Macroeconomics

Assignment 4

Chang Yen Cheng

29 Nov, 2019

Question 1: SVAR Modelling of Supply and Demand Disturbnces

We replicated the results of Blanchard (1989), A Traditional Interpretation of Macroeconomic Fluctuations, AER, 79(5) during lectures in the computer lab. Specifically, we estimated the IRFs (pp1159-60) for a sample covering 1965 to 1986.

Your assignment is to run Blanchard's model for data from 1987 to 2018.

The code to download the data is in the structural VAR lecture slides 8 and 9. Calculate IRFs and FEVDs.

Are your results broadly consistent with those in Blanchard's article? Discuss the macroeconomic implications of your IRF and FEVD results.

```
library(quantmod)
```

```
## Loading required package: xts

## Loading required package: zoo

##
## Attaching package: 'zoo'

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

## Registered S3 method overwritten by 'xts':
##   method     from
##   as.zoo.xts zoo

## Loading required package: TTR

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

## Version 0.4-0 included new data defaults. See ?getSymbols.
```

```
library(vars)
```

```
## Loading required package: MASS

## Loading required package: strucchange

## Loading required package: sandwich
```

```
## Loading required package: urca

## Loading required package: lmtest
```

```r
U <- getSymbols("UNRATE",src='FRED', auto.assign=F)
```

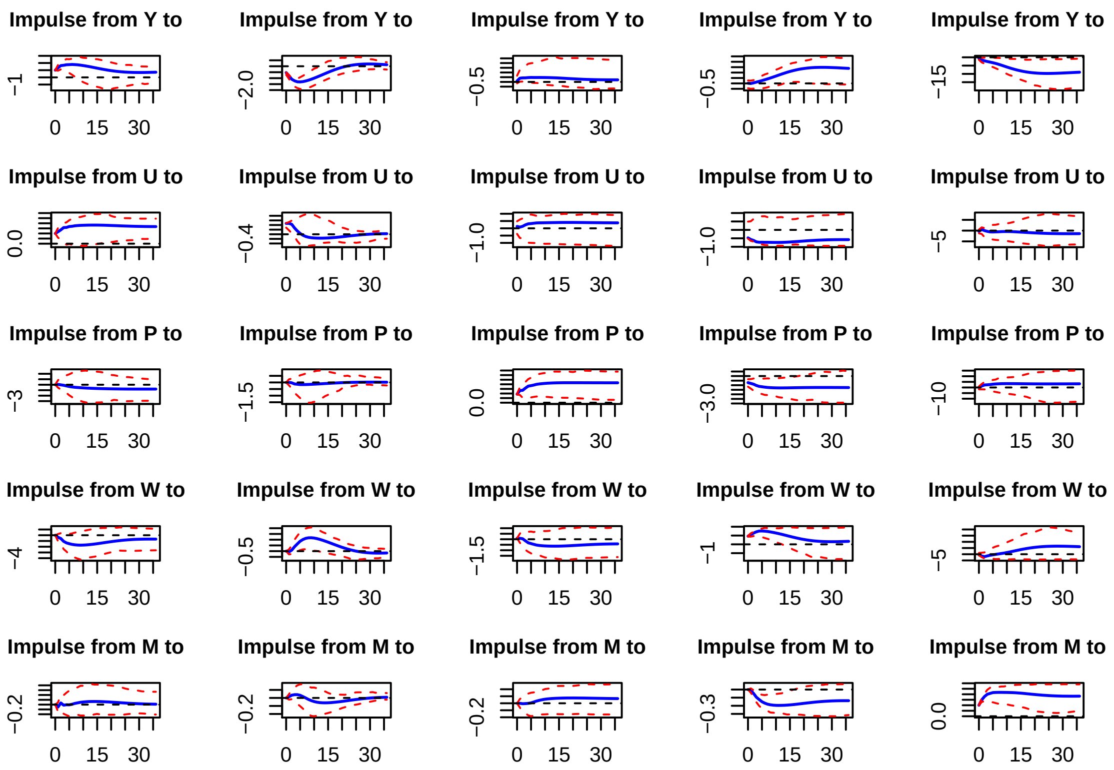
```
## 'getSymbols' currently uses auto.assign=TRUE by default, but will
## use auto.assign=FALSE in 0.5-0. You will still be able to use
## 'loadSymbols' to automatically load data. getOption("getSymbols.env")
## and getOption("getSymbols.auto.assign") will still be checked for
## alternate defaults.
##
## This message is shown once per session and may be disabled by setting
## options("getSymbols.warning4.0"=FALSE). See ?getSymbols for details.
```

```r
U <- ts(U["1964/2018"], start = c(1964,1),end = c(2018,12), frequency = 12 )
U <- as.xts(aggregate(U, nfrequency=4)/3)
Y <- getSymbols("GNPC96",src='FRED', auto.assign=F)
Y <- 100*diff(log(Y),lag=1)
M <- getSymbols("M1SL",src='FRED', auto.assign=F)
M <- ts(M["1964/2018"], start = c(1964,1),end = c(2018,12), frequency = 12 )
M <- as.xts(aggregate(M, nfrequency=4)/3)
M <- 100*diff(log(M),lag=1)
W <- getSymbols("LCEAPR01USQ661S",src='FRED', auto.assign=F)
W <- 100*diff(log(W),lag=1)
P <- getSymbols("DPCERD3Q086SBEA",src='FRED', auto.assign=F)
P <- 100*diff(log(P),lag=1)
B.all <- cbind(Y,U,P,W,M)["1987/2018"]
names(B.all) <- c("Y","U","P","W","M")
B <- B.all["1987/2018"]
VARselect(B, lag.max = 12)
```

