Macroeconometrics - Homework 4

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2023-06-03

#Exercise 1

For this exercise we tried to change λ_1 holding λ_2 constant, then varying λ_2 holding λ_1, and then varying both λ_1 and λ_2. For each of those, we compare 6 different values of lambda. The corresponding coefficients are depicted in the first 3 figures in Appendix.

Changes in the estimated AR coefficients:

For small values of λ_1 given λ_2, we see that all AR coefficients except constant are pushed towards their expectation given by $\underline{A}$ strongly. For each variable, its first lag is close to one and all other coefficients are close to 0. For high values of λ_1, the distinction between the coefficients of own first lags and others gets less pronounced. This was expected since in Minnesota prior λ_1 induces global shrinkage for all parameters except the constant term. Low value of λ_2 pushes the cross-variable coefficients to 0, while the own-variable coefficients have more freedom given by a medium value of λ_1. For high values of λ_2, the cross-variable coefficients fluctuate more freely around 0. Varying λ_1 and λ_2 combines these two effects.

Changes in the estimated IRFs (we use Cholesky for illustration):

Low λ_1 pushes all median IRFs to a constant response since all coefficients except for constant are pushed strongly to 0. Low λ_2 pushes the cross-variable responses to a constant. High λ_1 and λ_2 let the data speak. Notice that in Cholesky, the right-upper triangle of IRFs starts at 0 by definition, thus they are pushed towards 0.

Changes in forecast:

Low λ_1 makes the forecasts look more like a random walk. Low λ_2 not necessarily, since the dependence on own lags and constant seem to cause substantial variation in the forecasts.

Exercise 2

Read Kilian (2009), who discusses how to disentangle different oil shocks; focus on section II. Load the provided data by Kilian (2009), which contains a measure of change in oil production, a measure of real economic activity, and the real price of oil.

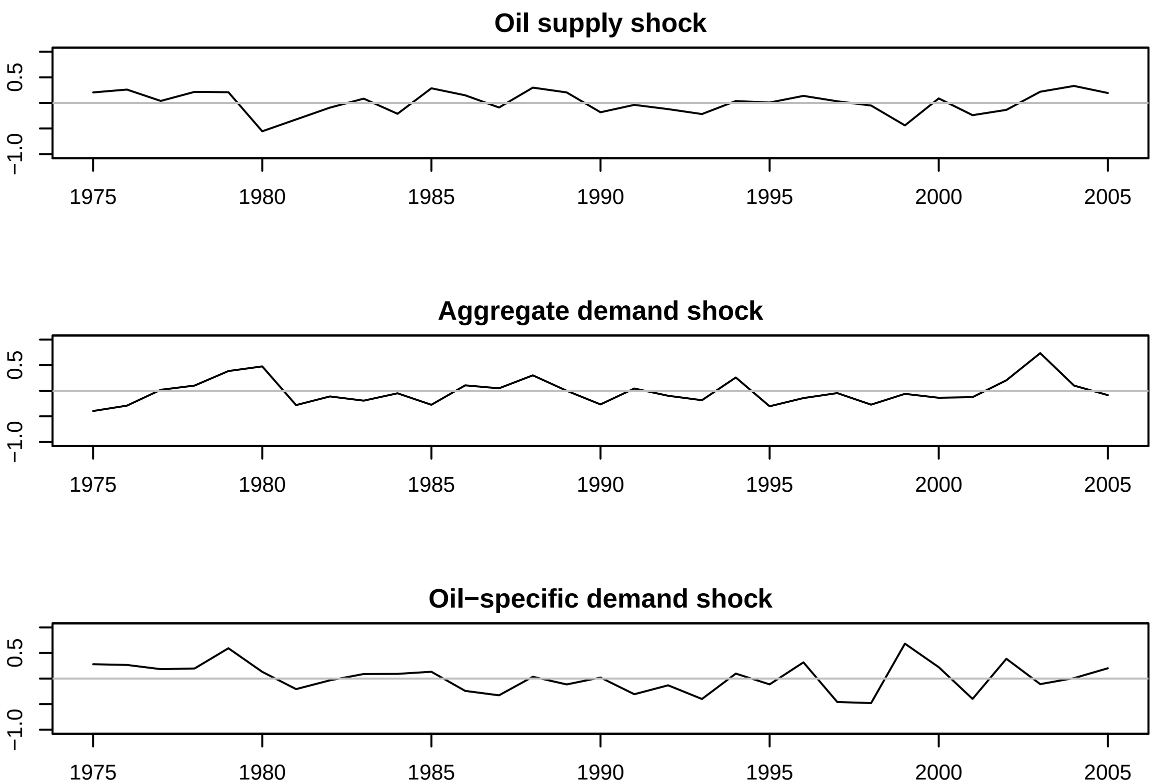
Subquestion 2.1

Using the code for the Bayesian VAR, estimate the VAR described in section II.A. Using the provided code from the lecture, we estimate the Bayesian VAR based on Kilian (2009). We increased the λ_1 to 0.6 to account for higher frequency of the data. The lag shrinkage in the formula of V in Minnesota prior is given by $1/k$ where k is the lag. This shrinkage is specific to quarterly or yearly data so for monthly data less aggressive lag shrinkage like 6/k is appropriate. To implement this we simply set λ_1 to 0.6 instead of 0.1.

