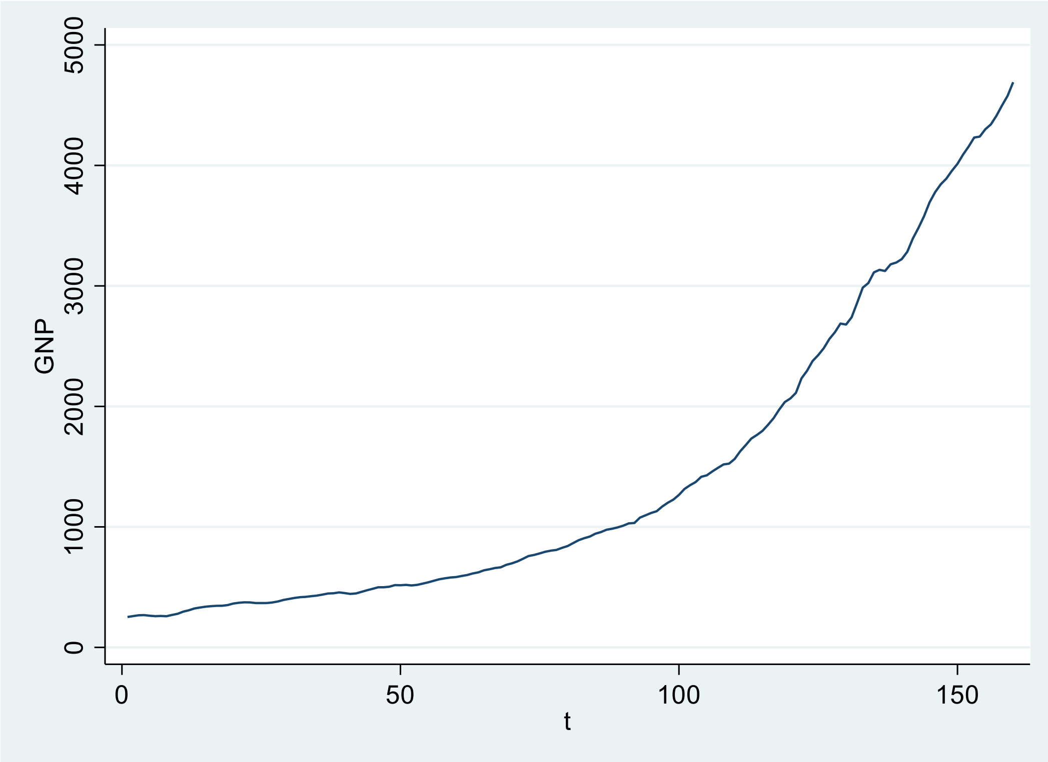
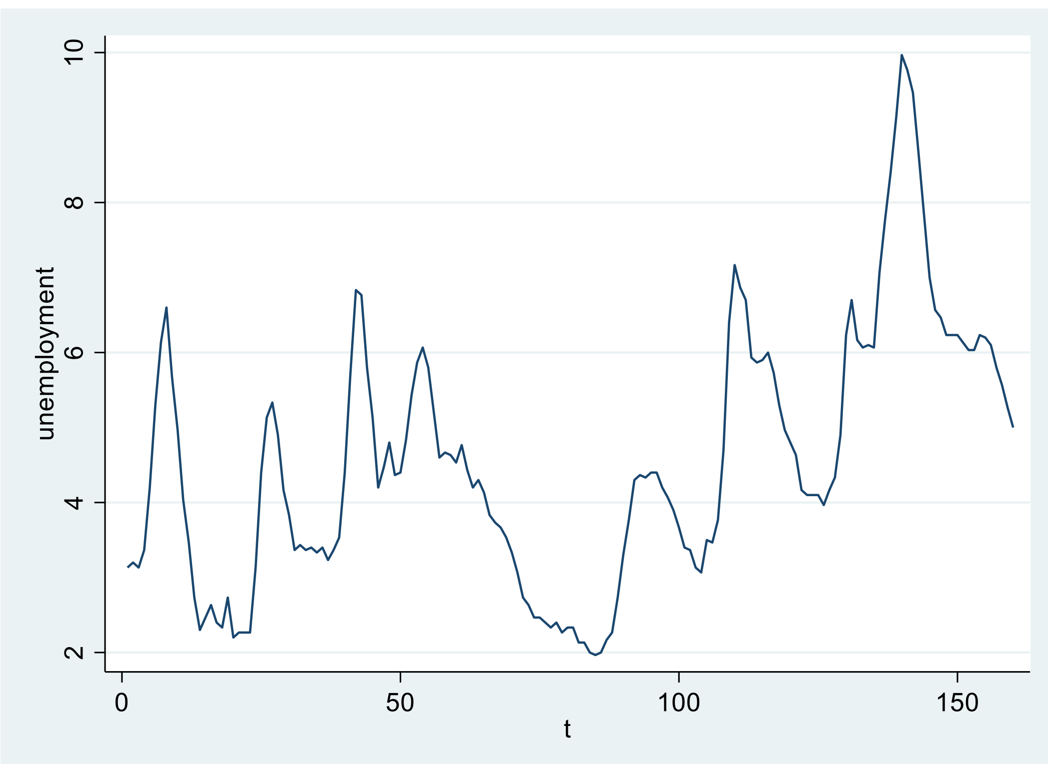
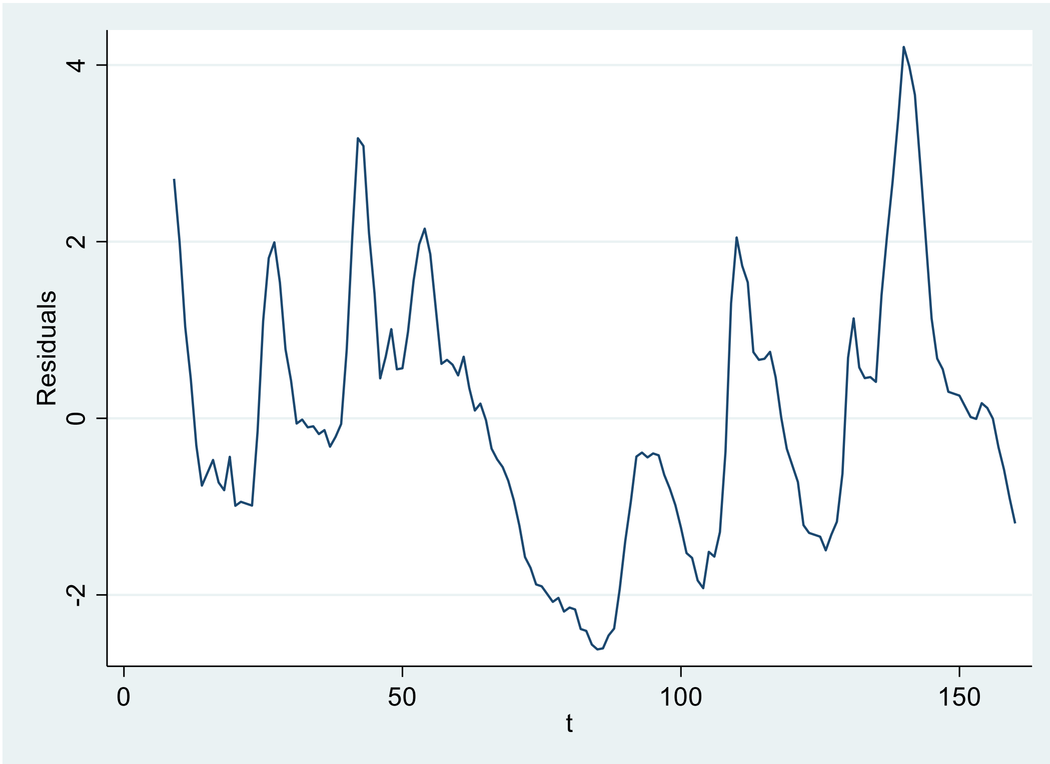
Graph a_1:



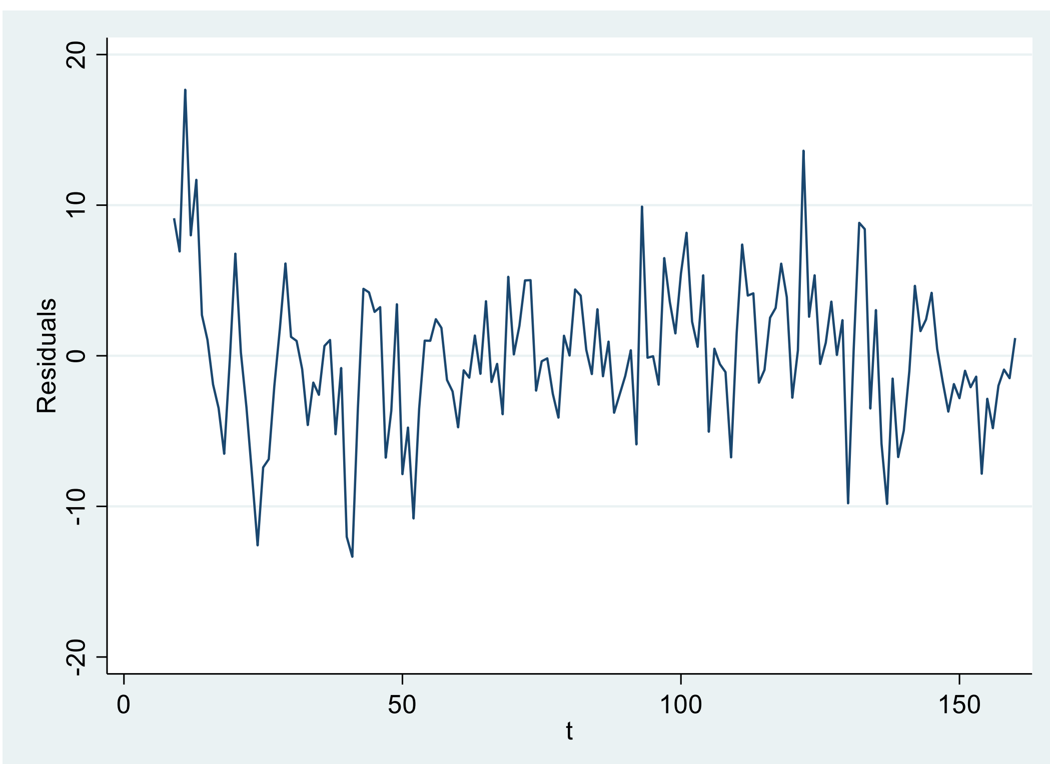
Graph a_2:



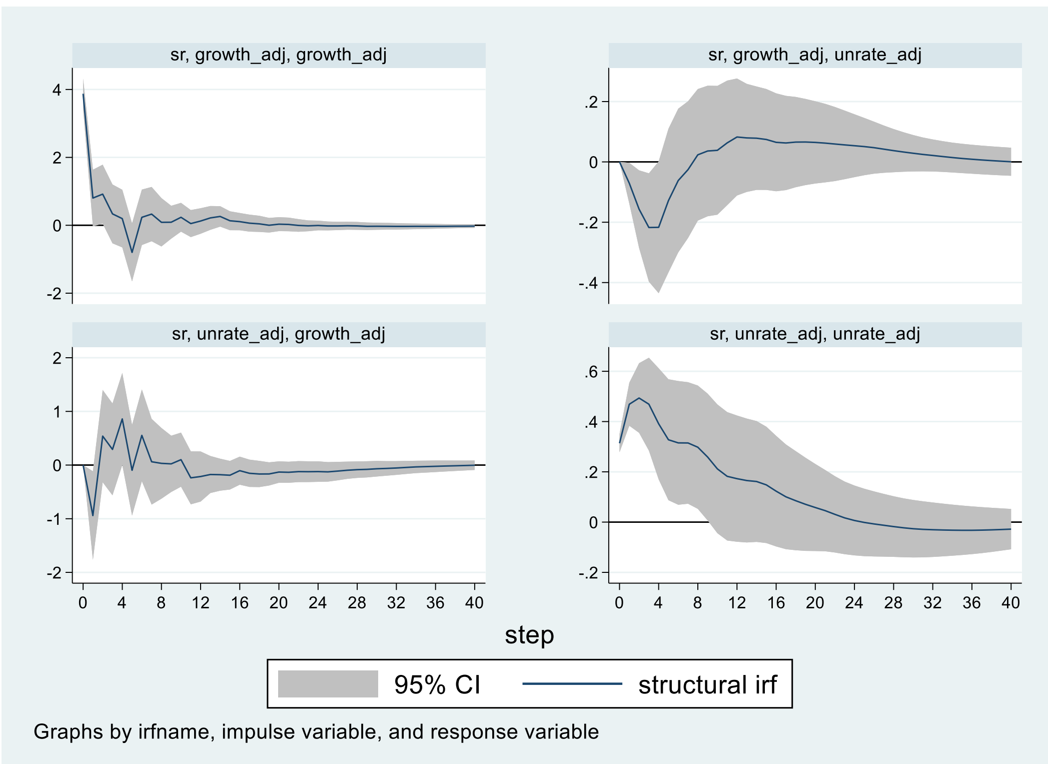
Graph b_1:



Graph b_2:

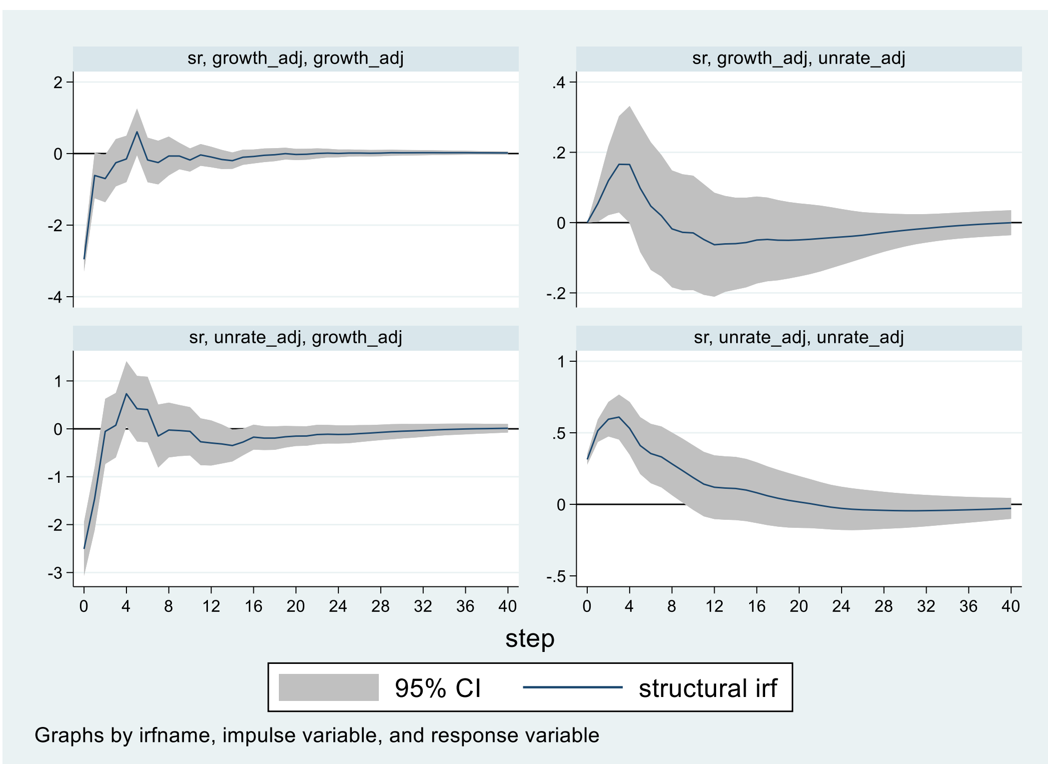


Graph g_1:



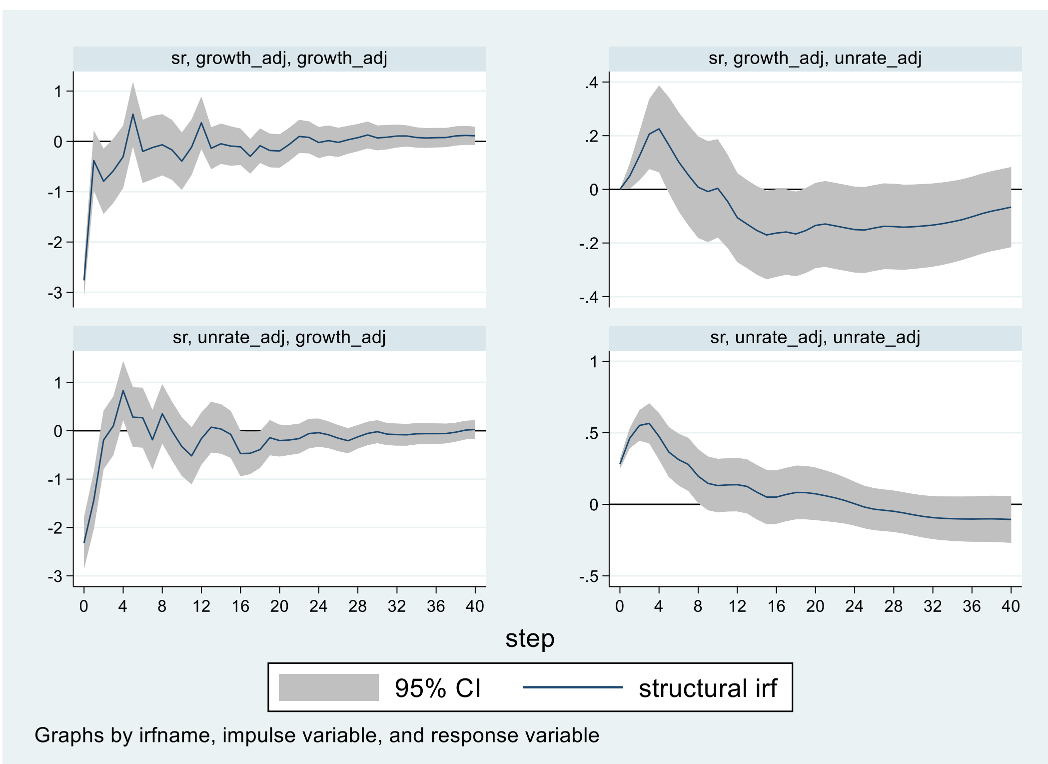
sr, growth_adj, growth_adj
sr, growth_adj, unrate_adj
sr, unrate_adj, growth_adj
sr, unrate_adj, unrate_adj
4
2
0
-2
.2
0
-.2
-.4
2
1
0
-1
-2
.6
.4
.2
0
-.2
0 4 8 12 16 20 24 28 32 36 40
step
95% CI
structural irf
Graphs by irfname, impulse variable, and response variable

Graph k_1:



sr, growth_adj, growth_adj
sr, growth_adj, unrate_adj
sr, unrate_adj, growth_adj
sr, unrate_adj, unrate_adj
step
95% CI
structural irf
Graphs by irfname, impulse variable, and response variable

Graph I_1:



sr, growth_adj, growth_adj
sr, growth_adj, unrate_adj
sr, unrate_adj, growth_adj
sr, unrate_adj, unrate_adj
step
95% CI
structural irf
Graphs by irfname, impulse variable, and response variable

```
-----------------------------------------------------------
      name:  <unnamed>
       log:  C:\Users\Fjolla\Desktop\Time Series\HW6\A6_Q1
> .log
  log type:  text
 opened on:   7 Apr 2021, 16:09:03

.
. use "Q1Data.dta"

.
. destring , replace
A: contains nonnumeric characters; no replace
gnp already numeric; no replace
GD87 already numeric; no replace
unrate already numeric; no replace
year already numeric; no replace
quarter already numeric; no replace
t already numeric; no replace
lngnp already numeric; no replace
laglngnp already numeric; no replace
growth already numeric; no replace

.
.
. *(a)
.
. *Time series command
. tsset t
        time variable:  t, 1 to 160
                delta:  1 unit

. *Graph of series
. tsline gnp

. *The gnp rate increases with time. There seems to be a t
> rend present in the series.
. tsline unrate

. *The unemployment rate shows a persistent and trending p
> attern.
. *In order to remove the trend in the series we can try t
> o apply transformations. For gnp we can try removing the
>  mean in the series, and try to regress unemployment wit
> h a time trend.
.
. *(b)
.
. keep if year >= 1950
(8 observations deleted)

. keep if year <= 1987
(0 observations deleted)
```

```
. quietly regress unrate t

. predict unrate_adj, resid

. generate bp1 = (year<1974)

. generate bp2 = (year>=1974)

. quietly regress growth bp1 bp2, noconstant

. predict growth_adj, resid

.
. *Trends can result in a varying mean over time, whereas
> seasonality can result in a changing variance over time.
>  Both of which lead to the time series being non-station
> ary. Hence, when the authors take the trend off the unem
> ployment series, they are adjusting the data for time tr
> ends. On the other hand, the sample average is an unbias
> ed estimator of the population mean, so it may seem inno
> cuous that for estimating model parameters that do not i
> nvolve the population mean, the data can be demeaned fir
> st. The authors extract separate means from the GNP grow
> th series so as to scale the data.
.
. tsline unrate_adj


.
. *After adjusting the unemployment rate for the time tren
> d we get stationary time series.
.
. tsline growth_adj


.
. *After removing the mean from the gnp growth rate we get
>  stationary time series.
.
. *(e)
. *We want to identify the long-run relationship among var
> iables.  We are interested in identifying the exogenous
> effect of each one of the variables in question. In our
> case it is very likely that the demand shock affects une
> mployment. Hence, unemployment cannot generally be consi
> dered exogenous. Similarly, the supply shock affects out
> put growth, and thus output growth cannot be considered
> exogenous either.  Without sufficient exogeneity on the
> coefficients we want to estimate, we are likely to run i
> nto an identification problem. Hence, additional restric
> tions are necessary in order to get rid of endogeneity.
.
. *(f)
.
. *The two shocks, termed as the "supply" and "demand" sho
> cks, and the long-run response of GNP growth and unemplo
```

```
> yment to those shocks must be zero because these variabl
> es are stationary. The identifying restriction is that a
> n impulse to the “demand” shock has no effect on the lev
> el of GNP in the long run. Hence, the cumulative respons
> e of GNP growth to the demand shock will be constrained
> to equal zero. The supply shock is thus defined in such
> a way that it leads to a long-run change in the level of
>  GNP, and the demand shock is defined such that it does
> not change the long-run level of GNP. We would use the C
> holesky decomposition and assume that the beta inverse(a
> ssuming we are still talking about short-run restriction
> s) is a lower triangular, instead of decomposing the lon
> g run variance-covariance matrix. We would identify our
> model by imposing short-run restrictions. This would the
> n allow us to move from the parameters of a reduced form
>  VAR to the parameters of interest in the structural VAR
> . With a Cholesky decomposition we can reduce our symmet
> ric matrix into a lower triangular matrix. We use the Ch
> olesky decomposition to make certain short-run assumptio
> ns on our variables of interest (output growth and unemp
> loyment). Through it we can assume that the contemporane
> ous effect of one of our variables is equal to zero. Thi
> s, in turn, allows us to identify our model.
.
. *(g)
. *Short-run restrictions
. matrix A2 = (1,0 \ 0,1)

. matrix B2 = (.,0\ 0,.)

. svar unrate_adj growth_adj, lags(1/8) aeq(A2) beq(B2)
Estimating short-run parameters

Iteration 0:   log likelihood = -1216.3135
Iteration 1:   log likelihood = -515.17511
Iteration 2:   log likelihood = -437.61109
Iteration 3:   log likelihood = -436.91343
Iteration 4:   log likelihood =   -436.913
Iteration 5:   log likelihood =   -436.913

Structural vector autoregression

 ( 1)  [/A]1_1 = 1
 ( 2)  [/A]1_2 = 0
 ( 3)  [/A]2_1 = 0
 ( 4)  [/A]2_2 = 1
 ( 5)  [/B]1_2 = 0
 ( 6)  [/B]2_1 = 0

Sample:  17 - 160                                Number of
> obs
>         =        144
Overidentified model                             Log likeli
> hood
```

```
>         =   -436.913

------------------------------------------------------------
> --------------------
             |      Coef.   Std. Err.      z    P>|z|
> [95% Con
>         f. Interval]
-------------+----------------------------------------------
> --------------------
/A           |
         1_1 |          1  (constrained)
         2_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
-------------+----------------------------------------------
> --------------------
/B           |
         1_1 |   .3139804   .0185015    16.97   0.000
> .2777182
>             .3502426
         2_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   3.875465    .228364    16.97   0.000
>  3.42788
>              4.32305
------------------------------------------------------------
> --------------------
LR test of identifying restrictions: chi2(1) = 78.07
>  Prob > chi2
>              = 0.000

. irf create sr, set(srirf1) step(40) replace
(file srirf1.irf created)
(file srirf1.irf now active)
irfname sr not found in srirf1.irf
(file srirf1.irf updated)


.
. irf graph sirf, irf(sr) yline(0,lcolor(black)) xlabel(0(
> 4)40) byopts(yrescale) set(srirf1)