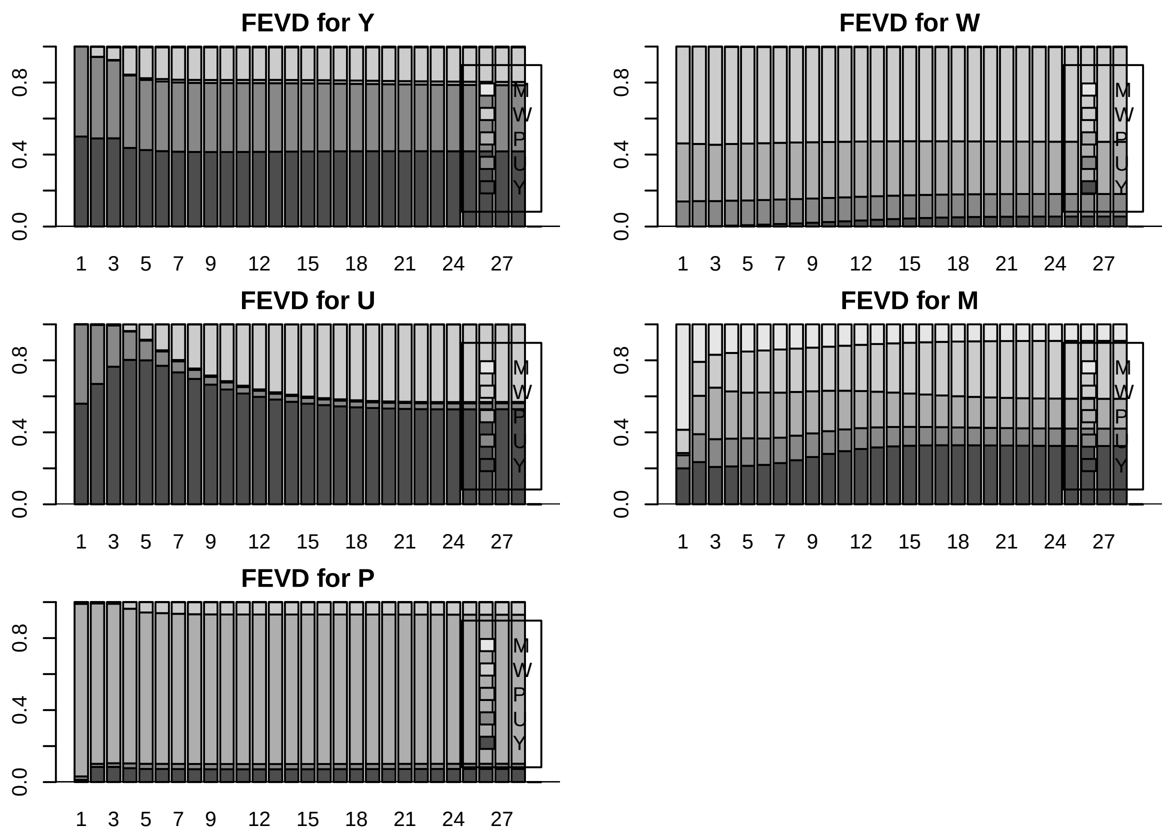
```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      2      2      1      2
##
## $criteria
##                    1             2             3             4
## AIC(n) -1.038130e+01 -1.088670e+01 -1.086473e+01 -1.077175e+01
## HQ(n)  -1.009222e+01 -1.035671e+01 -1.009383e+01 -9.759948e+00
## SC(n)  -9.669169e+00 -9.581122e+00 -8.965702e+00 -8.279277e+00
## FPE(n)  3.102112e-05  1.875883e-05  1.929081e-05  2.141166e-05
##                    5             6             7             8
## AIC(n) -1.068783e+01 -1.068689e+01 -1.048203e+01 -1.048747e+01
## HQ(n)  -9.435123e+00 -9.193280e+00 -8.747516e+00 -8.512051e+00
## SC(n)  -7.601911e+00 -7.007526e+00 -6.209221e+00 -5.621216e+00
## FPE(n)  2.372164e-05  2.441288e-05  3.116508e-05  3.269892e-05
##                    9            10            11            12
## AIC(n) -1.062420e+01 -1.075114e+01 -1.072770e+01 -1.053897e+01
## HQ(n)  -8.407874e+00 -8.293909e+00 -8.029565e+00 -7.599921e+00
```

```
## SC(n)  -5.164497e+00 -4.697992e+00 -4.081106e+00 -3.298922e+00
## FPE(n)  3.060908e-05  2.954306e-05  3.398674e-05  4.756072e-05
```

```r
B.vm <- VAR(B, p=3, type="both", season=4)
A.m <- diag(5)
A.m[2,1] <- NA
A.m[3,1] <- A.m[3,4] <- NA
A.m[4,2] <- A.m[4,3] <- NA
A.m[5,1] <- A.m[5,2] <- A.m[5,3] <- A.m[5,4]<- NA
A.m[3,4] <- -0.1
A.m[4,2] <- 0.18
B.m <- diag(5)
B.m[1,2] <- 1
B.m[3,2] <- NA
B.m[4,2] <- NA
B.svm <- SVAR(B.vm, Amat=A.m , Bmat=B.m, estmethod = "direct", max.iter = 500)
B.irf1 <- irf(B.svm, n.ahead=36, ortho=T, cumulative=F,  boot=T,runs=200, ci=0.95)
B.irf2 <- irf(B.svm, n.ahead=36, ortho=T, cumulative=T,  boot=T,runs=200, ci=0.95)
B.irf2[["irf"]][["Y"]][,2] <- B.irf1[["irf"]][["Y"]][,2]
B.irf2[["irf"]][["U"]][,2] <- B.irf1[["irf"]][["U"]][,2]
B.irf2[["irf"]][["P"]][,2] <- B.irf1[["irf"]][["P"]][,2]
B.irf2[["irf"]][["W"]][,2] <- B.irf1[["irf"]][["W"]][,2]
B.irf2[["irf"]][["M"]][,2] <- B.irf1[["irf"]][["M"]][,2]
B.irf2[["Lower"]][["Y"]][,2] <- B.irf1[["Lower"]][["Y"]][,2]
B.irf2[["Lower"]][["U"]][,2] <- B.irf1[["Lower"]][["U"]][,2]
B.irf2[["Lower"]][["P"]][,2] <- B.irf1[["Lower"]][["P"]][,2]
B.irf2[["Lower"]][["W"]][,2] <- B.irf1[["Lower"]][["W"]][,2]
B.irf2[["Lower"]][["M"]][,2] <- B.irf1[["Lower"]][["M"]][,2]
B.irf2[["Upper"]][["Y"]][,2] <- B.irf1[["Upper"]][["Y"]][,2]
B.irf2[["Upper"]][["U"]][,2] <- B.irf1[["Upper"]][["U"]][,2]
B.irf2[["Upper"]][["P"]][,2] <- B.irf1[["Upper"]][["P"]][,2]
B.irf2[["Upper"]][["W"]][,2] <- B.irf1[["Upper"]][["W"]][,2]
B.irf2[["Upper"]][["M"]][,2] <- B.irf1[["Upper"]][["M"]][,2]
source('~/GitHub/assignment-4-q319-Chang-Yen-Cheng/plotIRF.R')
par(mar = rep(2, 4))
plotIRF(B.irf2)
```




```r
B.vd <- fevd(B.svm, 28)
par(mar = rep(2, 4))
plot(B.vd)
```



Positive demand innovations increase output and decrease unemployment, and it also lead to an increase in price and wage just as the previous data(1965-1986). But the decrease on money supply is much bigger than before. The supply innovations increase output in a short term and then it is stabled. The result (temporary decrease in output following a supply shock) Blanchard found to be difficult to fit into the Keynasian model doesn't seen in the new data results(1987-2018). Supply innovations increases unemployment just as the previous result but it actually increase a bit in price in the new result. Comparing to the previous data(1965-1986), for FEVD of Y and U,the influence of M increased. For FEVD of P, it doesn't change much. For FEVD of W, the effect of P remain stable over time wherea P increases it's influence over time in the previous data. For FEVD of M, P shows more stronger influence than the data before. ## Question 2:

Summarise the results of Miyao (2002) and Uhlig (2005) regarding the effects of monetary policy (in your own words). Write one to two pages.