Subquestion 2.2 - Figure 2 Replication

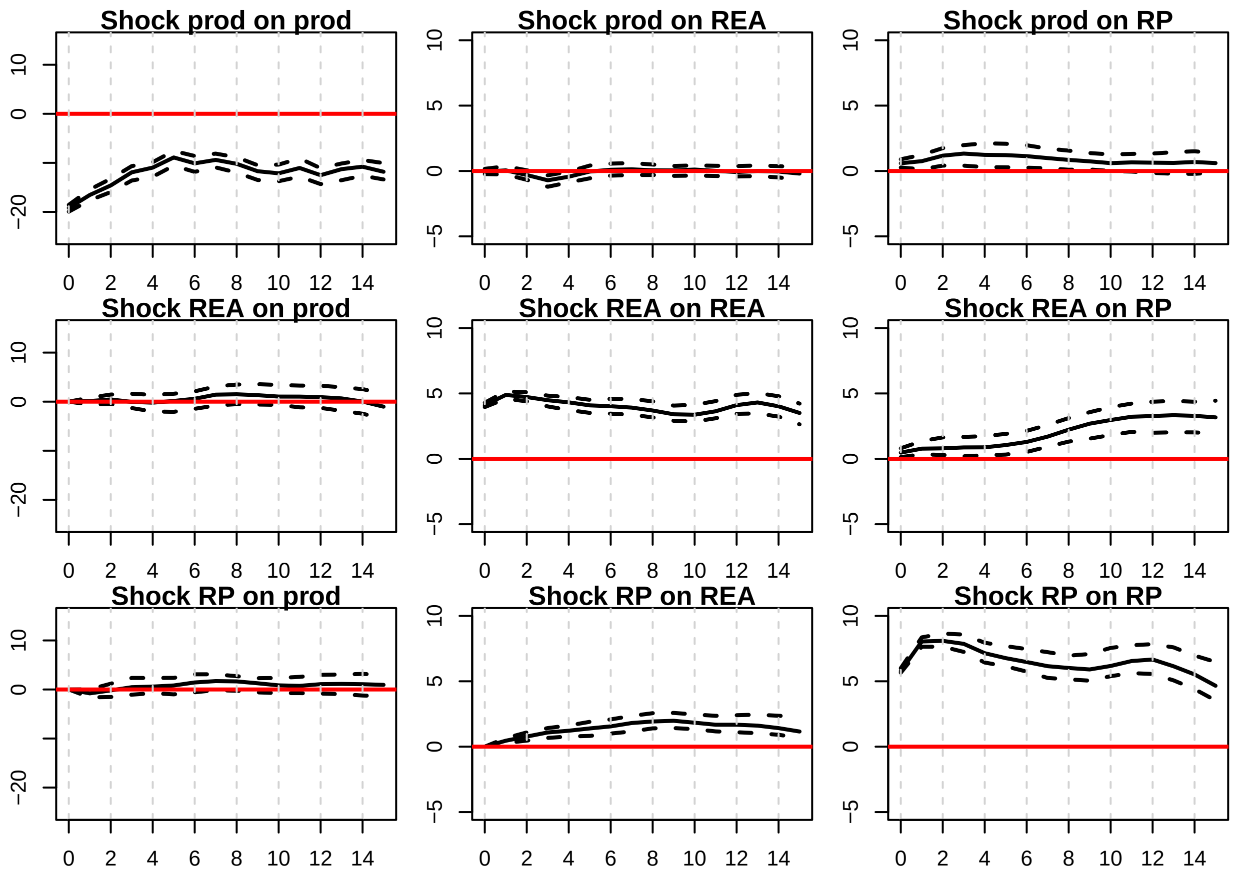
Replicate figures 2 and 3 of Kilian, 2009 by recovering the structural form of the model by recursive ordering of variables.

Below we replicate figure 2.



Subquestion 2.2 - Figure 3 Replication

Below we replicate figure 3. The IRFs remind of those in the paper by Kilian, but are more smooth with values pushed more towards zero due to our prior. If we wanted to get IRFs which correspond more to those in the paper, we could increase the value of λ_1.



Subquestion 2.3 - Sign Restrictions

Think of reasonable sign restrictions to identify the model at hand; discuss and implement them. Recreate figure 3 using these restrictions and discuss differences to the one identified by recursive ordering. Briefly discuss potential shortcomings of both identifcation schemes.

