```
------------------------------------------------------------------------
      name:  <unnamed>
       log:  C:\Users\Fjolla\Desktop\Time Series\Assignment 5\A5_Q1.log
  log type:  text
 opened on:  25 Mar 2021, 17:12:52

.
. use "fredgraphs5.dta"

.
. destring , replace
observation_date: contains nonnumeric characters; no replace
ln_Y: all characters numeric; replaced as double
(54 missing values generated)
ffr: all characters numeric; replaced as double
(54 missing values generated)
CPI: all characters numeric; replaced as double
(54 missing values generated)
index: all characters numeric; replaced as int
(54 missing values generated)

.
. *Time series command (index)
. tsset index
        time variable:  index, 1 to 110
                delta:  1 unit

. *Graph your series
. tsline ln_Y

. tsline CPI

. tsline ffr

.
. *The series do not appear to be stationary. In order to transform the d
> ata we can try differencing the series or differencing the log of the s
> eries
.
. *(a)
.
. generate d_P=d.CPI
(55 missing values generated)

. generate ln_P=log(CPI)
(54 missing values generated)

. generate d_lnY=d.ln_Y
(55 missing values generated)

. generate d_ffr=d.ffr
(55 missing values generated)

.
```

```
. *Graph the transformations.
. tsline ln_P

. *The log(CPI) is not stationary. Instead, we use the difference of the
> CPI to get a stationary series.
. tsline d_P

. tsline d_lnY

. tsline d_ffr

.
. *The series look a lot more stationary once they have been transformed.
>
.
. *(b)
.
. ** Run VAR on transformed series
.
. ***Specification 1
. ** Run VAR on transformed series
. *Short Run Restrictions; A as lower triangular
.
. matrix A2 = (1,0,0 \ .,1,0 \ .,.,1)

.
. **Orthogonal shocks
. matrix B2 = (.,0,0 \ 0,.,0 \ 0,0,.)

.
. svar d_P d_lnY d_ffr, lags(1/8) aeq(A2) beq(B2)
Estimating short-run parameters

Iteration 0:   log likelihood = -348.45798
Iteration 1:   log likelihood = -180.27445
Iteration 2:   log likelihood = -107.52696
Iteration 3:   log likelihood =  172.55055
Iteration 4:   log likelihood =  274.36967
Iteration 5:   log likelihood =   301.9345
Iteration 6:   log likelihood =  303.65368
Iteration 7:   log likelihood =  303.69374
Iteration 8:   log likelihood =  303.69375

Structural vector autoregression

 ( 1)  [/A]1_1 = 1
 ( 2)  [/A]1_2 = 0
 ( 3)  [/A]1_3 = 0
 ( 4)  [/A]2_2 = 1
 ( 5)  [/A]2_3 = 0
 ( 6)  [/A]3_3 = 1
 ( 7)  [/B]1_2 = 0
 ( 8)  [/B]1_3 = 0
 ( 9)  [/B]2_1 = 0
```

```
 (10)  [/B]2_3 = 0
 (11)  [/B]3_1 = 0
 (12)  [/B]3_2 = 0

Sample:  10 - 110                              Number of obs     =
>   101
Exactly identified model                       Log likelihood    =   303
> .6938

------------------------------------------------------------------------------
> -----
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Inte
> rval]
-------------+----------------------------------------------------------------
> -----
/A           |
         1_1 |          1  (constrained)
         2_1 |   .0017339   .0009537     1.82   0.069    -.0001353    .00
> 36031
         3_1 |  -.1563201   .0885502    -1.77   0.078    -.3298752    .01
> 72351
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |  -26.73021   9.091532    -2.94   0.003    -44.54929   -8.9
> 11136
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
-------------+----------------------------------------------------------------
> -----
/B           |
         1_1 |   .4370206   .0307487    14.21   0.000     .3767543    .49
> 72869
         2_1 |          0  (constrained)
         3_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   .0041885   .0002947    14.21   0.000     .0036109    .00
> 47661
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   .3827004   .0269267    14.21   0.000      .329925    .43
> 54758
------------------------------------------------------------------------------
> -----

.
. **It makes more sense from a monetary policy perspective to put the fed
> eral funds rate equation last. This is because the federal funds rate i
> s relatively less exogenous than CPI or real GDP per capita. However, w
> e are not certain as to whether CPI or real GDP per capita goes first,
> so we start with one of the two.
.
.
```

```
. *c)
.
. *We assume that matrix A is a lower triangular where the contemporanoeu
> s effects of a12, a13 and a23 are set to equal zero. That is, in the sh
> ort-run they can have no impact on the economy. Our short-run restricti
> ons are that a shock in ffr does not have a short run effect on the rea
> l GDP per capital, nor does it have a short run effect on the inflation
>  rate.
.
. *(d)
.
. *Plot irfs
. irf create var2irf, step(24) set(var2,replace)
(file var2.irf created)
(file var2.irf now active)
(file var2.irf updated)

. irf graph sirf, irf(var2irf) yline(0,lcolor(black))

. //irf graph oirf, irf(var2irf) yline(0,lcolor(black))
.
. *The irfs seem to be taking on an odd shape. In the graph on the upper
> right-hand corner we see that the response of inflation to the shocks o
> f inflation follow a repetitive cycle. This is indicative that inflatio
> n is not stable to its own shocks. This is not what we would usually ex
> pect to happen. Normally we assume that these shocks are a stationary p
> rocess of an AR(1) or AR(2). A similar attitude is observed on the othe
> r two graphs below on the right-hand side.
.
. **On the other hand, we do not observe any graphs on the three graphs o
> n the right-hand side because the graphs do not share the same scale. B
> efore we do further analysis we need to taylor the scale of graphs to a
> ccomodate for the difference in scales.
.
. *In order to improve on the previous graph we can try to use the log of
>  GDP and inflation. Although this method will not give us correct point
>  estimates, the irfs will sucessfully capture the dynamic relationship
> among variables.
.
.
. ***Specification 2
. ** Run VAR on log series; leave the rates as is.
. *Short Run Restrictions; A as lower triangular
.
. //matrix A2 = (1,.,. \ 0,1,. \ 0,0,1)
. //matrix B2 = (.,0,0 \ 0,.,0 \ 0,0,.)
.
. *I put the policy equation last, as I know that makes sense for monetar
> y policy.
. *I am not very sure if I should put P or Y first, I start with one of t
> he two, CPI.
. svar ln_P ln_Y ffr, lags(1/8) aeq(A2) beq(B2)
Estimating short-run parameters
```

```
Iteration 0:   log likelihood = -326.74714
Iteration 1:   log likelihood =   223.0555
Iteration 2:   log likelihood =  762.29023
Iteration 3:   log likelihood =  817.47859
Iteration 4:   log likelihood =  822.09133
Iteration 5:   log likelihood =  822.31679
Iteration 6:   log likelihood =  822.31718
Iteration 7:   log likelihood =  822.31718

Structural vector autoregression

 ( 1)  [/A]1_1 = 1
 ( 2)  [/A]1_2 = 0
 ( 3)  [/A]1_3 = 0
 ( 4)  [/A]2_2 = 1
 ( 5)  [/A]2_3 = 0
 ( 6)  [/A]3_3 = 1
 ( 7)  [/B]1_2 = 0
 ( 8)  [/B]1_3 = 0
 ( 9)  [/B]2_1 = 0
 (10)  [/B]2_3 = 0
 (11)  [/B]3_1 = 0
 (12)  [/B]3_2 = 0

Sample:  9 - 110                                Number of obs     =
>   102
Exactly identified model                        Log likelihood    =   822
> .3172

-------------------------------------------------------------------------
> -----
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Inte
> rval]
-------------+-----------------------------------------------------------
> -----
/A           |
         1_1 |          1  (constrained)
         2_1 |   .2614852   .1547921     1.69   0.091    -.0419017    .56
> 48721
         3_1 |  -10.35325   13.75088    -0.75   0.452    -37.30447    16.
> 59797
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |  -22.17351   8.675407    -2.56   0.011    -39.17699   -5.1
> 70025
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
-------------+-----------------------------------------------------------
> -----
/B           |
         1_1 |   .0027529   .0001927    14.28   0.000     .0023751    .00
> 31306
         2_1 |          0  (constrained)
```

```
         3_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   .0043036   .0003013    14.28   0.000      .003713    .00
> 48942
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   .3770695   .0264001    14.28   0.000     .3253261    .42