The results for Miyao(2002):Impulse responses to a call rate disturbance(one-unit call rate shock, contractionary monetary policy): Real output decreases persistently. Stock prices also respond negatively(suggests that the monetary transmission via stock prices is operating to that degree). Monetary base also declines (which is plausible in light of the downward-sloping reserve demand curve). Impulse responses to a money base disturbance: A rise in money demand is followed by a rise in call rate(suggesting that this is money demand disturbance).The disturbance in turn raises stock prices(implies the rise in money demand is caused by an increase lending to business firms and households, which fuel rise in stock prices). Output is slightly raised(the possible negative effect on real output that is implied by higher interest rates is offset and perhaps out weighed by the positive effect due to the persistent rise in stock prices).Stock price disturbances: Long-lasting effect on output.Plausible positive impacts on call rate and base money. Most influenced by itself.Real output disturbances, productivity/technology shocks: Raise real output in the long run. Stock prices are slightly raised but the standard error band appears relatively wide(may suggest while stock price disturbances influence real output, the opposite effect from real shocks to stock prices may not be so significant).By graph of the Historical Decomposition of Real Output: it is obvious that when Bank of Japan implemented active monetary policy -initial easing in 1986-1987(where the output started to soar) and subsequent tightening monetary policy in 1989-1990(where the output started to fall from the maximum point), we can interpret that the Bank of Japan is partly responsible for the occurence and burst of Japan's "bubble economy". The results for Uhlig(2005):Uhlig used a VAR to observe how monetary policy affects output,too. The different part is that he didn't use the varselect procedure but actually tried all kinds of different time lags(K=0,..,5,11,23) where he found that with 2/3(66%) probability, the impulse response for real GDP is within a $\pm 0.2\%$ interval around zero at any point during the first five years following the shock,which is very different to the essays produced previously. So the conclusions of the previous VAR papers should be reviewed by using different time lags to see if the conclusion changes and how it will affect us thinking about the issue. He also talked about avoiding the "price puzzle"(by conventional wisdom, r rise will lead to a y and p fall, but price actually moves somewhat above zero first before declining below zero after a monetary policy shock) by using his agnositic identification approach. His results showed that GDP deflator drops really slow,and the commodity price index he included reacts swiftly. Monetary policy shocks account for only a small fraction of the forecast error variance in the federal funds rate, excepts at horizons shorter than half a year. They account for about one quarter of the variation in price at longer horizons.

Question 3:

In the final lecture we examine Gali (1999). Run Gali's model on data for 1948-2018 and 1996-2018.Use the data we download in class. Are your results similar to Gali's original results? Comment and interpret your results.

```r
library(tseries)
P <- getSymbols("OPHNFB", src = 'FRED', auto.assign = FALSE )
H <- getSymbols("HOANBS", src = 'FRED', auto.assign = FALSE )
y <- 100*log(cbind(P,H))
names(y) <- c("prod","hours")
yd <- diff(y,lag=1)
yd1 <- yd["1948/2018"]
pp.test(y$prod["1948/2018"])
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  y$prod["1948/2018"]
## Dickey-Fuller Z(alpha) = -7.1821, Truncation lag parameter = 5,
## p-value = 0.7076
## alternative hypothesis: stationary
```

```r
pp.test(yd1$prod)
```

```
## Warning in pp.test(yd1$prod): p-value smaller than printed p-value
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  yd1$prod
## Dickey-Fuller Z(alpha) = -293.08, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
```

```r
pp.test(y$hours["1948/2018"])
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  y$hours["1948/2018"]
## Dickey-Fuller Z(alpha) = -8.5731, Truncation lag parameter = 5,
## p-value = 0.6295
## alternative hypothesis: stationary
```

```r
pp.test(yd1$hours)
```

```
## Warning in pp.test(yd1$hours): p-value smaller than printed p-value
```

```
##
```

```
##  Phillips-Perron Unit Root Test
##
## data:  yd1$hours
## Dickey-Fuller Z(alpha) = -103.55, Truncation lag parameter = 5,
## p-value = 0.01
## alternative hypothesis: stationary
```

```r
VARselect(yd1, lag.max = 8)
```

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      3      2      2      3
##
## $criteria
##                 1          2          3          4          5          6
## AIC(n) -1.1426390 -1.2217568 -1.2278580 -1.2075371 -1.2004317 -1.1783879
## HQ(n)  -1.1110562 -1.1691189 -1.1541650 -1.1127889 -1.0846283 -1.0415293
## SC(n)  -1.0639346 -1.0905828 -1.0442145 -0.9714240 -0.9118490 -0.8373356
## FPE(n)  0.3189767  0.2947143  0.2929257  0.2989464  0.3010897  0.3078175
##                 7          8
## AIC(n) -1.1504192 -1.1723923
## HQ(n)  -0.9925055 -0.9934234
## SC(n)  -0.7568974 -0.7264009
## FPE(n)  0.3165719  0.3097220
```

```r
G.vm1 <- VAR(yd1, p=3, type="both")
G.svm1 <- BQ(G.vm1)
G.svm1[["LRIM"]]
```