(file srirf1.irf now active)


.
. *The shock on adjusted gnp starts from a high level of a
> djusted gnp and then declines rapidly in the first few p
> eriods and then declines more steadily in the following
> periods. It then levels off to zero later on in time. Th
> e shock of unemployment on the adjusted gnp, on the othe
> r hand, causes adjusted gnp to first decline below zero,
>  then gradually increase and level off at zero. The adju
> sted gnp causes the adjusted unemployment rate to drop i
> nitially and then increase with repeated declines in the
>  first 12 periods, then it levels off at zero. The shock
>  on the adjusted unemployment rate causes the adjusted u
```

```
> nemployment rate to first jump and then steadily decline
>  unitl it gradually adjusts towards zero. The adjustment
>  around zero in the latter, however, is a lot slower and
>  tends to go to slighly negative values.
.
. *(h)
. * The cumulative impulse response function tracks and pl
> ots the accumulation of the impact of the shock to our v
> ariables across time, instead of looking at the impact o
> f the shock at a single point in time.
.
. *(k)
. matrix C = (.,0 \ .,.)

. svar unrate_adj growth_adj, lags(1/8) aeq(C)
Estimating short-run parameters

Iteration 0:   log likelihood = -1321.5769
Iteration 1:   log likelihood = -846.45715
Iteration 2:   log likelihood =  -583.9896
Iteration 3:   log likelihood = -499.67545
Iteration 4:   log likelihood = -455.19187
Iteration 5:   log likelihood = -402.58104
Iteration 6:   log likelihood = -398.31584
Iteration 7:   log likelihood = -397.87754
Iteration 8:   log likelihood = -397.87703
Iteration 9:   log likelihood = -397.87703

Structural vector autoregression

 ( 1)  [/A]1_2 = 0
 ( 2)  [/B]1_1 = 1
 ( 3)  [/B]1_2 = 0
 ( 4)  [/B]2_1 = 0
 ( 5)  [/B]2_2 = 1

Sample:  17 - 160                               Number of
> obs
>         =        144
Exactly identified model                        Log likeli
> hood
>         =   -397.877

------------------------------------------------------------
> --------------------
             |      Coef.   Std. Err.      z    P>|z|
> [95% Con
>         f. Interval]
-------------+----------------------------------------------
> --------------------
/A           |
         1_1 |   3.184912   .1876727    16.97   0.000
>  2.81708
>              3.552744
```

```
         2_1 |  -2.701977   .3095024    -8.73   0.000    -
> 3.308591
>            -2.095364
         1_2 |          0  (constrained)
         2_2 |  -.3383811   .0199393   -16.97   0.000    -
> .3774614
>            -.2993008
-------------+----------------------------------------
> --------------------
/B           |
         1_1 |          1  (constrained)
         2_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
------------------------------------------------------
> --------------------

. irf create sr, set(srirf1) step(40) replace
(file srirf1.irf now active)
(file srirf1.irf updated)

.
. irf graph sirf, irf(sr) yline(0,lcolor(black)) xlabel(0(
> 4)40) byopts(yrescale) set(srirf1)
(file srirf1.irf now active)

.
. *A shock on the adjusted gnp intially causes the respons
> e variable of adjusted gnp to drastically rise, but then
>  very soon it levels off arounf zero. Similarly, the sho
> ck on growth gnp causes the response variable of unemplo
> yment to rise and then level off around zero not long af
> ter. The two graphs are also very similar in shape. Alth
> ough they both start differetnyl from the graphs with sh
> ort-run restrictions, they all level off around zero aft
> er not too long. Similarly, on the right hand side of th
> e graph we have the shock of the unemploymnet rate to th
> e response of the adjusted gnp. The adjusted unemploymen
> t shock causes the adjusted gnp rate to rise above zero
> and then level off around zero as time goes by. Similarl
> y, the shock on unemployment on the response variable of
>  unemployment causes the latter to increase and then go
> back to its mean. The two latter graphs are slightly dif
> ferent from the ones with short-run restrictions at the
> beginning of the time period, but then act similarly wit
> h time going by.
.
.
. *(l)
.
. matrix C = (.,0 \ .,.)

. svar unrate_adj growth_adj, lags(1/12) aeq(C)
Estimating short-run parameters
```

```
Iteration 0:   log likelihood = -1149.6587
Iteration 1:   log likelihood = -551.84421
Iteration 2:   log likelihood = -465.75931
Iteration 3:   log likelihood = -380.13593
Iteration 4:   log likelihood = -364.27817
Iteration 5:   log likelihood = -362.25844
Iteration 6:   log likelihood = -362.24999
Iteration 7:   log likelihood = -362.24999

Structural vector autoregression

 ( 1)  [/A]1_2 = 0
 ( 2)  [/B]1_1 = 1
 ( 3)  [/B]1_2 = 0
 ( 4)  [/B]2_1 = 0
 ( 5)  [/B]2_2 = 1

Sample:  21 - 160                              Number of
> obs
>          =        140
Exactly identified model                       Log likeli
> hood
>          =    -362.25

-----------------------------------------------------------
> --------------------
             |      Coef.   Std. Err.      z    P>|z|
> [95% Con
>          f. Interval]
-------------+---------------------------------------------
> --------------------
/A           |
         1_1 |   3.548429   .2120592    16.73   0.000
> 3.132801
>             3.964057
         2_1 |  -2.978367   .3487394    -8.54   0.000    -
> 3.661884
>            -2.294851
         1_2 |          0  (constrained)
         2_2 |  -.3619939   .0216333   -16.73   0.000    -
> .4043944
>            -.3195935
-------------+---------------------------------------------
> --------------------
/B           |
         1_1 |          1  (constrained)
         2_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
-----------------------------------------------------------
> --------------------

. irf create sr, set(srirf1) step(40) replace
```

```
(file srirf1.irf now active)
(file srirf1.irf updated)

.
. irf graph sirf, irf(sr) yline(0,lcolor(black)) xlabel(0(
> 4)40) byopts(yrescale) set(srirf1)
(file srirf1.irf now active)

.
. *With 12 lags the shape of the graphs remains similar to
>  those with long run restrictions of 8 lags. However, wh
> at we see in this case is more variability on how the sh
> ape of the curve performs with time. In particular, the
> graphs are less likely to completely go back to zero wit
> h time. As such, the confidence bands are wider for the
> graphs with 12 lags than for those with 8 lags.
.
end of do-file

. exit, clear
```