> 88128
------------------------------------------------------------------------
> -----

.
. *Plot irfs
. irf create var2irf, step(24) set(var2,replace)
(file var2.irf created)
(file var2.irf now active)
(file var2.irf updated)

. irf graph sirf, irf(var2irf) yline(0,lcolor(black))

.
. **The responses in this graph on the left-hand side now have improved s
> ince we get an effect of inflation on the shocks of inflation that dies
>  out with time. This is what we would also expect to see. On the other
> hand, however, we are not able to see the other graphs due to the scale
>  being too large. Again, we need to tailor the scale and run the graphs
>  one-by-one in order to see the graph responses.
.
. *What we observe in these graphs is that an output shock increases the
> federal funds rate. An inflation shock mildly decreases the federal fun
> ds rate. However, in the latter we do not observe a strong effect.  An
> inflation shock results in subsequant increase in inflation which then
> slowly decreases and dies out.
.
. irf graph sirf, impulse(ln_Y) response(ln_Y)

. *This is the response of shocks of output on output. Here the shock see
> ms to be pretty persistent. This is because it still remains positive a
> fter 24 quarters.
.
. irf graph sirf, impulse(ln_Y) response(ln_P)


.
. **In this graph we observe the shock in output on inflation. We start o
> ut at zero due to our assumption that demand shocks have no contemporan
> oeus effect. From that point onwards we observe a positive lagged effec
> t on output. It seems that the effect does not die out quickly. Hence,
> inflation has a lagged effect on output.
.
. irf graph sirf, impulse(ln_P) response(ln_Y)


.
. *This is the response of inflation to the shocks of output. Shocks of o
```

```
> utput seem to decrease the inflation rate. With time, however, the infl
> ation rate goes back to its mean.
.
. irf graph sirf, impulse(ln_P) response(ln_P)

. *Shocks of inflation appear to be very persistent. We can repeat this p
> rocess for more periods to see if the graph responds any different.
.
. irf create var2irf, step(50) set(var2,replace)
(file var2.irf created)
(file var2.irf now active)
(file var2.irf updated)

. irf graph sirf, impulse(ln_P) response(ln_P)


.
. *If we repeat the process for enough periods we can see that the effect
>  of the shock eventually dies out.
.
. irf graph sirf, impulse(ffr) response(ln_Y)

. irf graph sirf, impulse(ffr) response(ln_P)


.
. svar ln_P ln_Y ffr, lags(1/8) aeq(A2) beq(B2)
Estimating short-run parameters

Iteration 0:   log likelihood = -326.74714
Iteration 1:   log likelihood =   223.0555
Iteration 2:   log likelihood =  762.29023
Iteration 3:   log likelihood =  817.47859
Iteration 4:   log likelihood =  822.09133
Iteration 5:   log likelihood =  822.31679
Iteration 6:   log likelihood =  822.31718
Iteration 7:   log likelihood =  822.31718

Structural vector autoregression

 ( 1)  [/A]1_1 = 1
 ( 2)  [/A]1_2 = 0
 ( 3)  [/A]1_3 = 0
 ( 4)  [/A]2_2 = 1
 ( 5)  [/A]2_3 = 0
 ( 6)  [/A]3_3 = 1
 ( 7)  [/B]1_2 = 0
 ( 8)  [/B]1_3 = 0
 ( 9)  [/B]2_1 = 0
 (10)  [/B]2_3 = 0
 (11)  [/B]3_1 = 0
 (12)  [/B]3_2 = 0

Sample:  9 - 110                                Number of obs     =
>   102
Exactly identified model                        Log likelihood    =   822
```

```
> .3172

------------------------------------------------------------------------------
> -----
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Inte
> rval]
-------------+----------------------------------------------------------------
> -----
/A           |
         1_1 |          1  (constrained)
         2_1 |   .2614852   .1547921     1.69   0.091    -.0419017    .56
> 48721
         3_1 |  -10.35325   13.75088    -0.75   0.452    -37.30447    16.
> 59797
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |  -22.17351   8.675407    -2.56   0.011    -39.17699   -5.1
> 70025
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
-------------+----------------------------------------------------------------
> -----
/B           |
         1_1 |   .0027529   .0001927    14.28   0.000     .0023751    .00
> 31306
         2_1 |          0  (constrained)
         3_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   .0043036   .0003013    14.28   0.000      .003713    .00
> 48942
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   .3770695   .0264001    14.28   0.000     .3253261    .42
> 88128
------------------------------------------------------------------------------
> -----

. irf create svar1, set(myGraph1, replace)
(file myGraph1.irf created)
(file myGraph1.irf now active)
(file myGraph1.irf updated)

. irf cgraph (svar1 ln_Y ln_Y sirf) (svar1 ln_Y ln_P sirf) (svar1 ln_Y ff
> r sirf) ///
>             (svar1 ln_P ln_Y sirf) (svar1 ln_P ln_P sirf) (svar1 ln_P ff
> r sirf) ///
>                     (svar1 ffr ln_Y sirf) (svar1 ffr ln_P sirf) (svar1 f
> fr ffr sirf), ///
>                     title ("Irfs of VAR Model 2", size(vsmall))

.
.
```

```
. *(e)
.
. *The part that are due to assumptions we have made are cells a13 and a2
> 3. That is, we've assumed that ffr does not have a short-run effect on
> real GDP per capital and inflation level.
.
. *(f)
.
. *We are able to observe insignificant effects of ffr on output growth a
> nd a mild price increase as ffr increases. It appears that the shock on
>  real GDP per capita doesn't have any persistent effects on any of the
> variables. The inflation shock, on the other hand, has a persistent eff
> ect on inflation and possibly on ffr, but not on real GDP per capita. T
> he shock of ffr has somewhat of a persistent effect on each one of the
> three variables, but the persistency does not apper to be largely signi
> ficant.
.
.
. *(g)
.
. *I check a different ordering.
.
.
. svar ln_Y ln_P ffr, lags(1/8) aeq(A2) beq(B2)
Estimating short-run parameters

Iteration 0:   log likelihood = -326.74681
Iteration 1:   log likelihood =  222.91504
Iteration 2:   log likelihood =  731.38945
Iteration 3:   log likelihood =  793.88201
Iteration 4:   log likelihood =  821.32662
Iteration 5:   log likelihood =  822.31222
Iteration 6:   log likelihood =  822.31718
Iteration 7:   log likelihood =  822.31718

Structural vector autoregression

 ( 1)  [/A]1_1 = 1
 ( 2)  [/A]1_2 = 0
 ( 3)  [/A]1_3 = 0
 ( 4)  [/A]2_2 = 1
 ( 5)  [/A]2_3 = 0
 ( 6)  [/A]3_3 = 1
 ( 7)  [/B]1_2 = 0
 ( 8)  [/B]1_3 = 0
 ( 9)  [/B]2_1 = 0
 (10)  [/B]2_3 = 0
 (11)  [/B]3_1 = 0
 (12)  [/B]3_2 = 0

Sample:  9 - 110                                Number of obs     =
>   102
Exactly identified model                        Log likelihood    =   822
> .3172
```

```
------------------------------------------------------------------------------
> -----
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Inte
> rval]
-------------+----------------------------------------------------------------
> -----
/A           |
         1_1 |          1  (constrained)
         2_1 |   .1040797   .0616123     1.69   0.091    -.0166783    .22
> 48377
         3_1 |  -22.17351   8.675407    -2.56   0.011    -39.17699   -5.1
> 70025
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |  -10.35325   13.75088    -0.75   0.452    -37.30447    16.
> 59797
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
-------------+----------------------------------------------------------------
> -----
/B           |
         1_1 |   .0043634   .0003055    14.28   0.000     .0037646    .00
> 49621
         2_1 |          0  (constrained)
         3_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   .0027151   .0001901    14.28   0.000     .0023425    .00
> 30877
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   .3770695   .0264001    14.28   0.000     .3253261    .42
> 88128
------------------------------------------------------------------------------
> -----

. irf create svar1, set(myGraph1, replace)
(file myGraph1.irf created)
(file myGraph1.irf now active)
(file myGraph1.irf updated)

. irf cgraph (svar1 ln_Y ln_Y sirf) (svar1 ln_Y ln_P sirf) (svar1 ln_Y ff
> r sirf) ///
>            (svar1 ln_P ln_Y sirf) (svar1 ln_P ln_P sirf) (svar1 ln_P ff