```
##             prod    hours
## prod   0.6842958 0.000000
## hours -0.3051227 1.386542
```

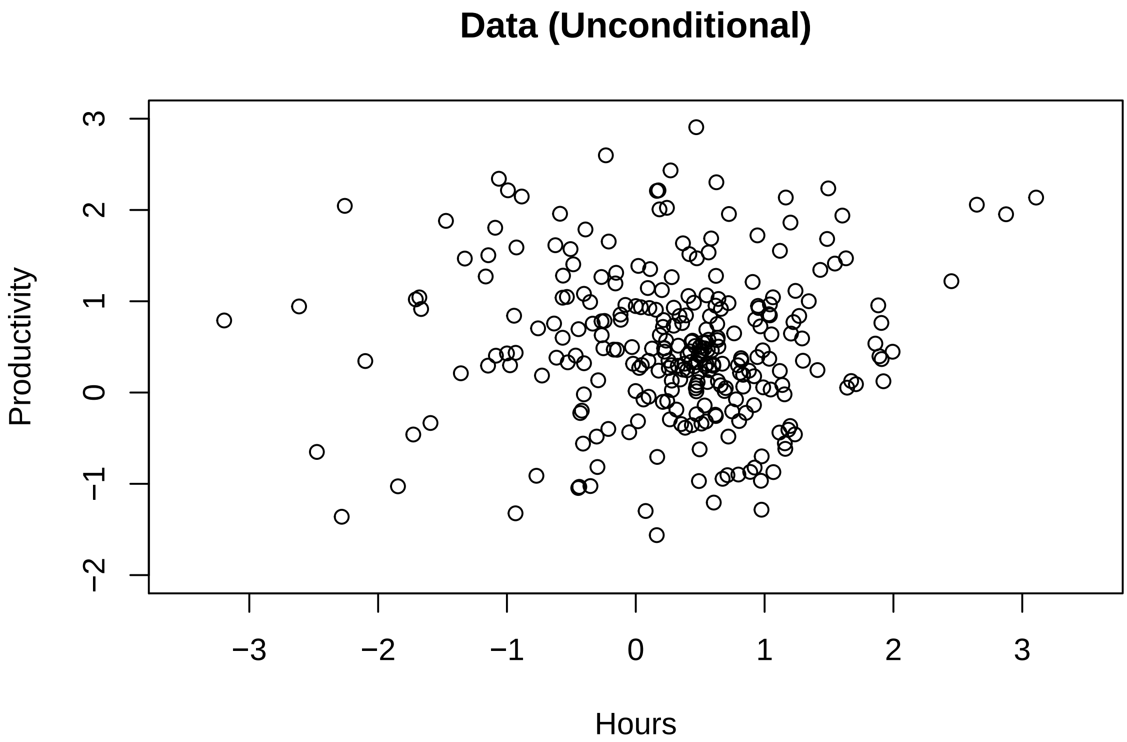
```r
G.svm1[["B"]]
```

```
##             prod     hours
## prod   0.6360947 0.4574811
## hours -0.3339732 0.5940888
```

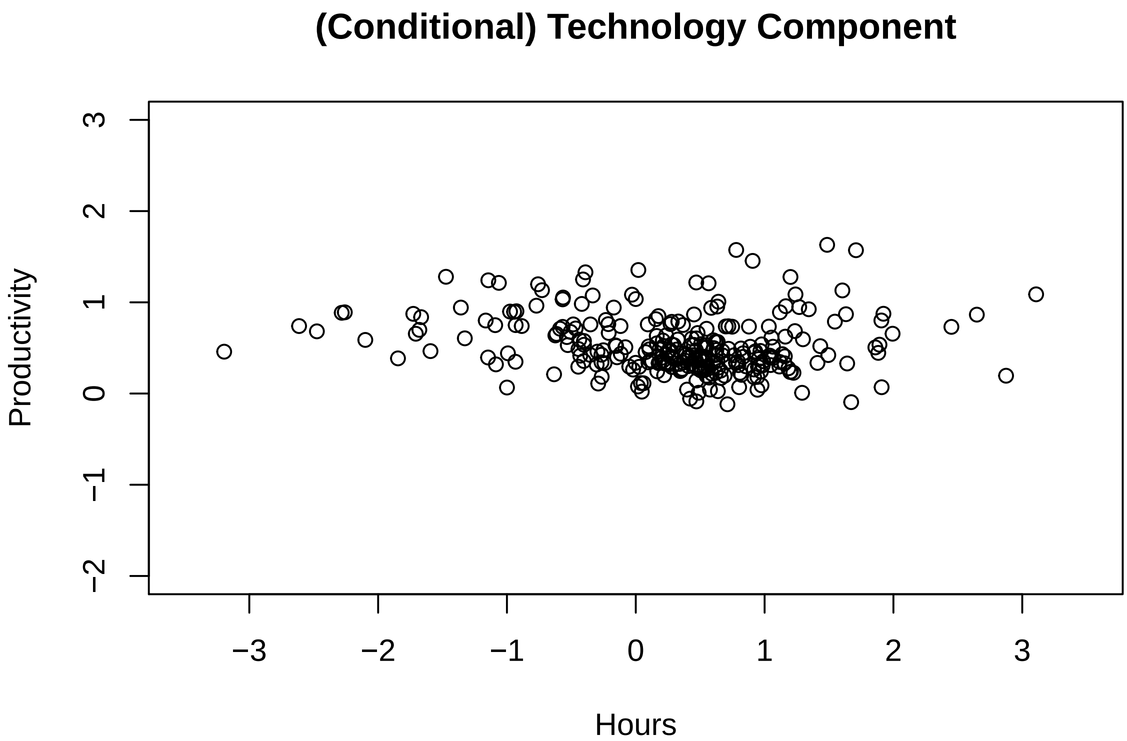
```r
x1 <- cbind(yd1[-c(1:3)],G.svm1[["var"]][["varresult"]][["prod"]][["fitted.values"]],
names(x1) <- c("prod", "hours", "tech", "ntech")
cor(x1)
```