We propose the following sign restrictions, based on Kilian & Murphy (2012). It might be important to note here that the proposed columns are not linear combinations of each other, which would result in the model not being identified.

$$\begin{bmatrix} e^{OP} \\ e^{RA} \\ e^{P} \end{bmatrix} = \begin{bmatrix} - & + & + \\ - & + & - \\ + & + & + \end{bmatrix} \begin{bmatrix} e^{OS} \\ e^{AD} \\ e^{OD} \end{bmatrix} \tag{1}$$

The shortcoming of both identifications schemes comes from their definition. A *zero short run restriction* assumes that some variables do not react contemporaneously to a shock of other variables. The sign restrictions assume that reaction of some of the variables to a shock to other variables are positive or negative. Additionally when using sign restrictions the causal coefficients are set identified, which gives rise to larger confidence bands.

```r
# Code for replication sign restriction
#New storage for cumulative IRFs
IRFsign_store_tmp <- IRFsign_store

for (i in 1:3) {
  IRFsign_store_tmp[, 1, i, ] <- t(apply(IRFsign_store[, 1, i, ], 1, cumsum))
}

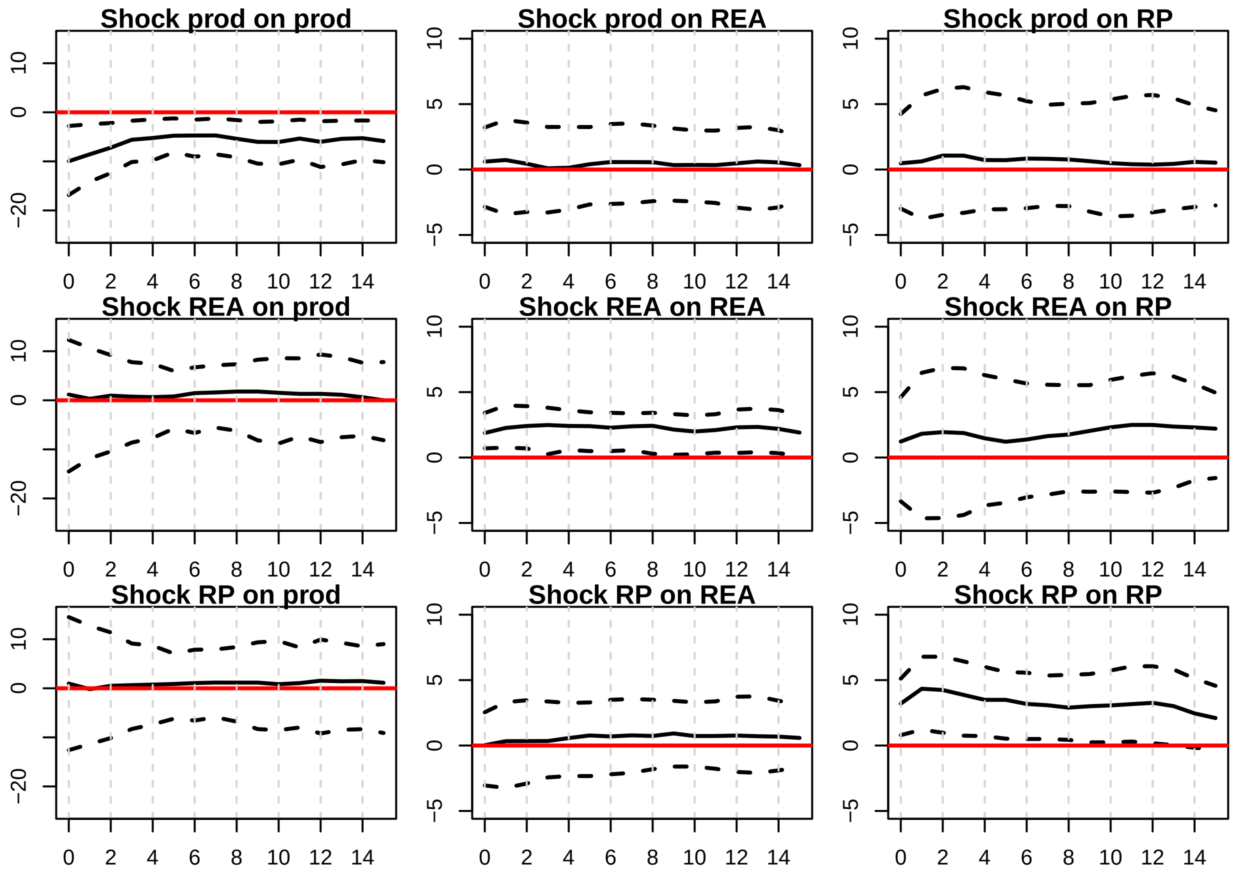
#Quantiles over the first dimension (number of saved draws)
IRFsign_low    <- apply(IRFsign_store_tmp, c(2,3,4), quantile, 0.16,na.rm=TRUE)
IRFsign_high   <- apply(IRFsign_store_tmp, c(2,3,4), quantile, 0.84,na.rm=TRUE)
IRFsign_median <- apply(IRFsign_store_tmp, c(2,3,4), median, na.rm=TRUE)

#changing signs of the Cholesky decomposition for the oil supply shock
for(jj in 1:3){
  for(ii in 1:16){
    IRFsign_low[jj,1,ii] <- (-1)* IRFsign_low[jj,1,ii]
    IRFsign_high[jj,1,ii] <- (-1)* IRFsign_high[jj,1,ii]
    IRFsign_median[jj,1,ii] <- (-1)* IRFsign_median[jj,1,ii]
}}

#Start plotting the IRFs w.r.t. different shocks
yaxis <- list(c(-25, 15),
               c(-5, 10),
               c(-5, 10))

par(mfrow=c(3,3),mar=c(2,2,1,1))

for(jj in 1:3){
  for(ii in 1:3){
    plot.ts(IRFsign_median[ii,jj,], ylab="", xlab="", main=paste0("Shock ",colnames(Y)[jj], " on ",colna
    lines(IRFsign_low[ii,jj,], lty = 2, lwd=2)
    lines(IRFsign_high[ii,jj,], lty = 2, lwd=2)
    abline(h=0,col="red",lwd=2)
    abline(v=seq(1,nhor,by=2), col="lightgrey", lty=2)
    axis(1, at=seq(1,nhor,by=2), labels=seq(0,nhor-1,by=2))
          }
        }
```