> r sirf) ///
>                    (svar1 ffr ln_Y sirf) (svar1 ffr ln_P sirf) (svar1 f
> fr ffr sirf), ///
>                    title ("Irfs of VAR Model 2", size(vsmall))

.
.
.                    svar d_P d_lnY  ffr, lags(1/8) aeq(A2) beq(B2)
```

```
Estimating short-run parameters

Iteration 0:   log likelihood = -347.56618
Iteration 1:   log likelihood = -177.00223
Iteration 2:   log likelihood = -103.48651
Iteration 3:   log likelihood =  176.73278
Iteration 4:   log likelihood =  279.11155
Iteration 5:   log likelihood =  308.33435
Iteration 6:   log likelihood =  310.85409
Iteration 7:   log likelihood =  310.93484
Iteration 8:   log likelihood =  310.93487
Iteration 9:   log likelihood =  310.93487

Structural vector autoregression

 ( 1)  [/A]1_1 = 1
 ( 2)  [/A]1_2 = 0
 ( 3)  [/A]1_3 = 0
 ( 4)  [/A]2_2 = 1
 ( 5)  [/A]2_3 = 0
 ( 6)  [/A]3_3 = 1
 ( 7)  [/B]1_2 = 0
 ( 8)  [/B]1_3 = 0
 ( 9)  [/B]2_1 = 0
 (10)  [/B]2_3 = 0
 (11)  [/B]3_1 = 0
 (12)  [/B]3_2 = 0

Sample:  10 - 110                               Number of obs     =
>   101
Exactly identified model                        Log likelihood    =   310
> .9349

------------------------------------------------------------------------
> -----
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Inte
> rval]
-------------+----------------------------------------------------------
> -----
/A           |
         1_1 |          1  (constrained)
         2_1 |   .0016961   .0009529     1.78   0.075    -.0001715    .00
> 35636
         3_1 |   -.141456   .0827604    -1.71   0.087    -.3036634    .02
> 07514
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |  -32.13629   8.509979    -3.78   0.000    -48.81554   -15.
> 45704
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
-------------+----------------------------------------------------------
> -----
```

```
/B           |
        1_1 |   .4364564    .030709    14.21   0.000     .3762679    .49
> 66448
        2_1 |          0  (constrained)
        3_1 |          0  (constrained)
        1_2 |          0  (constrained)
        2_2 |   .0041795   .0002941    14.21   0.000     .0036032    .00
> 47559
        3_2 |          0  (constrained)
        1_3 |          0  (constrained)
        2_3 |          0  (constrained)
        3_3 |   .3574513   .0251502    14.21   0.000     .3081579    .40
> 67448
--------------------------------------------------------------------------
> -----

. irf create svar1, set(myGraph1, replace)
(file myGraph1.irf created)
(file myGraph1.irf now active)
(file myGraph1.irf updated)

. irf cgraph (svar1 d_lnY d_lnY sirf) (svar1 d_lnY d_P sirf) (svar1 d_lnY
>  ffr sirf) ///
>           (svar1 d_P d_lnY sirf) (svar1 d_P d_P sirf) (svar1 d_P ffr s
> irf) ///
>                   (svar1 ffr d_lnY sirf) (svar1 ffr d_P sirf) (svar1 f
> fr ffr sirf), ///
>                   title ("Irfs of VAR Model 2", size(vsmall))

.
.
. svar d_lnY d_P ffr, lags(1/8) aeq(A2) beq(B2)
Estimating short-run parameters

Iteration 0:   log likelihood = -339.78556
Iteration 1:   log likelihood =  -41.52817
Iteration 2:   log likelihood = -30.109624
Iteration 3:   log likelihood =  155.29251
Iteration 4:   log likelihood =  293.47389
Iteration 5:   log likelihood =  310.70815
Iteration 6:   log likelihood =   310.9346
Iteration 7:   log likelihood =  310.93487
Iteration 8:   log likelihood =  310.93487

Structural vector autoregression

 ( 1)  [/A]1_1 = 1
 ( 2)  [/A]1_2 = 0
 ( 3)  [/A]1_3 = 0
 ( 4)  [/A]2_2 = 1
 ( 5)  [/A]2_3 = 0
 ( 6)  [/A]3_3 = 1
 ( 7)  [/B]1_2 = 0
 ( 8)  [/B]1_3 = 0
```

```
 ( 9)  [/B]2_1 = 0
 (10)  [/B]2_3 = 0
 (11)  [/B]3_1 = 0
 (12)  [/B]3_2 = 0

Sample:  10 - 110                               Number of obs     =
>   101
Exactly identified model                        Log likelihood    =   310
> .9349

------------------------------------------------------------------------------
> -----
             |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Inte
> rval]
-------------+----------------------------------------------------------------
> -----
/A           |
         1_1 |          1  (constrained)
         2_1 |   17.93303   10.07484     1.78   0.075     -1.81329    37.
> 67935
         3_1 |  -32.13629   8.509979    -3.78   0.000    -48.81554   -15.
> 45704
         1_2 |          0  (constrained)
         2_2 |          1  (constrained)
         3_2 |   -.141456   .0827604    -1.71   0.087    -.3036634    .02
> 07514
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |          1  (constrained)
-------------+----------------------------------------------------------------
> -----
/B           |
         1_1 |   .0042446   .0002986    14.21   0.000     .0036592    .00
> 48299
         2_1 |          0  (constrained)
         3_1 |          0  (constrained)
         1_2 |          0  (constrained)
         2_2 |   .4297676   .0302383    14.21   0.000     .3705015    .48
> 90336
         3_2 |          0  (constrained)
         1_3 |          0  (constrained)
         2_3 |          0  (constrained)
         3_3 |   .3574513   .0251502    14.21   0.000     .3081579    .40
> 67448
------------------------------------------------------------------------------
> -----

. irf create svar1, set(myGraph1, replace)
(file myGraph1.irf created)
(file myGraph1.irf now active)
(file myGraph1.irf updated)

. irf cgraph (svar1 d_lnY d_lnY sirf) (svar1 d_lnY d_P sirf) (svar1 d_lnY
>  ffr sirf) ///
```

```
>             (svar1 d_P d_lnY sirf) (svar1 d_P d_P sirf) (svar1 d_P ffr s
> irf) ///
>                     (svar1 ffr d_lnY sirf) (svar1 ffr d_P sirf) (svar1 f
> fr ffr sirf), ///
>                     title ("Irfs of VAR Model 2", size(vsmall))

.
. *Although we change the ordering of the variables, our short run restri
> ctions remain the same. Without differencing our first two variables, t
> he estimates and the graphs remain identical, regardless of whether we
> set real GDP per capita or inflation to be our first variable. On the o
> ther hand, when we difference the variables, we get back the persistenc
> y in most of our variables. The short-run restrictions, thus, do not ch
> ange with regards to the previous model with a different ordering. The
> results do change, however, when we difference the variables.
.
. *(h)
.
. ** When I run more specifications, such as changing the ordering of CPI
>  and real GDP per capita. What we observe is that regardless of whether
>  we put CPI or real GDP per capita first, our graph results remain unch
> anged. Hence, the estimation results remain the same regardless of the
> ordering of the two variables. On the other hand, the difference on our
>  response and shock variables gives us the zig-zag shape of the respons
> e of the variables to the shocks of the other variable. This is an indi
> cation that the difference method is not the right method to use. We wo
> uld not normally expect to see inflation having a repetitive pattern on
>  the shocks of inflation, for instance. On the other hand, the third co
> lumn with ffr as a response variable, remains unchanged regardless of w
> hether or not we transform our first two variables or change their orde
> r.
.
. irf graph fevd

. *This graph shows that the response of the variables attribute almost 1
> 00% of their variation to the shocks of that same variable. This is wit
> nessed in the diagonal plots of our variables. On the other hand, a sho
> ck in inflation causes GDP to gradually increase, while the ffr rate se
> ems to remain rather stable and unchanged. On a similar note, a shock o
> n GDP does not seem to have any significant effect on inflation, while
> it does seem to have an increasing effect on ffr. It does so at a decre
> asing rate, howeevr. A shock on ffr does not seem to have any major eff
> ects neither on inflation nor on GDP, according to this graph.
.
.
. irf table fevd

                            Results from svar1

+--------------------------------------------+
|        |    (1)         (1)         (1)     |
|  step  |   fevd        Lower       Upper    |
|--------+-----------------------------------|
|0       | 0           0           0          |
```