```
##              prod       hours       tech       ntech
## prod   1.00000000  0.01968709  0.3774649 -0.08796073
## hours  0.01968709  1.00000000 -0.1532441  0.65761478
## tech   0.37746487 -0.15324414  1.0000000 -0.23303025
## ntech -0.08796073  0.65761478 -0.2330303  1.00000000
```

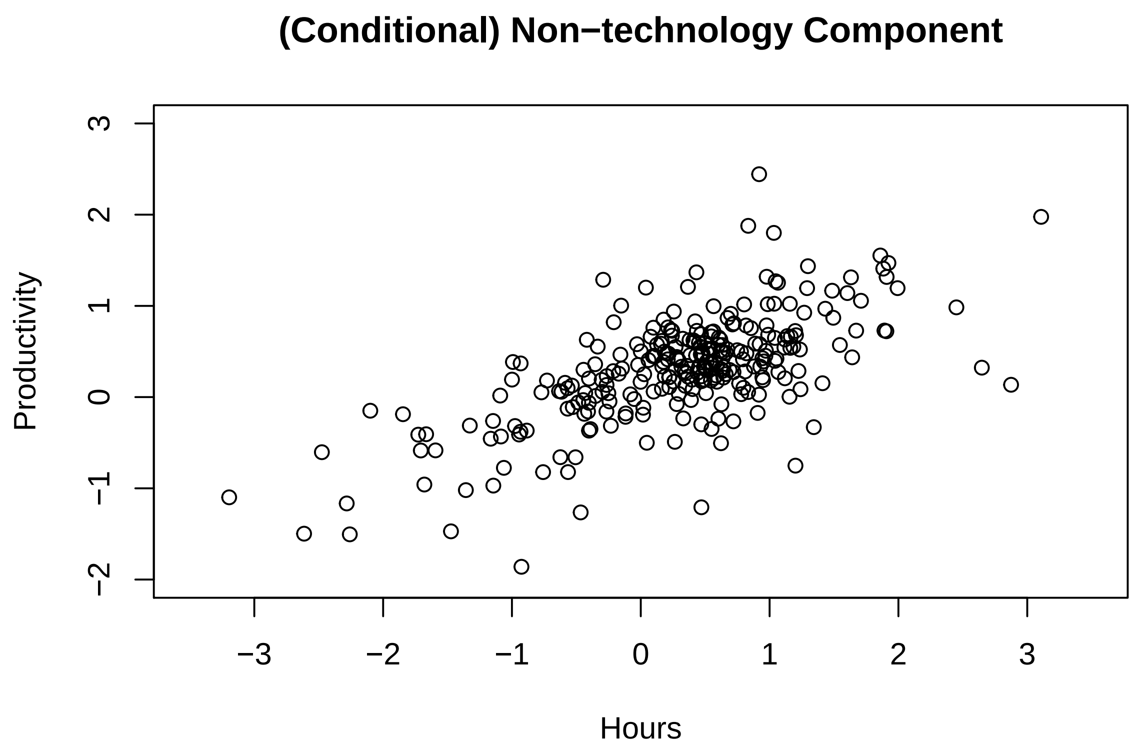
```r
plot(G.svm1[["var"]][["datamat"]][["prod"]]~G.svm1[["var"]][["datamat"]][["hours"]],m
```



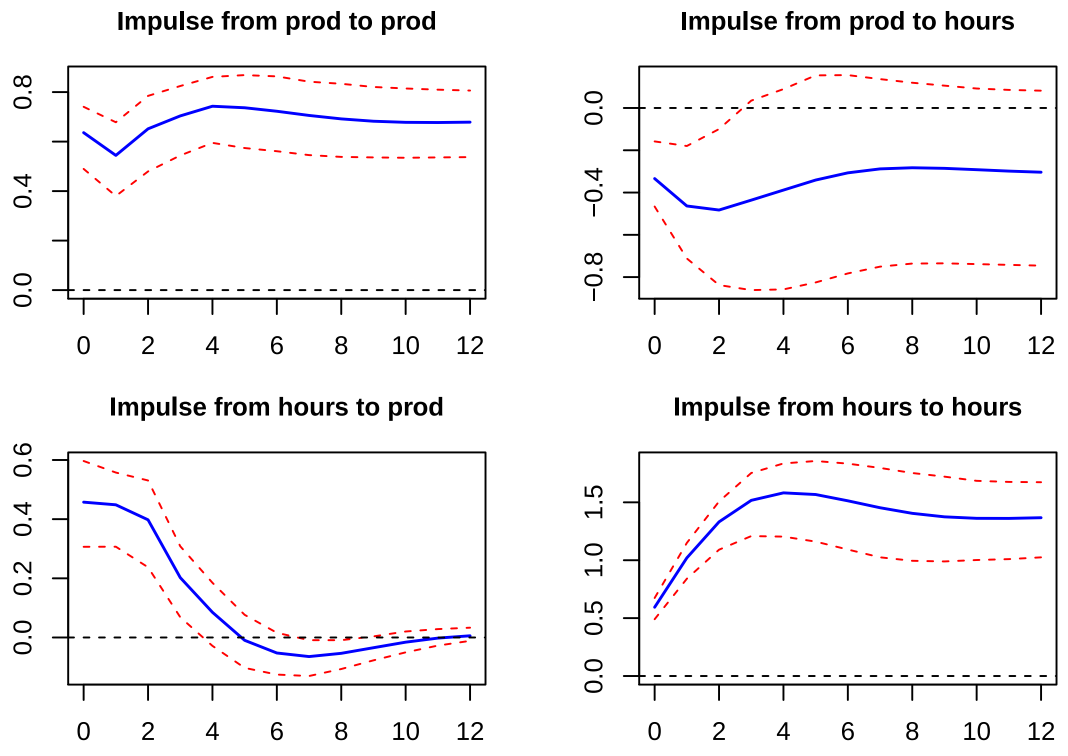

```
plot(G.svm1[["var"]][["varresult"]][["prod"]][["fitted.values"]]~G.svm1[["var"]][["da
```



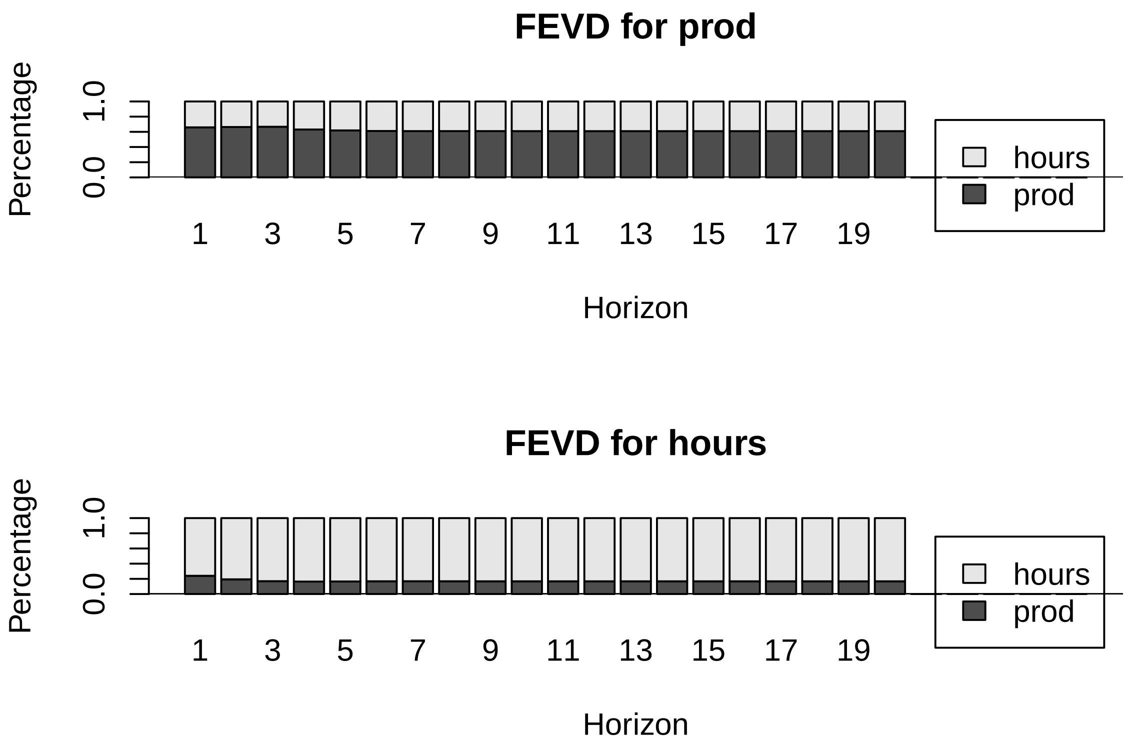
```
plot(G.svm1[["var"]][["varresult"]][["hours"]][["fitted.values"]]~G.svm1[["var"]][["d
```