Shock prod on prod
Shock prod on REA
Shock prod on RP
Shock REA on prod
Shock REA on REA
Shock REA on RP
Shock RP on prod
Shock RP on REA
Shock RP on RP

Subquestion 2.4 - Other Variables

Think of other variables that might be influenced by oil market shocks and collect data that fits the frequency and time period of the provided data. Transform the additional data appropriately and estimate the reduced form of a suitable VAR model. Identify the different shocks (using recursive ordering and sign restrictions), compute impulse responses and discuss your results.

We decided to use the Variable "S.P.500" from the dataset "current.csv" and as a measure for the CPI the Variable "CPIAUCSL".

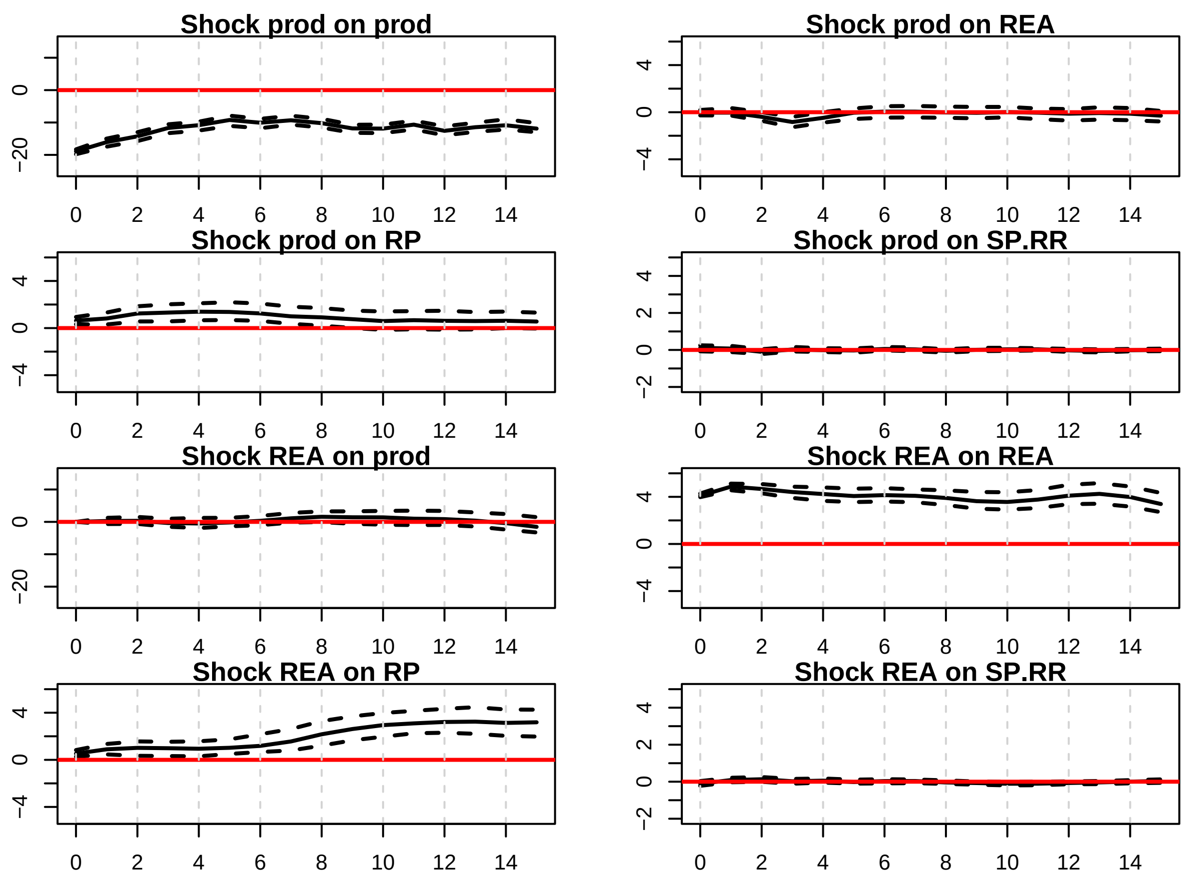
```
FRED <- read.csv("current.csv",sep = ",", dec = ".")[-1,]
data.SP.CPI.raw <- ts(FRED[c("S.P.500","CPIAUCSL")], start=c(1959,1),frequency=12)
data.SP.CPI <- window(data.SP.CPI.raw, start = c(1973, 1), end = c(2006, 12))
data.returns.inf <- diff(log(data.SP.CPI)) * 100
SP.RR <- (1 + data.returns.inf[,1]) / (1 + data.returns.inf[,2]) - 1

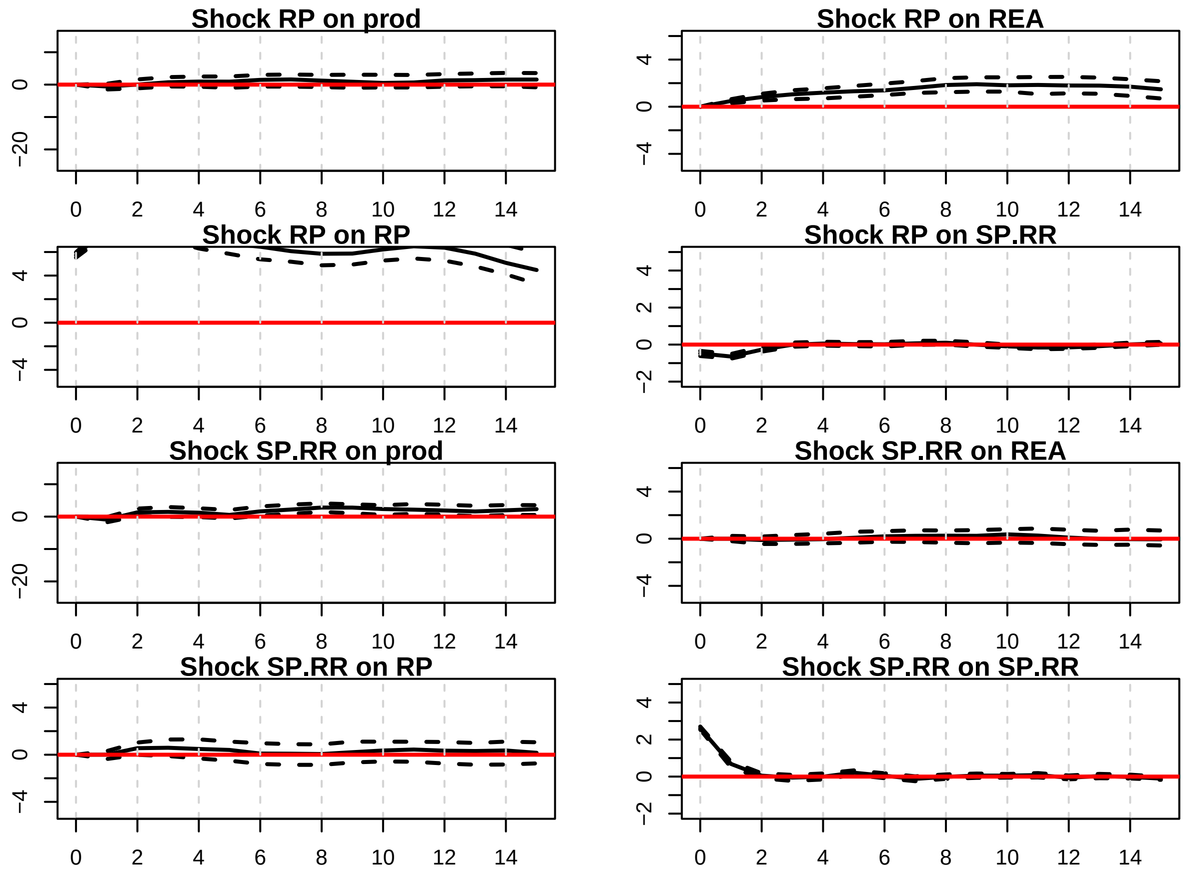
data.returns <- ts(data.frame(data.kilian[,1:3], SP.RR), start = c(1972, 12), frequency=12)

Traw <- nrow(data.returns)
Yraw <- data.returns
```