1	1	1	1
2	.993335	.964104	1.02257
3	.97212	.908372	1.03587
4	.944649	.846069	1.04323
5	.904887	.784232	1.02554
6	.89476	.763072	1.02645
7	.87384	.728489	1.01919
8	.853508	.704502	1.00251

step	(2) fevd	(2) Lower	(2) Upper
0	0	0	0
1	.030416	-.03554	.096371
2	.043223	-.026374	.11282
3	.084913	-.010219	.180044
4	.076669	-.010154	.163493
5	.104809	-.004214	.213833
6	.102091	-.005848	.21003
7	.103762	-.004866	.21239
8	.09989	-.004767	.204547

step	(3) fevd	(3) Lower	(3) Upper
0	0	0	0
1	.107196	-.006819	.221211
2	.207387	.051916	.362857
3	.297213	.10846	.485966
4	.368161	.154177	.582145
5	.414325	.180741	.647909
6	.452078	.202979	.701177
7	.456867	.191197	.722537
8	.459698	.178765	.740631

step	(4) fevd	(4) Lower	(4) Upper
0	0	0	0
1	0	0	0
2	.003951	-.019602	.027503
3	.021228	-.034742	.077198
4	.042913	-.045587	.131413
5	.068543	-.045026	.182112
6	.077468	-.046832	.201767
7	.096227	-.040273	.232727
8	.115095	-.028203	.258393

step	(5) fevd	(5) Lower	(5) Upper
0	0	0	0
1	.969584	.903629	1.03554
2	.929197	.840903	1.01749
3	.882303	.767669	.996937
4	.893307	.789514	.997099
5	.865711	.743258	.988164
6	.868682	.74715	.990215
7	.856945	.731868	.982022
8	.859963	.735148	.984779

step	(6) fevd	(6) Lower	(6) Upper
0	0	0	0
1	.025099	-.031826	.082023
2	.045684	-.034256	.125623
3	.064562	-.040312	.169436
4	.069354	-.049196	.187904
5	.060572	-.056782	.177925
6	.048301	-.052834	.149436
7	.041518	-.046087	.129123
8	.037737	-.039956	.11543

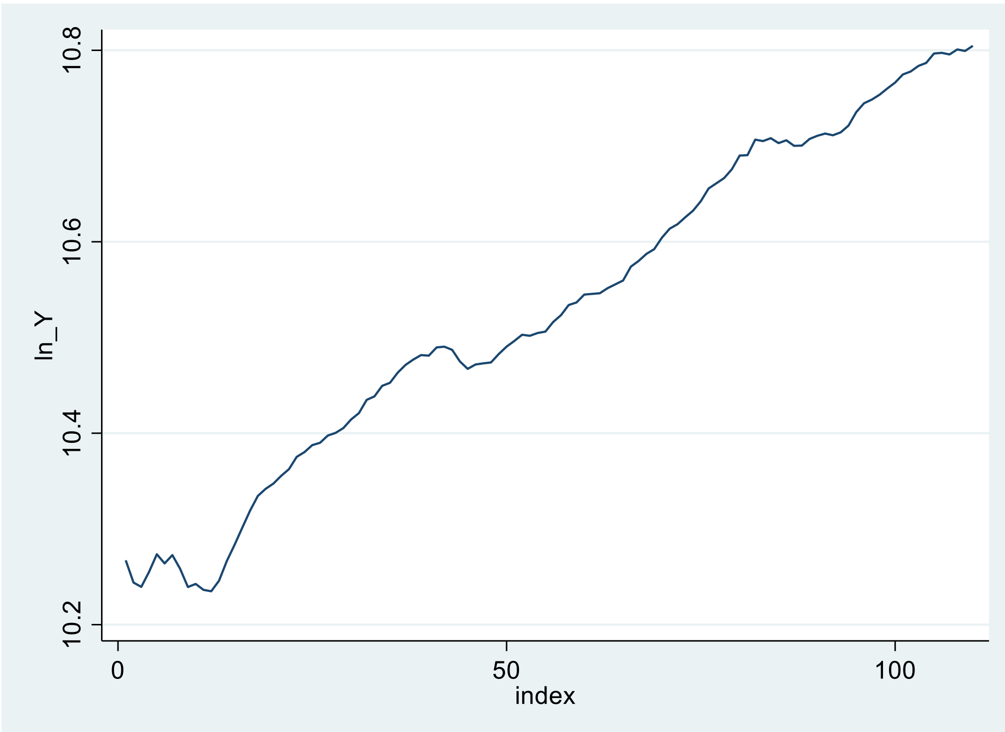
step	(7) fevd	(7) Lower	(7) Upper
0	0	0	0
1	0	0	0
2	.002714	-.014931	.020359
3	.006652	-.022733	.036037
4	.012438	-.034191	.059067
5	.02657	-.018029	.071169
6	.027772	-.019179	.074723
7	.029932	-.026084	.085949
8	.031397	-.01993	.082723

step	(8) fevd	(8) Lower	(8) Upper
0	0	0	0
1	0	0	0
2	.02758	-.027418	.082578
3	.032784	-.029988	.095556

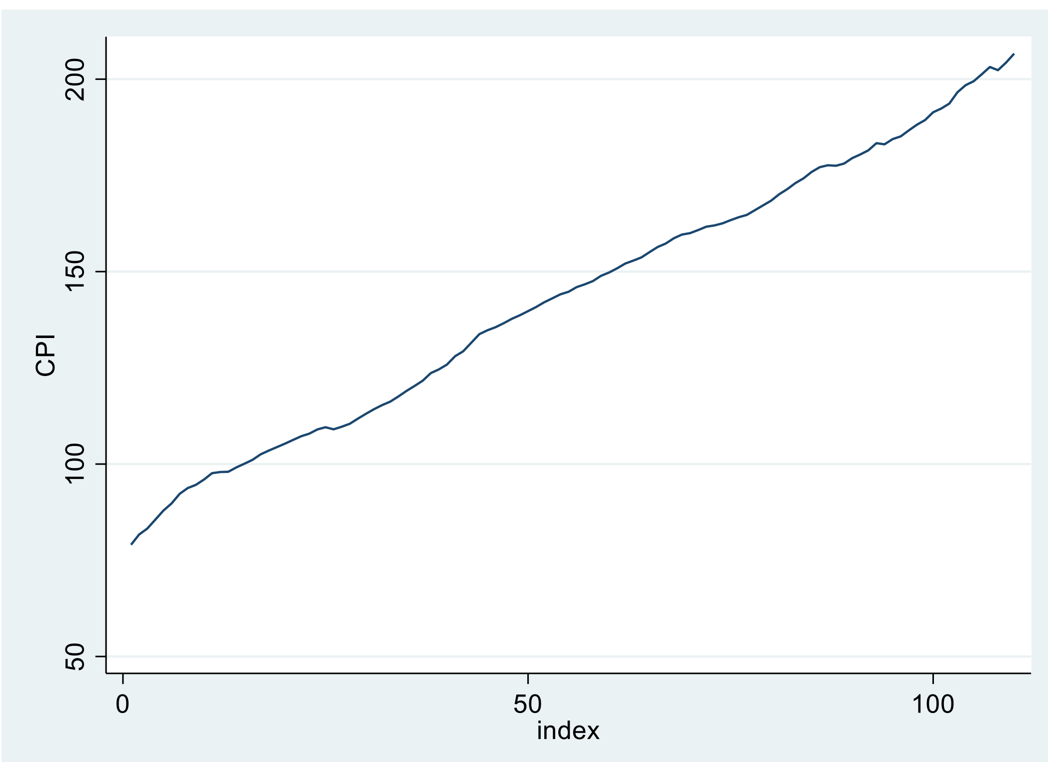
```
|4       | .030024     -.024079    .084127   |
|5       | .02948      -.025119    .084079   |
|6       | .029227     -.02484     .083293   |
|7       | .039293     -.013696    .092282   |
|8       | .040146     -.014683    .094976   |
+----------------------------------------------+

+----------------------------------------------+
|        |   (9)         (9)         (9)       |
|  step  |   fevd        Lower       Upper     |
|--------+-------------------------------------|
|0       | 0           0           0           |
|1       | .867705     .744605     .990806     |
|2       | .74693      .583818     .910041     |
|3       | .638225     .444811     .83164      |
|4       | .562485     .347752     .777218     |
|5       | .525103     .292528     .757679     |
|6       | .499621     .252413     .74683      |
|7       | .501615     .237132     .766099     |
|8       | .502565     .222788     .782343     |
+----------------------------------------------+
95% lower and upper bounds reported
(1) irfname = svar1, impulse = d_lnY, and response = d_lnY
(2) irfname = svar1, impulse = d_lnY, and response = d_P
(3) irfname = svar1, impulse = d_lnY, and response = ffr
(4) irfname = svar1, impulse = d_P, and response = d_lnY
(5) irfname = svar1, impulse = d_P, and response = d_P
(6) irfname = svar1, impulse = d_P, and response = ffr
(7) irfname = svar1, impulse = ffr, and response = d_lnY
(8) irfname = svar1, impulse = ffr, and response = d_P
(9) irfname = svar1, impulse = ffr, and response = ffr

.
. *FEVDs is another tool for interpreting how the orthogonalized innovati
> ons affect the K variables over time. The FEVD from j to i gives the fr
> action of the s-step forecast-error variance of variable i that can be
> attributed to the jth orthogonalized innovation.
.
end of do-file

. exit, clear
```