```
G.irf1 <- irf(G.svm1, n.ahead=12, cumulative=T, boot=T, runs=500)
source('~/GitHub/assignment-4-q319-Chang-Yen-Cheng/plotIRF.R')
plotIRF(G.irf1)
```




```
plot(fevd(G.svm1, n.ahead=20), addbars=5)
```




```
yd2 <- yd["1996/2018"]
pp.test(y$prod["1996/2018"])
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  y$prod["1996/2018"]
## Dickey-Fuller Z(alpha) = -1.0573, Truncation lag parameter = 3,
## p-value = 0.985
## alternative hypothesis: stationary
```

```
pp.test(yd2$prod)
```

```
## Warning in pp.test(yd2$prod): p-value smaller than printed p-value
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  yd2$prod
## Dickey-Fuller Z(alpha) = -104.75, Truncation lag parameter = 3,
## p-value = 0.01
## alternative hypothesis: stationary
```

```
pp.test(y$hours["1996/2018"])
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  y$hours["1996/2018"]
## Dickey-Fuller Z(alpha) = -4.6213, Truncation lag parameter = 3,
## p-value = 0.848
## alternative hypothesis: stationary
```

```
pp.test(yd2$hours)
```

```
##
##  Phillips-Perron Unit Root Test
##
## data:  yd2$hours
## Dickey-Fuller Z(alpha) = -23.604, Truncation lag parameter = 3,
## p-value = 0.02411
## alternative hypothesis: stationary
```

```
VARselect(yd2, lag.max = 8)
```

```
## $selection
## AIC(n)  HQ(n)  SC(n) FPE(n)
##      8      2      1      8
##
## $criteria
##                  1           2           3          4           5
## AIC(n) -2.36438466 -2.45451163 -2.40668523 -2.4515932 -2.39710225
## HQ(n)  -2.29458695 -2.33818212 -2.24382391 -2.2422001 -2.14117733
```

```
## SC(n)  -2.19075489 -2.16512868 -2.00154910 -1.9307039 -1.76045976
## FPE(n)  0.09401284  0.08592935  0.09018336  0.0862986  0.09125688
##                  6           7           8
## AIC(n) -2.34567686 -2.47596315 -2.48479297
## HQ(n)  -2.04322013 -2.12697461 -2.08927263
## SC(n)  -1.59328118 -1.60781429 -1.50089093
## FPE(n)  0.09626386  0.08473537  0.08429262
```

```
G.vm2 <- VAR(yd2, p=3, type="both")
G.svm2 <- BQ(G.vm2)
G.svm2[["LRIM"]]
```

```
##             prod    hours
## prod   0.5404979 0.000000
## hours -1.3265491 1.171112
```

```
G.svm2[["B"]]
```

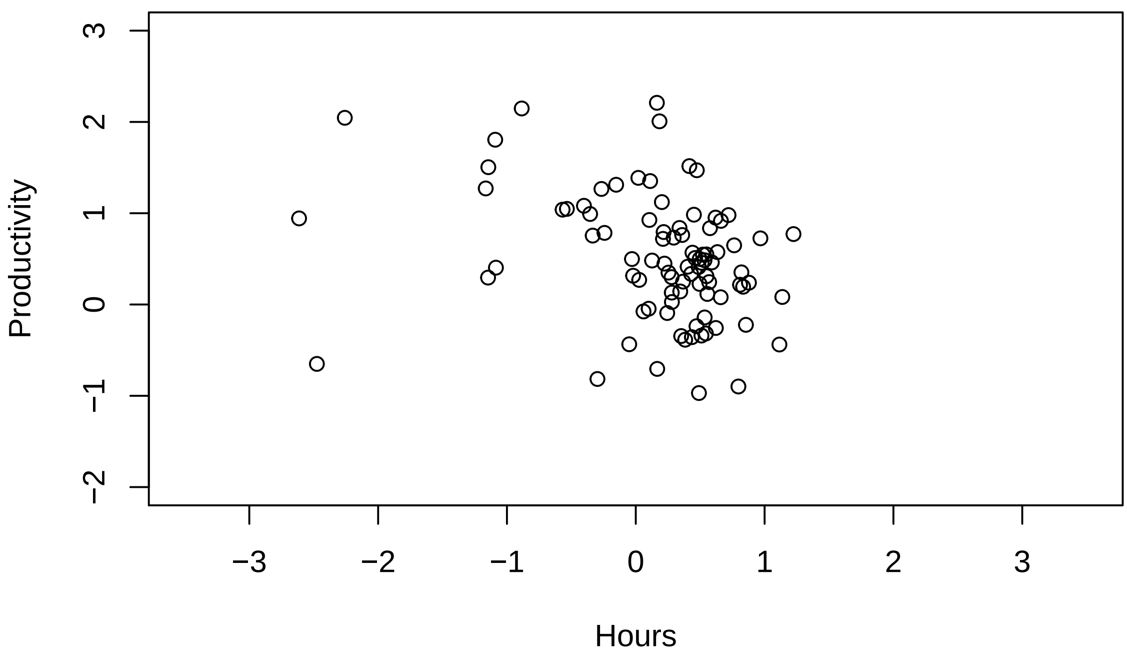
```
##             prod     hours
## prod   0.2088739 0.5468223
## hours -0.3989186 0.1448985
```

```
x2 <- cbind(yd2[-c(1:3)],G.svm2[["var"]][["varresult"]][["prod"]][["fitted.values"]],
names(x2) <- c("prod", "hours", "tech", "ntech")
cor(x2)
```