TIME SERIES ASSIGNMENT 6

QUESTION 1

(c) 2x2 Model : Output growth & unemployment

- Using just one lag of the variables for all the theoretical parts :

Output growth : $Y_{1t} = y_{10} + \beta_{12} Y_{2t} + y_{11} Y_{1,t-1} + y_{12} Y_{2,t-1} + \varepsilon_{1t}$

Unemployment : $Y_{2t} = y_{20} + \beta_{21} Y_{1t} + y_{21} Y_{1,t-1} + y_{22} Y_{2,t-1} + \varepsilon_{2t}$

As a system of equations :

$$\begin{bmatrix} 1 & -\beta_{12} \\ -\beta_{21} & 1 \end{bmatrix} \begin{bmatrix} Y_{1t} \\ Y_{2t} \end{bmatrix} = \begin{bmatrix} y_{10} \\ y_{20} \end{bmatrix} + \begin{bmatrix} y_{11} & y_{12} \\ y_{21} & y_{22} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

Matrix notation :

$$B_{2\times2} \, Y_{t\,2\times1} = \Gamma_{0\,2\times1} + \Gamma_{1\,2\times2} \, Y_{t-1\,2\times1} + \varepsilon_{t\,2\times1}$$

(d) REDUCED - FORM VAR

$$Y_t = B^{-1}\Gamma_0 + B^{-1}\Gamma_1 Y_{t-1} + B^{-1}\varepsilon_t$$
$$= C + \Phi Y_{t-1} + e_t$$

Where,

$$e_t = B^{-1}\varepsilon_t$$

$$e_t = B^{-1}\varepsilon_t = \begin{bmatrix} 1 & -\beta_{12} \\ -\beta_{21} & 1 \end{bmatrix}^{-1} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} =$$

$$= \frac{1}{1-\beta_{12}\beta_{21}} \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

$$= \frac{1}{1-\beta_{12}\beta_{21}} \begin{bmatrix} \varepsilon_{1t} + \beta_{12}\varepsilon_{2t} \\ \varepsilon_{2t} + \beta_{21}\varepsilon_{1t} \end{bmatrix} = \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$$

The reduced-form VAR is what allows us to use long-run restrictions to estimate the structural VAR. The reduced form model expresses each variable as a linear function of its own past values, the past values of all other variables being considered and a serially uncorrelated error term. All this being essential for estimating the structural VAR.

Question 1 (i)

Writing the MA form of the structural VAR would relate to the MA form of the reduced form VAR with the B matrix.

Let Ψ_s be the effect of e_t on Y_{t+s}.
This is the effect of $B^{-1}\varepsilon_t$ on Y_{t+s}.
Then, the effect of ε_t on Y_{t+s} is $\Theta_s = \Psi_s B^{-1}$.

If I know the impulse responses for the reduced-form model Ψ_s, and I know the matrix B, I can figure out the impulse responses of the structural model Θ_s.

$$B Y_t = \Gamma_0 + \Gamma_1 Y_{t-1} + \varepsilon_t$$

$$Y_t = B^{-1}\Gamma_0 + B^{-1}\Gamma_1 Y_{t-1} + B^{-1}\varepsilon_t$$

$$Y_t = C_{2\times 1} + \Phi_{2\times 2} Y_{t-1} + e_t$$

Solving for the vector MA in terms of structural shocks:

$$Y_t = \mu + e_t + \Psi_1 e_{t-1} + \Psi e_{t-2} + \dots$$

$$= \mu + B^{-1}\varepsilon_t + \Psi B^{-1} e_{t-1} + \Psi B^{-1}\varepsilon_{t-2} + \dots$$

$$= \mu + \Theta_0 \varepsilon_t + \Theta_1 \varepsilon_{t-1} + \Theta_2 \varepsilon_{t-2} + \dots,$$

where $\Theta_0 = B^{-1}$ and $\Theta_s = \Psi_s B^{-1}$.

In the 2x2 case:

$$\Theta_s = \begin{bmatrix} \theta_{11,s} & \theta_{12,s} \\ \theta_{21,s} & \theta_{22,s} \end{bmatrix} = \Psi B^{-1}$$

$$= \begin{bmatrix} \Psi_{11,s} & \Psi_{12,s} \\ \Psi_{21,s} & \Psi_{22,s} \end{bmatrix} \frac{1}{1-\beta_{12}\beta_{21}} \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix}$$

Cumulative Response Function: $\theta^*_{ij,s} = \sum_{k=0}^{s} \theta_{ij,k}$.

To calculate the structural IRFs we use the cumulative reduced form IRFs and the identified matrix B.

$$\Theta_s = \Psi B^{-1}$$

E.g. $\theta_{21,3} = \dfrac{\partial y_{2,t}}{\partial \varepsilon_{1,t-3}} \left(= \dfrac{\partial y_{2,t+3}}{\partial \varepsilon_{1,t}} \right)$

Cumulative: $\theta^*_{21,3} = \theta_{21,0} + \theta_{21,1} + \theta_{21,2} + \theta_{21,3}$

$$= \sum_{k=0}^{3} \theta_{21,k}$$

The cumulative matrix response then is:

$$\Theta_3^* = \Theta_0 + \Theta_1 + \Theta_2 + \Theta_3 = \sum_{k=0}^{3} \Theta_k, \text{ where}$$

$$\Theta_3^* = \begin{bmatrix} \theta^*_{11,3} & \theta^*_{12,3} \\ \theta^*_{21,3} & \theta^*_{22,3} \end{bmatrix} = \begin{bmatrix} \sum_{k=0}^{3} \theta_{11,k} & \sum_{k=0}^{3} \theta_{12,k} \\ \sum_{k=0}^{3} \theta_{21,k} & \sum_{k=0}^{3} \theta_{22,k} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{1-\beta_{12}\beta_{21}} \sum_{k=0}^{3} \left(\Psi_{11,k} + \beta_{21} \Psi_{21,k} \right) & \frac{1}{1-\beta_{12}\beta_{21}} \sum_{k=0}^{3} \left(\Psi_{12,k} + \beta_{12} \Psi_{11,k} \right) \\ \frac{1}{1-\beta_{12}\beta_{21}} \sum_{k=0}^{3} \left(\Psi_{21,k} + \beta_{21} \Psi_{22,k} \right) & \frac{1}{1-\beta_{12}\beta_{21}} \sum_{k=0}^{3} \left(\Psi_{21,k} + \beta_{12} \Psi_{22,k} \right) \end{bmatrix}$$

$$= \sum_{k=0}^{3} \begin{bmatrix} \Psi_{11,k} & \Psi_{12,k} \\ \Psi_{21,k} & \Psi_{22,k} \end{bmatrix} \frac{1}{1-\beta_{12}\beta_{21}} \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix} = \sum_{k=0}^{3} \Psi_k B^{-1}$$

So, $\Theta_3^{*} = \sum_{k=0}^{3} \Psi_k B^{-1} = \underline{\underline{\Psi_3^{*} B^{-1}}}$.