(A)

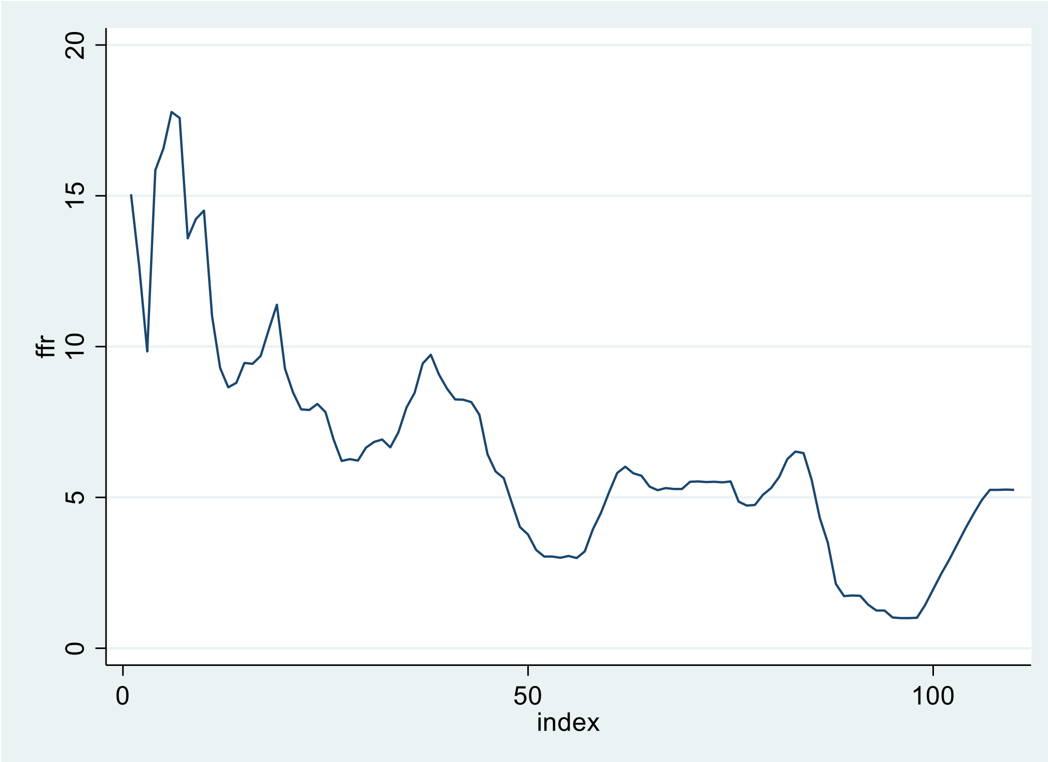
GRAPH 1



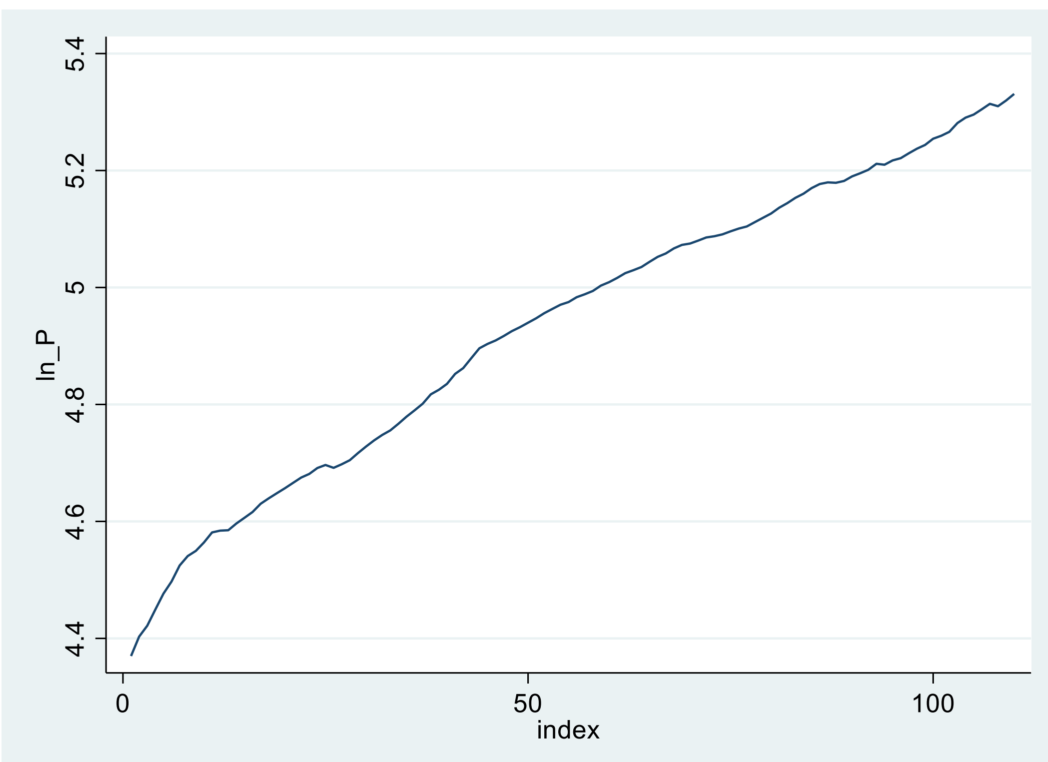
GRAPH 2



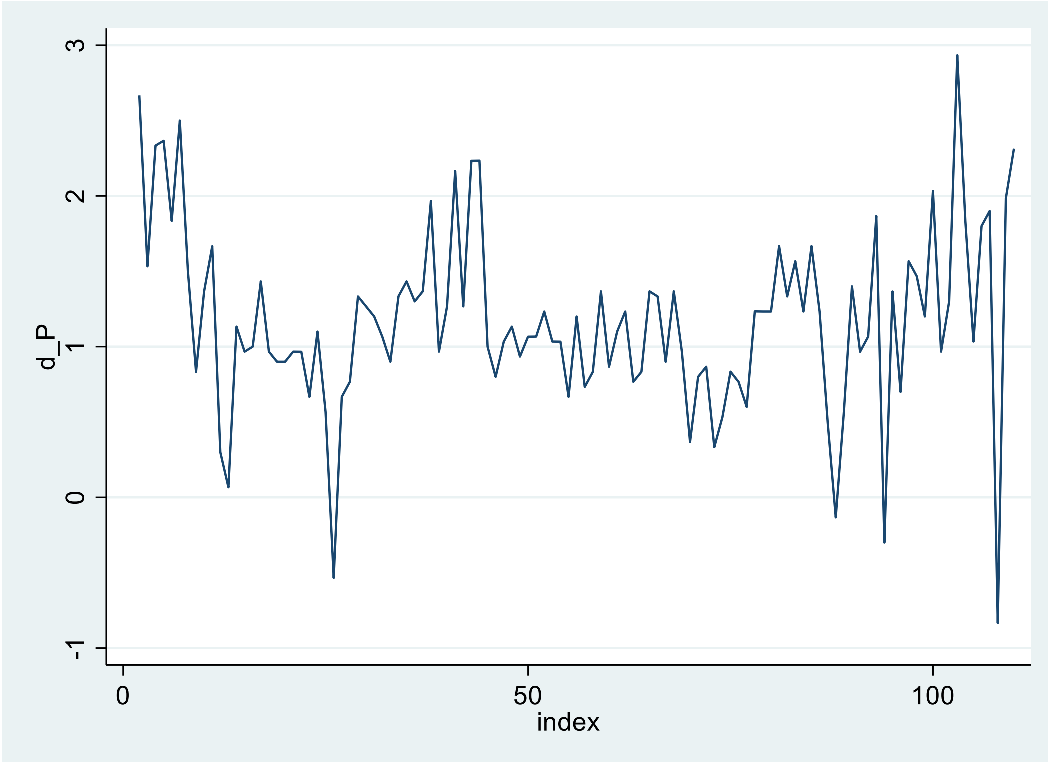
GRAPH 3



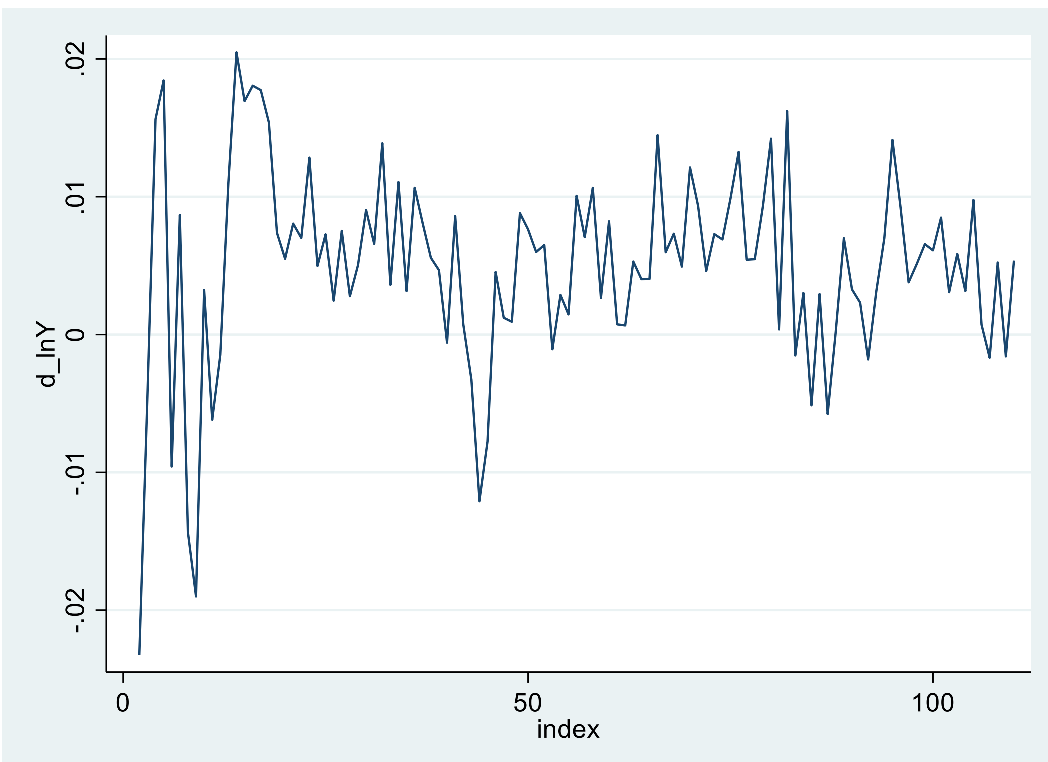
GRAPH 4



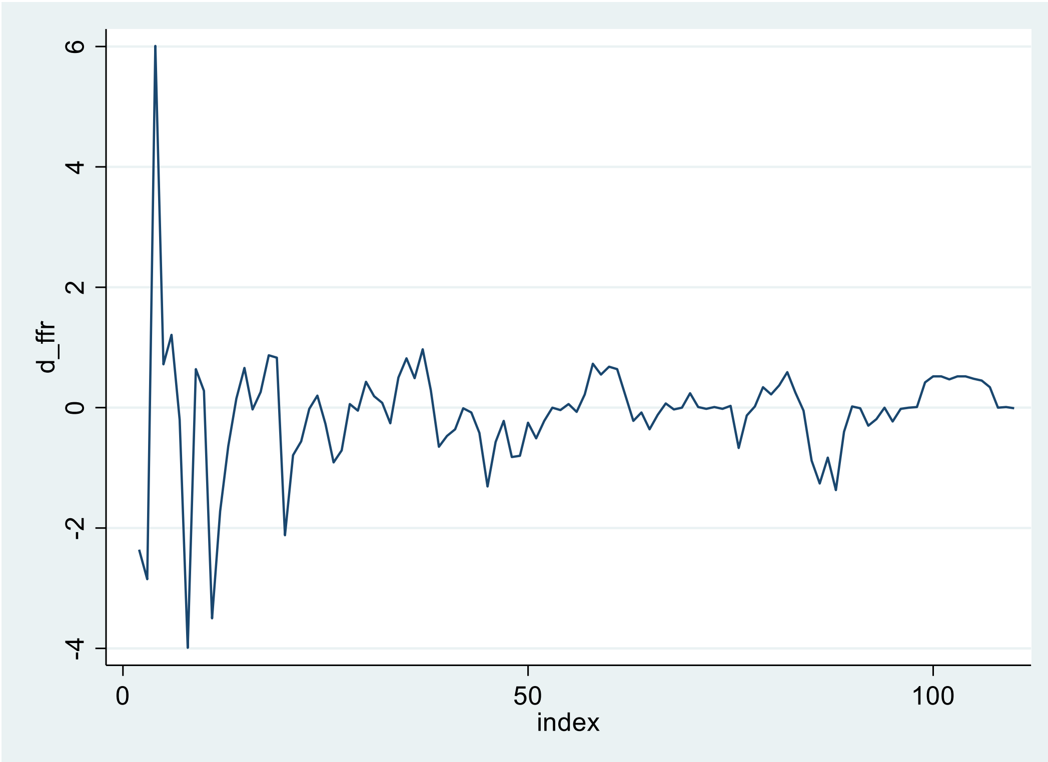