```
##             prod      hours       tech      ntech
## prod   1.0000000 -0.3116686  0.5634544 -0.3716682
## hours -0.3116686  1.0000000 -0.5392368  0.8174910
## tech   0.5634544 -0.5392368  1.0000000 -0.6596242
## ntech -0.3716682  0.8174910 -0.6596242  1.0000000
```

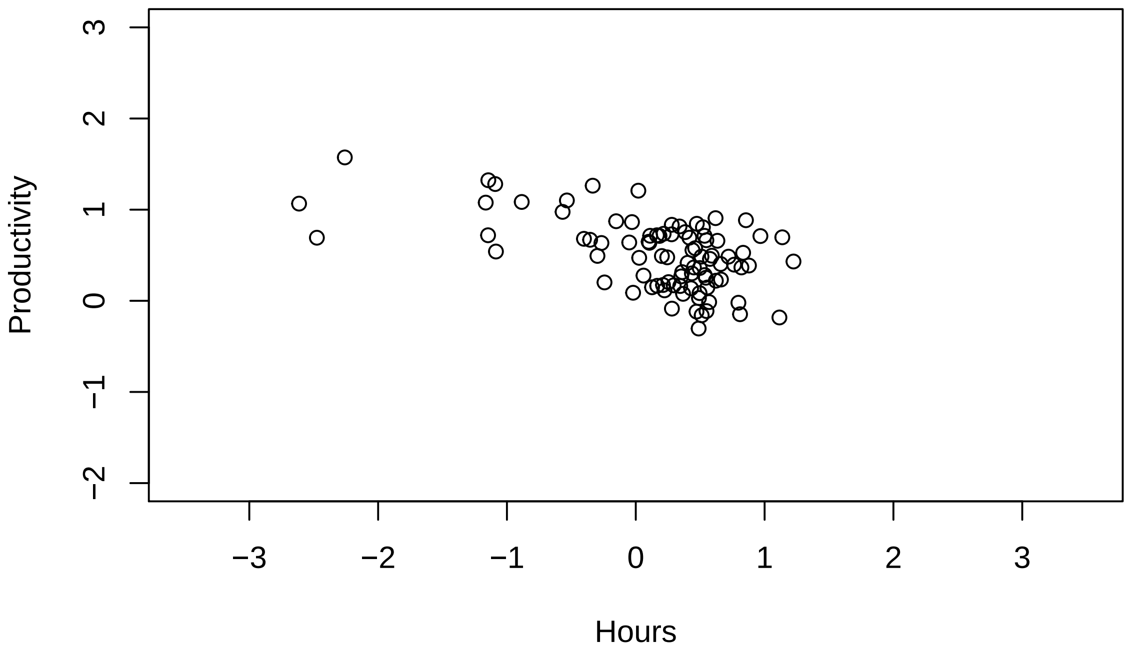
```
plot(G.svm2[["var"]][["datamat"]][["prod"]]~G.svm2[["var"]][["datamat"]][["hours"]],m
```

Data (Unconditional)

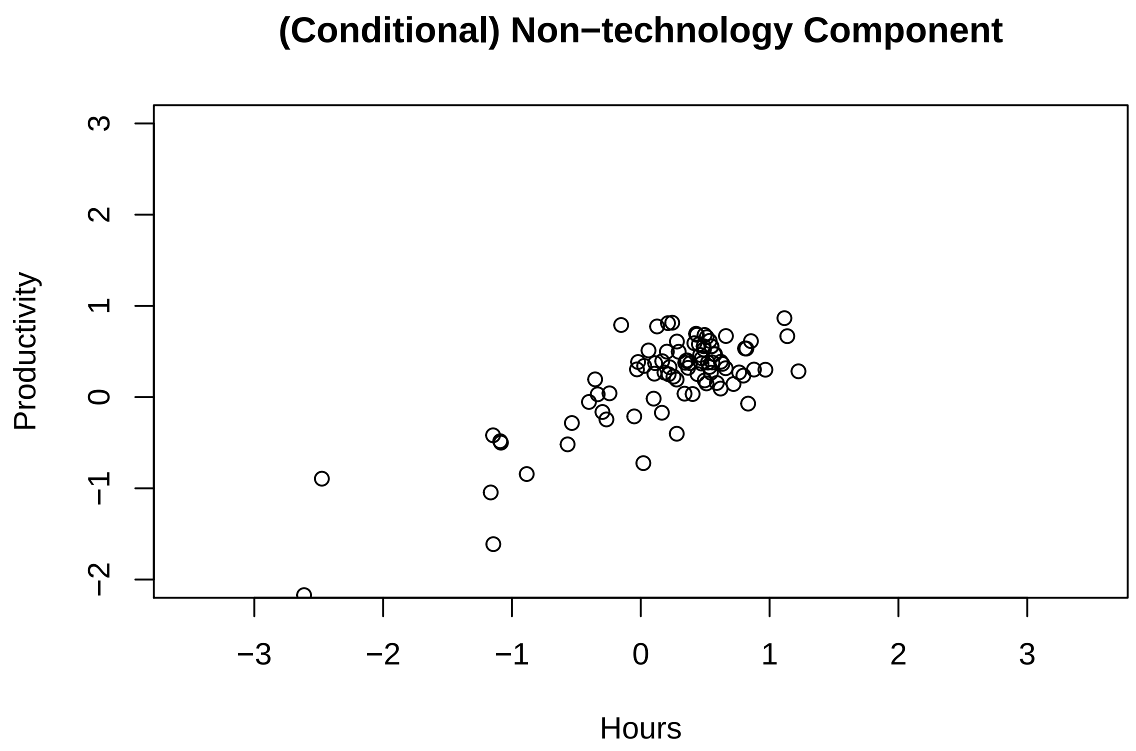