We again estimate the VAR…

… and compute the impulse response functions:






```
#New storage for cumulative IRFs
IRFchol_store2 <- IRFchol_store

for (i in 1:4) {
IRFchol_store2[, 4, i, ] <- t(apply(IRFchol_store[, 4, i, ], 1, cumsum))
}
#IRFchol_store2[,,3,1] <- IRFchol_store2[,,3,1]*(-1)
#Quantiles over the first dimension (number of saved draws)
IRFchol_low.68 <- apply(IRFchol_store2, c(2,3,4), quantile, 0.16,na.rm=TRUE)
IRFchol_high.68 <- apply(IRFchol_store2, c(2,3,4), quantile, 0.84,na.rm=TRUE)
IRFchol_low.95 <- apply(IRFchol_store2, c(2,3,4), quantile, 0.025,na.rm=TRUE)
IRFchol_high.95 <- apply(IRFchol_store2, c(2,3,4), quantile, 0.975,na.rm=TRUE)
IRFchol_median2 <- apply(IRFchol_store2, c(2,3,4), median, na.rm=TRUE)
#Start plotting the IRFs w.r.t. different shocks

par(mfrow=c(4,4),mar=c(2,1,1,2))
sign.list <- c(-1,1,1,1)
for(jj in seq_along(sign.list)){
for(ii in 1:4){
plot.ts(sign.list[jj]*IRFchol_median2[ii,jj,], ylab="", main=paste0("Shock ",colnames(Y)[jj], " on ",co
lines(sign.list[jj]*IRFchol_low.68[ii,jj,], lty = 2, lwd=2)
lines(sign.list[jj]*IRFchol_high.68[ii,jj,], lty = 2, lwd=2)
lines(sign.list[jj]*IRFchol_low.95[ii,jj,], lty = 3, lwd=2)
lines(sign.list[jj]*IRFchol_high.95[ii,jj,], lty = 3, lwd=2)
abline(h=0,col="red",lwd=2)
axis(1, at = seq(1, nhor, by = 2), labels = seq(0, nhor - 1, by = 2))
```

```
}}
```

Computing the Impulse Response Functions as always, we can have a look at what the effects of shocks of our original variables on the the S&P 500 measure are. The left most panel is the cumulative IRF of a shock in oil production, which seems to have little to non-significant effects on our inflation proxy, as can be seen from the confidence intervals. A similar effect can be seen in the shock related to real economic activity, which however shows signs of a decreasing effect in the later periods (starting at roughly period 8) The most significant effect can be seen in the IRF concerning a shock in the real price of oil, which shows to have a significant and sustainable decrease in the deflated stock returns. Similar to our non-bayesian aproach in assignment 1, the results are in line with the ones in Killian & Park (2009).