Question 1 (j) :

Long-Run Structural Variance :

$$V = \Theta^* D \Theta^{*'}$$
$$= \Psi^* B^{-1} D (B^{-1})' \Psi^{*'}$$
$$= \Psi^* \Omega \Psi^{*'}$$

where,

$$\Theta^* = \Psi^* B^{-1}$$

$$\Omega = B^{-1} D (B^{-1})'$$ – is not diagonal as both forecast errors are affected by both shocks.

$$D = \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{pmatrix}$$

Ω, a variance - covariance matrix (positive definite symmetric matrix) depends on B and on a diagonal matrix with positive elements, matrix D.

Our reduced form estimation gives Ψ^* and Ω. Thus, we have $V = \Psi^* \Omega \Psi$. This is the long run variance - covariance matrix.

$$V = T \Lambda T'$$

Λ = is a diagonal matrix with positive elements and T is the lower triangular matrix with 1s on diagonal.

Since Θ^* is a lower triangular,

$$T = \Theta^* \quad \text{and} \quad \Lambda = D$$

Hence, $V = \Theta^* D \, \Theta^{*\prime}$

The reduced-form cumulative and the Cholesky Decomposition gives us the structural cumulative form as long as Θ^* is lower triangular.

given $\Theta^* = \Phi B^{-1}$ we can also compute B^{-1}, which doesn't need to be lower triangular.

Time Series Assignment 6

Fjolle Gjonbalaj

April 9, 2021

Question 2

(a) The Romer and Romes montary policy shocks are exogenous shocks that are obtained by purging the federal funds rate from the endogenous adjustments in the target rate. The estimated residuals are then interpreted as exogenous innovations. They take the nominal interest rate and from that they subtract the estimated beta1 from the equation minus the estimated coefficient 2, will give us a shock that is relatively free from endogeneity. Estimates using this measure indicate that policy has large and statistically significant effects on both output and inflation. Thus, the innovation to the federal funds rate is identified as the monetary policy shock.

(b)

Line 30: This line generates a series which accounts for all 12 months within each year.

Line 32: Here we declare the data to be time series according to our specific monthly variable.

Line 34: Here we drop all observations that are before the third month of the year 1969.

Line 47-51: In these lines we loop the variables fed funds rate, log industrial production, log consumer price index and unemployment, and we quietly generate 90 percent confidence bands for our coefficients.

Line 68-80: Here the variable we are mostly interested in looking in these lines of code is the value of the monetary exogenous shocks. We want to estimate its coefficient as well as it standard error to compute the confidence intervals.We are looping over consecutive values from 0 to 48, and we are looping the variables fed funds rate, log industrial production, log consumer price index and unemployment. Then, we start regressing with Newey-West standard errors and perform local projection IRFs. We then generate a beta coefficient and standard error for our shock variable. Then, we quielty replace our 95 percent confidence interval bands. We are interested in the difference between the value of the future variable and the value of the current variable.

For the fed funds rate variable, for instance, the equation for the local projection IRFs for a 5 period horizon is the following:

$$Y_{ffr,5} = \theta_{ffr,5} * \epsilon_{i,5} + \text{controls} + \epsilon_{i,5}$$

Where controls in this case might be the constant, time trends, lags of $Y_{ffr,5}$ and lags of other variables. Hence,

$$Y_{ffr,5} = \theta_{ffr,5}\epsilon_{i,5} + \mathrm{Y}_{ffr,4} + Y_{ffr,3} + Y_{ffr,2} + Y_{ffr,1} + Y_{lip,4} + Y_{lip,3} + Y_{lip,2} + Y_{lip,1} + Y_{unemp,4} + Y_{unemp,3} + Y_{unemp,2} + Y_{unemp,1} + \ldots + \epsilon_{i,5}$$

Line 95-97: Here we build two-way tables with 90 percent confidence bands for four of our variables; specifying the color of the graphs as well as the thickness of lines for h less than or equal to 48.

Line 99: This line combines graphs for our three variables fed funds rate, log industrial production and log consumer price index, based on the exact specifications on lines 95-97.

(c) In this set of code what we get is the effect of a monetary policy shock on other macroeconomic variables fed funds rate, unemployment, log of CPI and log of industrial production. What I find is that the fed funds rate temporarily jumps up but then gradually declines with time (h) and falls to a value slightly below 0. On the other hand, the log of commodity price index first increases but then it declines drastically and remains below zero for the entire time. Industrial production shows a decline and troughs later in time. The unemployment rate exhibits a slight decline in the first few periods, but then it rises with the monetary policy shock and remains quite steady for a rather long period of time, and then declines slowly in the last few periods. With this monetary policy shock we would not be expecting an immediate effect in the fed funds rate. Hence, the results we get from the graphs are a little shocking with respect to the graph on the upper left-hand corner. Moreover, I would not expect to see unemployment rising from the shock in this monetary policy. However, we need to be a little more cautious here since here since there may be other confounding effects that affect the natural rate of unemployment other than the monetary policy itself. On the other hand, we would expect industrial production to decline after the expansionary monetary policy. The policy to control only inflation might have a reverse effect on the industrial production of the country.

This paper makes the strong assumption that the VAR model specifications are right. That is the variables have the relationships the VAR model specifies. As such, the long-run projection method gives us the same results as the VAR model. Empirically, however, that is not always what we find. While the long-run projection method is more convenient for certain questions and data sets, the VAR method is more convenient for other questions and data sets. What econometricians normally do it they show both results next to each other and compare the statistical differences among the two.