GRAPH 5



GRAPH 6

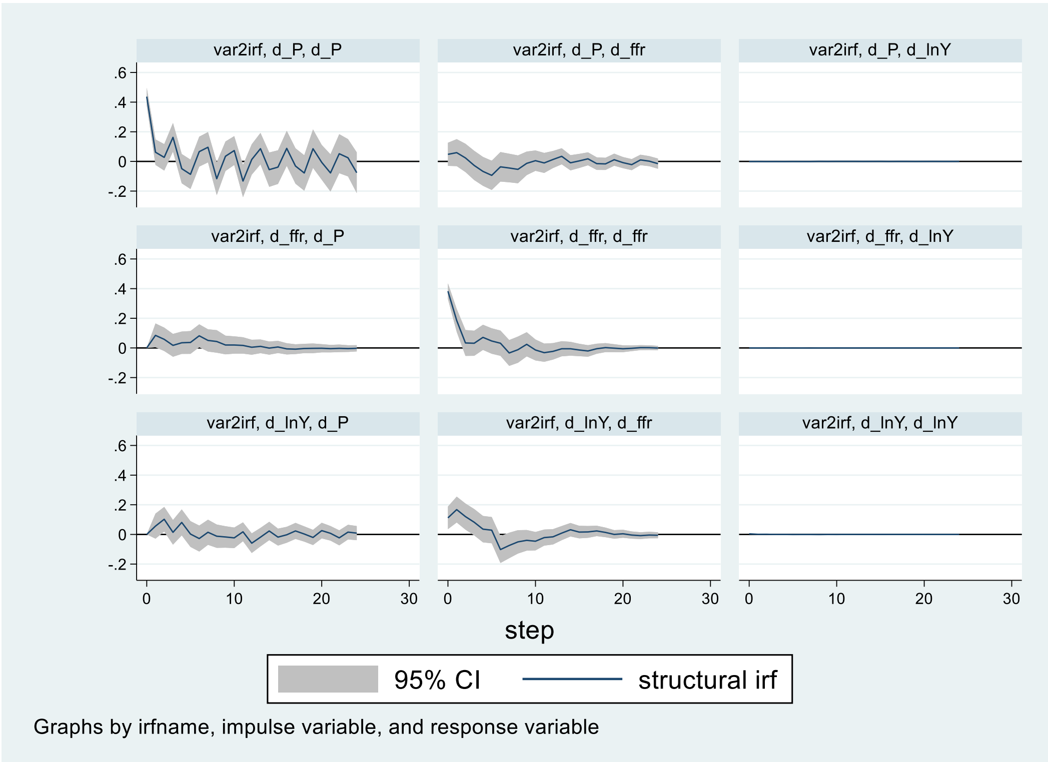


GRAPH 7

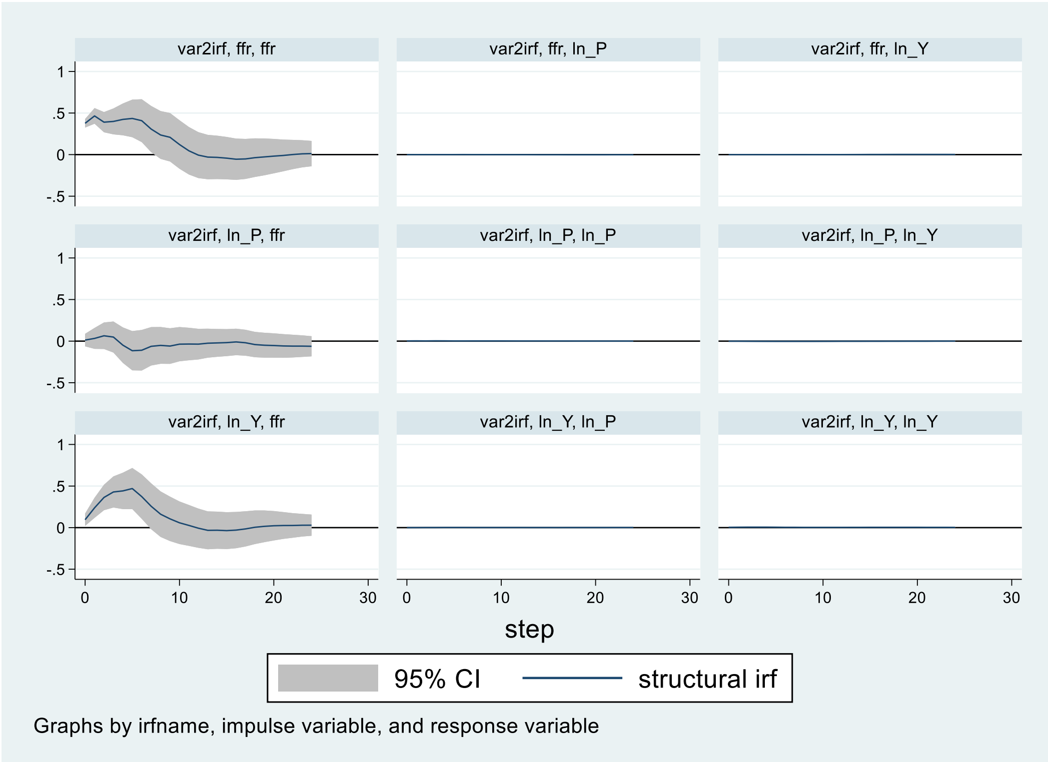


(D)

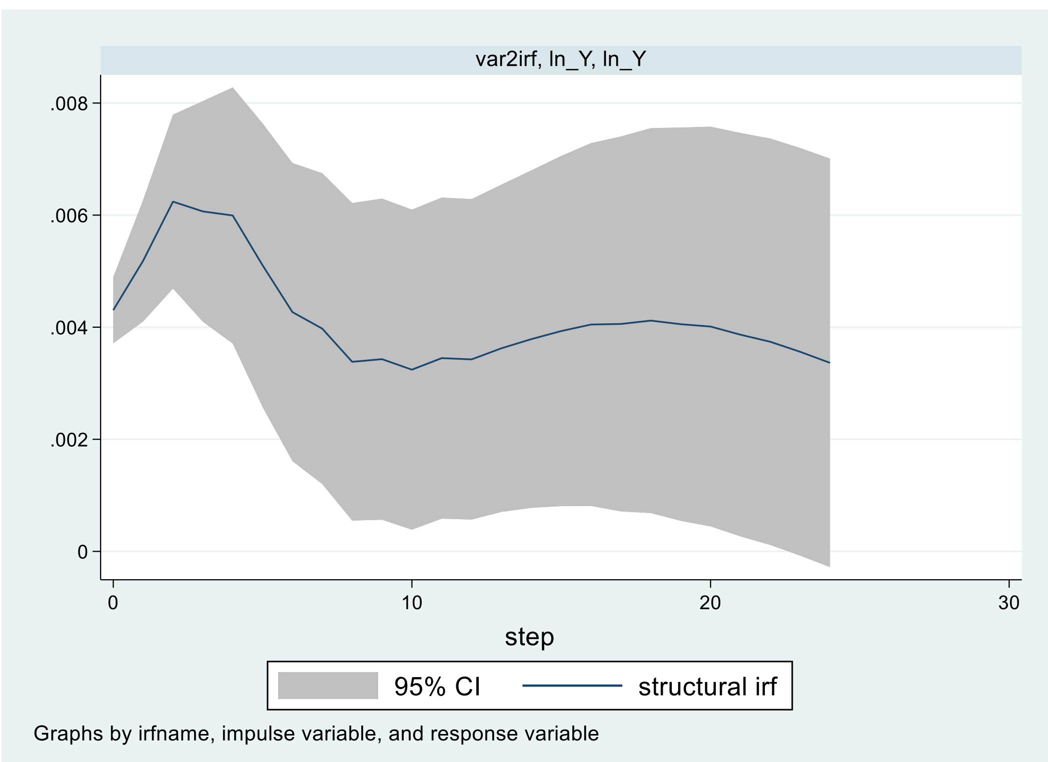
GRAPH 8


var2irf, d_P, d_P
var2irf, d_P, d_ffr
var2irf, d_P, d_lnY
var2irf, d_ffr, d_P
var2irf, d_ffr, d_ffr
var2irf, d_ffr, d_lnY
var2irf, d_lnY, d_P
var2irf, d_lnY, d_ffr
var2irf, d_lnY, d_lnY
.6
.4
.2
0
-.2
0
10
20
30
step
95% CI
structural irf
Graphs by irfname, impulse variable, and response variable