Sign restrictions:

```
# Code for replication sign restriction
#New storage for cumulative IRFs
IRFsign_store_tmp <- IRFsign_store

for (i in 1:4) {
  IRFsign_store_tmp[, 1, i, ] <- t(apply(IRFsign_store[, 1, i, ], 1, cumsum))
}

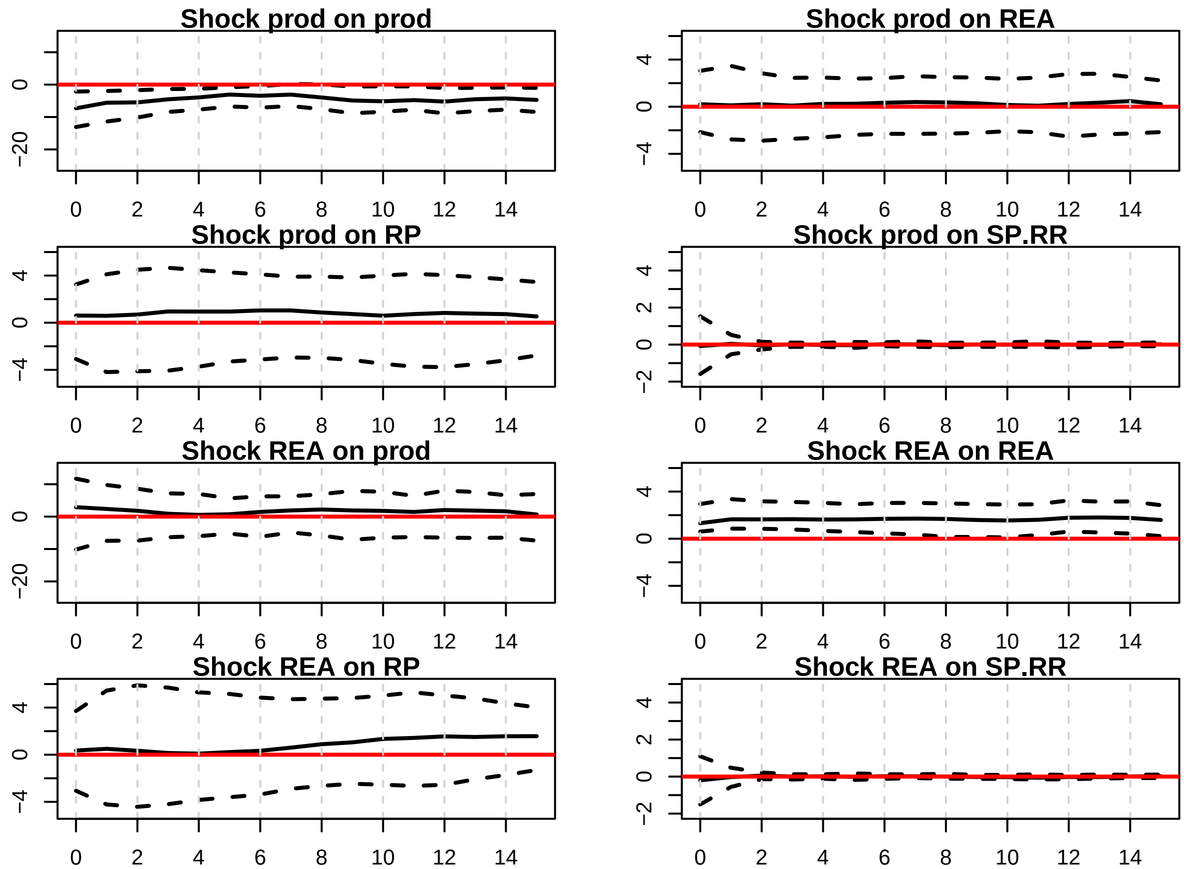
#Quantiles over the first dimension (number of saved draws)
IRFsign_low    <- apply(IRFsign_store_tmp, c(2,3,4), quantile, 0.16,na.rm=TRUE)
IRFsign_high   <- apply(IRFsign_store_tmp, c(2,3,4), quantile, 0.84,na.rm=TRUE)
IRFsign_median <- apply(IRFsign_store_tmp, c(2,3,4), median, na.rm=TRUE)

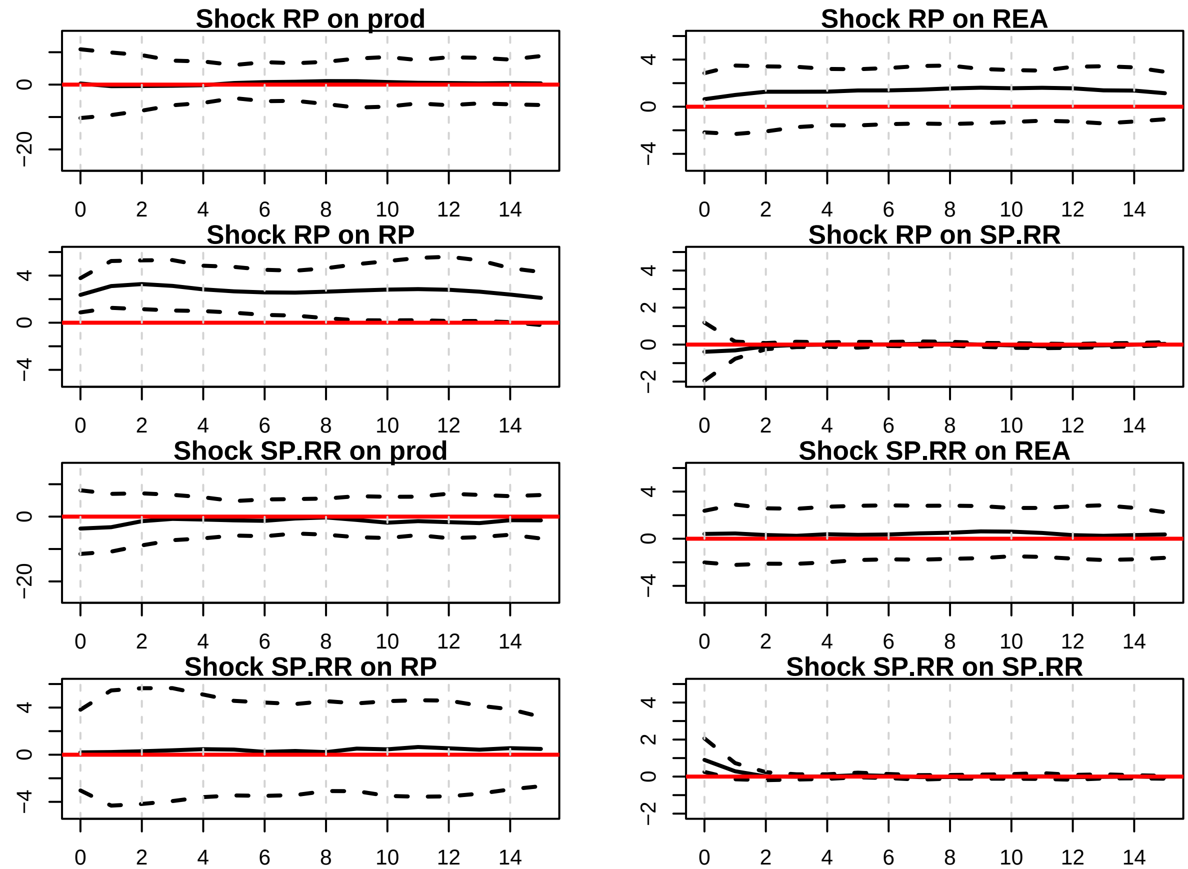
#changing signs of the Cholesky decomposition for the oil supply shock
for(jj in 1:4){
  for(ii in 1:16){
    IRFsign_low[jj,1,ii] <- (-1)* IRFsign_low[jj,1,ii]
    IRFsign_high[jj,1,ii] <- (-1)* IRFsign_high[jj,1,ii]
    IRFsign_median[jj,1,ii] <- (-1)* IRFsign_median[jj,1,ii]
}}

#Start plotting the IRFs w.r.t. different shocks
yaxis <- list(c(-25, 15),
               c(-5, 6),
               c(-5, 6),
                c(-2, 5))

par(mfrow=c(4,2),mar=c(2,3,1,2))

for(jj in 1:4){
  for(ii in 1:4){
    plot.ts(IRFsign_median[ii,jj,], ylab="", xlab="", main=paste0("Shock ",colnames(Y)[jj], " on ",colna
    lines(IRFsign_low[ii,jj,], lty = 2, lwd=2)
    lines(IRFsign_high[ii,jj,], lty = 2, lwd=2)
    abline(h=0,col="red",lwd=2)
    abline(v=seq(1,nhor,by=2), col="lightgrey", lty=2)
    axis(1, at=seq(1,nhor,by=2), labels=seq(0,nhor-1,by=2))
              }
            }
```


