
             y         pi          m
[1,] 0.2038939 0.1595907 0.6365154
[2,] 0.2029713 0.3280307 0.4689980
[3,] 0.2522958 0.3151666 0.4325376
[4,] 0.2845347 0.5769970 0.1384683
```

图 4: $p = 10$ 时,$j = 4, 8, 12, 36$ 期的预测方差分解