```
plot(G.svm2[["var"]][["varresult"]][["prod"]][["fitted.values"]]~G.svm2[["var"]][["da
```

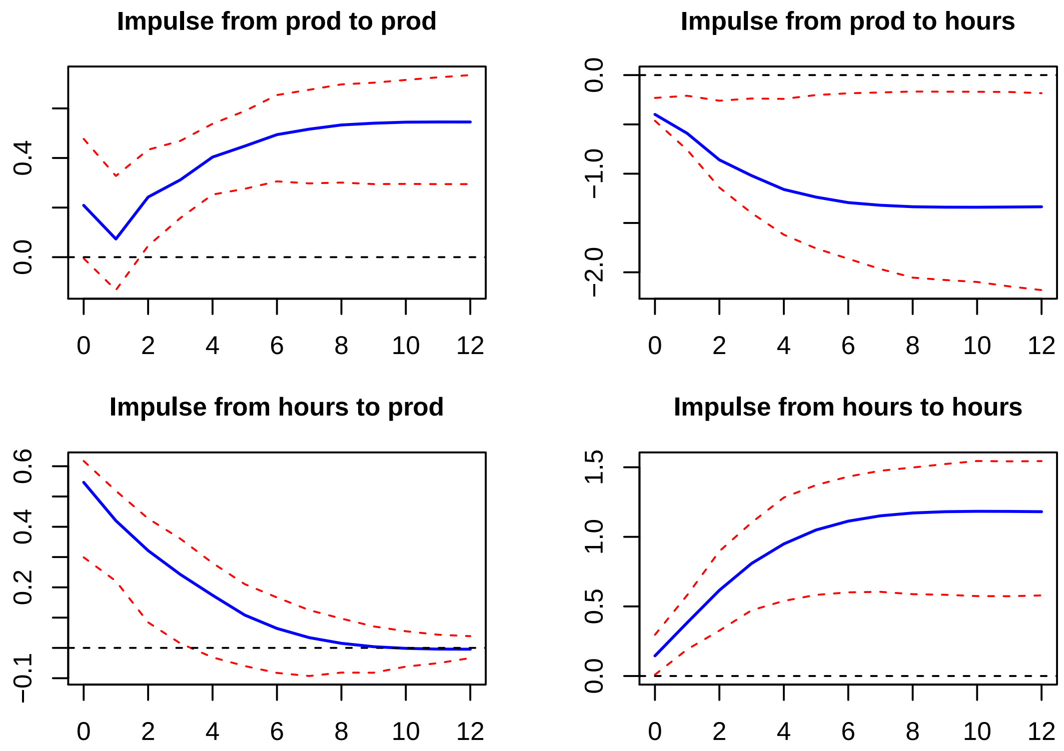
(Conditional) Technology Component



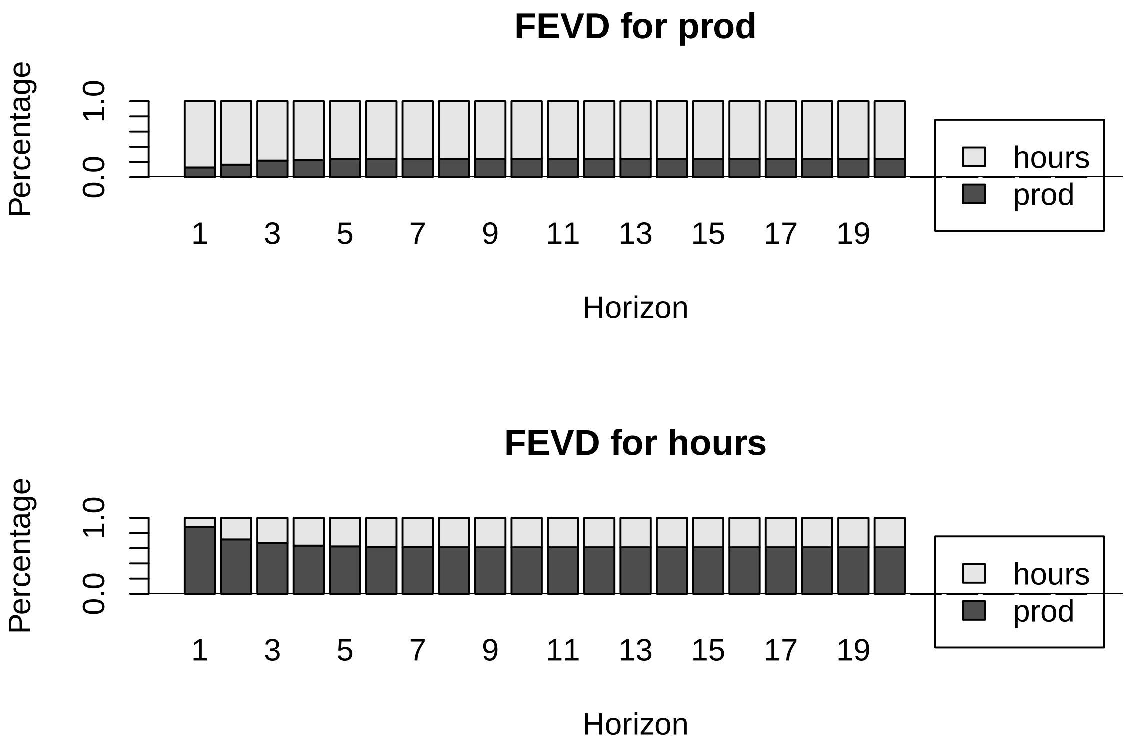
```r
plot(G.svm2[["var"]][["varresult"]][["hours"]][["fitted.values"]]~G.svm2[["var"]][["d
```




```r
G.irf2 <- irf(G.svm2, n.ahead=12, cumulative=T, boot=T, runs=500)
source('~/GitHub/assignment-4-q319-Chang-Yen-Cheng/plotIRF.R')
plotIRF(G.irf2)
```




```r
plot(fevd(G.svm2, n.ahead=20), addbars=5)
```



Comparing with the in class result (1948-1994), the data from 1948-2018: Productivity and hours also appear (unconditionally) uncorrelated. The (conditional) technology component are uncorrelated with hours. While estimates of the (conditional) non-technology component are positively correlated with hours. The data from 1996-2018: Productivity and hours appear (unconditionally) negatively related. The (conditional) technology component are negative correlated with hours. While estimates of the (conditional) non-technology component are positively correlated with hours. It is quite close to Gali's conclusion to dispute the basic RBC model prediction(productivity has a positive correlation with hours and that technology rises will make productivity rises then make labor hours rises). Comparing with the in class result(1948-1994), the data from 1948-2018: Technology shocks also cause productivity to increase permenantly but hours responses to decrease permanently, which is different from the in class result. Non-technology shocks also cause a short-run increase in productivity (for about four quarters) and output (hours). Hours also remain elevated after the shock, stabilizing after about eight to 10 quarters. Comparing with the in class result(1948-1994), the data from 1996-2018: Technology shocks cause productivity to increase permenantly but hours to decrease permanently (different from in class result). Non-technology shocks also cause a short-run increase in both productivity (for about four quarters) and output (hours). Hours remain elevated after the shock, stabilizing after about eight to 10 quarters.The major difference above is the technology shock causing hours to decrease permanently. To interpret it in a RBC model way is that the wage elasticity of labor supply is larger than labor demand, so when the firms want to hire more people(labor demand curve shifts right), the income effect due to the rising of the wageI(labor supply curve shifts left) does more effect so the new work hours equilibrium of the labor market is lower than the original equilibrium.