Shock prod on prod
Shock prod on REA
Shock prod on RP
Shock prod on SP.RR
Shock REA on prod
Shock REA on REA
Shock REA on RP
Shock REA on SP.RR
0
2
4
6
8
10
12
14
−20
−4

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# Code for replication sign restriction
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IRFsign_store2[, 4, i, ] <- t(apply(IRFsign_store[, 4, i, ], 1, cumsum))
}
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IRFsign_low.68 <- apply(IRFsign_store2, c(2,3,4), quantile, 0.16,na.rm=TRUE)
IRFsign_high.68 <- apply(IRFsign_store2, c(2,3,4), quantile, 0.84,na.rm=TRUE)
IRFsign_low.95 <- apply(IRFsign_store2, c(2,3,4), quantile, 0.025,na.rm=TRUE)
IRFsign_high.95 <- apply(IRFsign_store2, c(2,3,4), quantile, 0.975,na.rm=TRUE)
IRFsign_median2 <- apply(IRFsign_store2, c(2,3,4), median, na.rm=TRUE)
#Start plotting the IRFs w.r.t. different shocks

par(mfrow=c(4,4),mar=c(2,1,1,2))
sign.list <- c(-1,1,1,1)
main.list <- c("Oil supply shock", "Aggregate demand shock", "Oil-specific demand shock")
for(jj in seq_along(sign.list)){
for(ii in 1:4){
plot.ts(sign.list[jj]*IRFsign_median2[ii,jj,], ylab="", main=paste0("Shock ",colnames(Y)[jj], " on ",col
lines(sign.list[jj]*IRFsign_low.68[ii,jj,], lty = 2, lwd=2)
lines(sign.list[jj]*IRFsign_high.68[ii,jj,], lty = 2, lwd=2)
lines(sign.list[jj]*IRFsign_low.95[ii,jj,], lty = 3, lwd=2)
lines(sign.list[jj]*IRFsign_high.95[ii,jj,], lty = 3, lwd=2)
abline(h=0,col="red",lwd=2)
```

```
axis(1, at = seq(1, nhor, by = 2), labels = seq(0, nhor - 1, by = 2))

}}
```

Again as before, we can see that the confidence intervalls have increased drastically because of the sign restrictions.