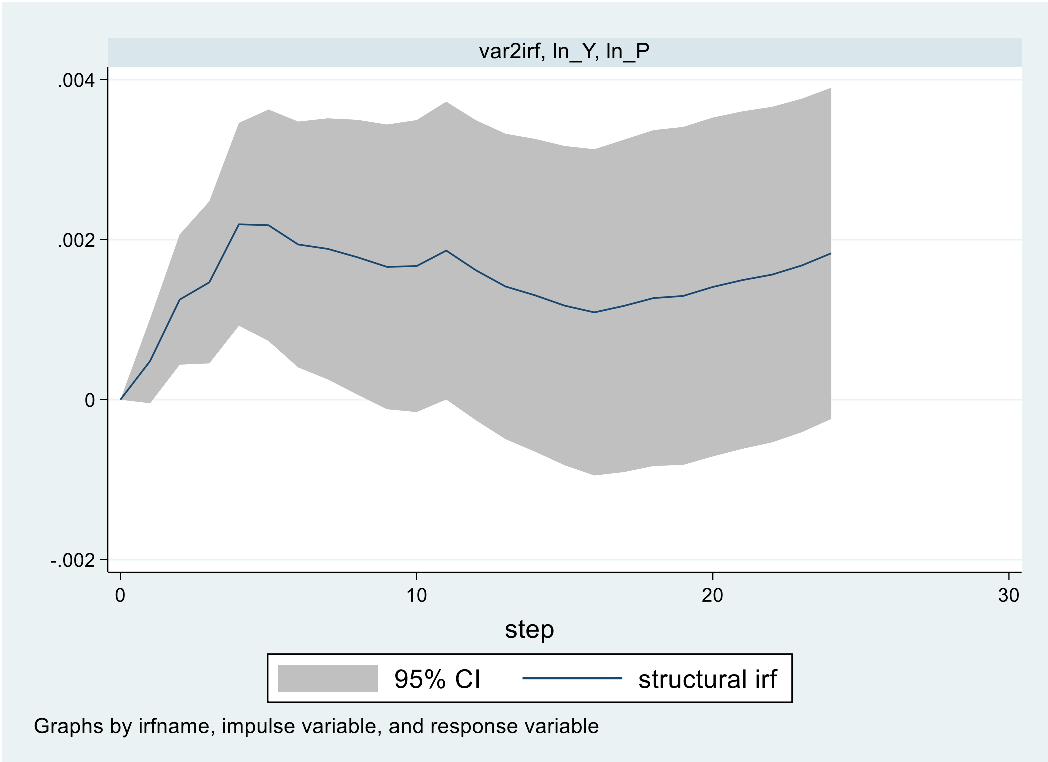
GRAPH 9



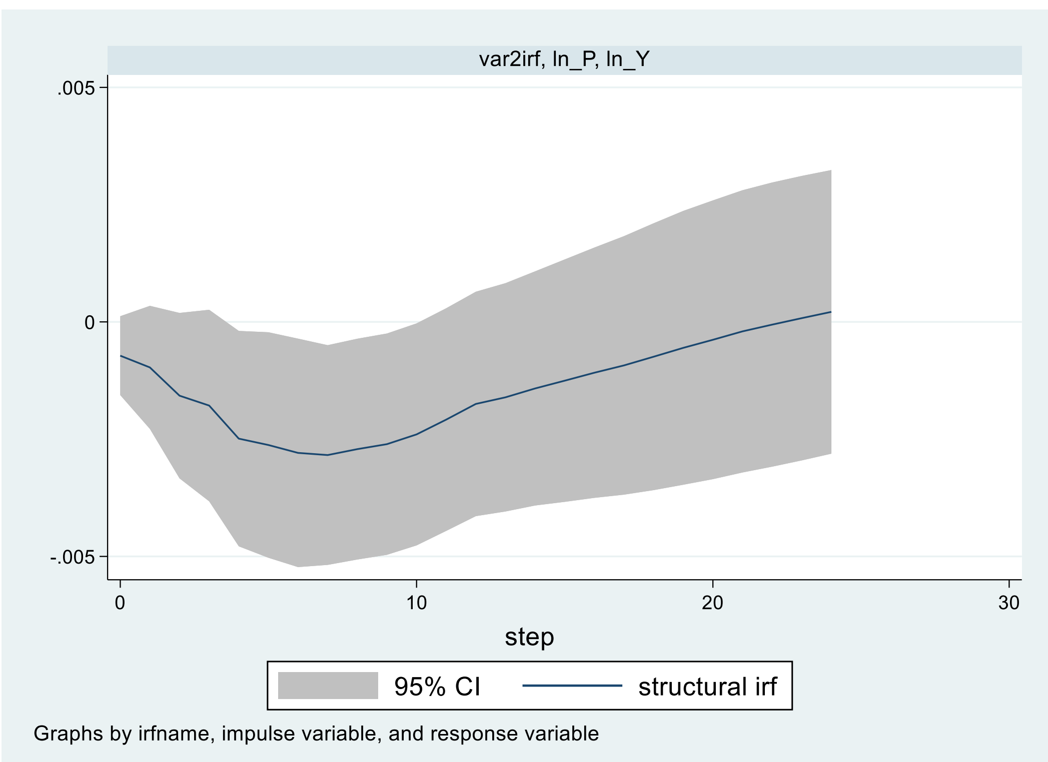
GRAPH 10



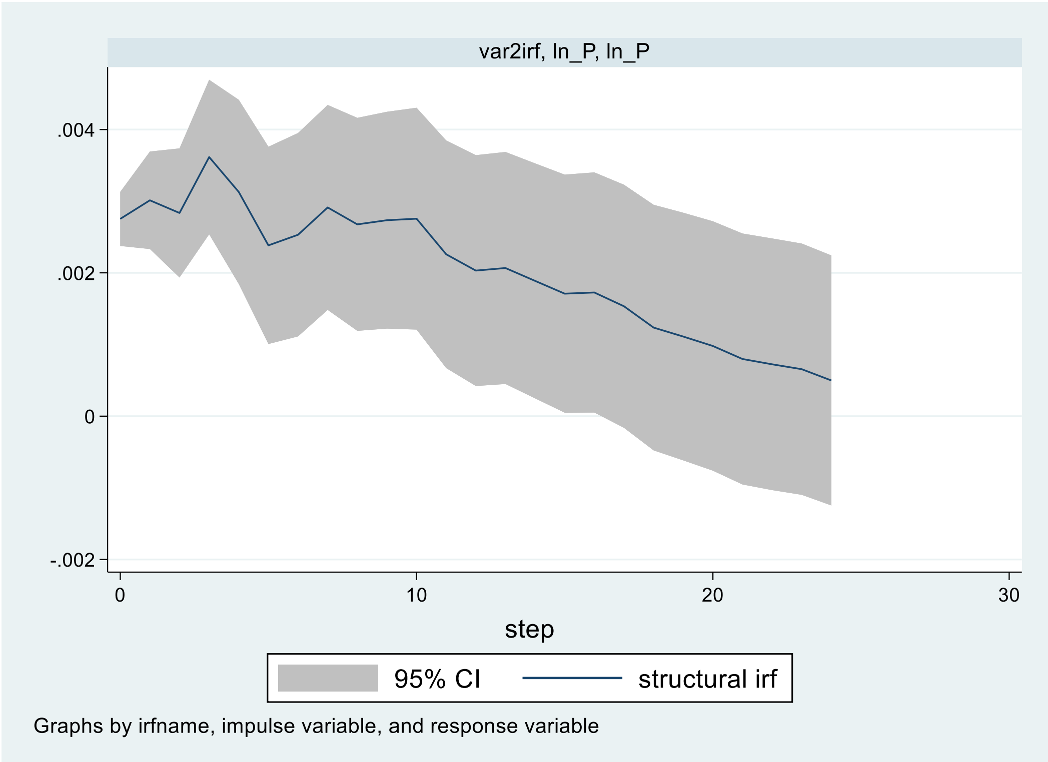
GRAPH 11



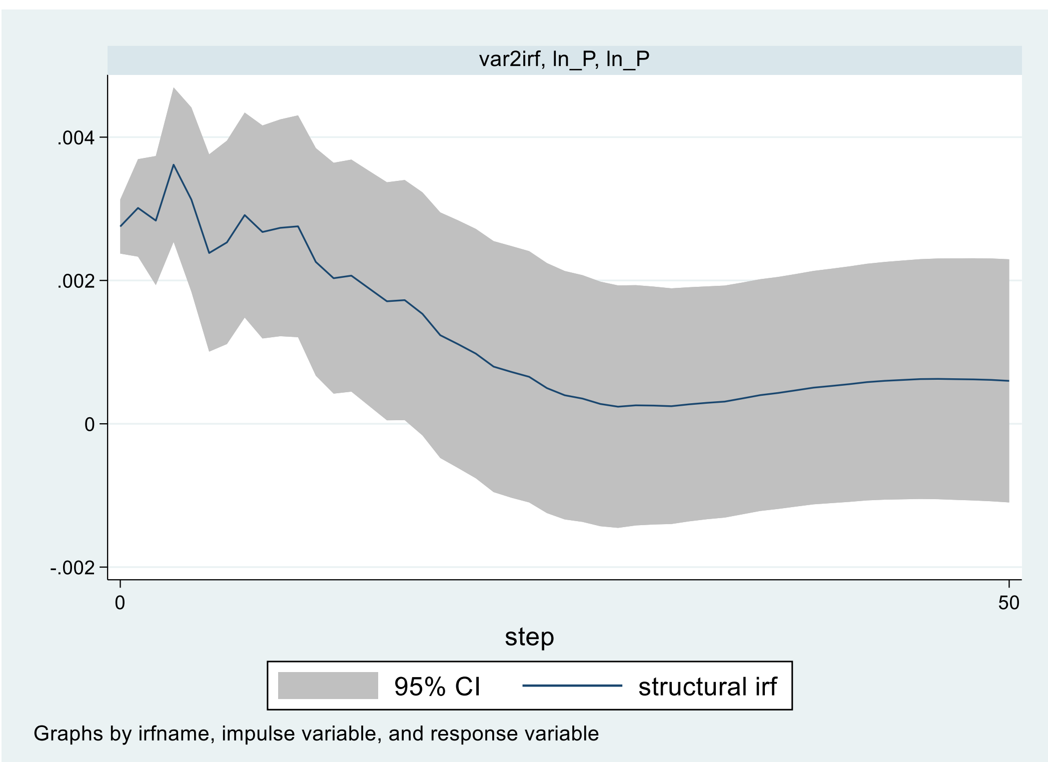
GRAPH 12



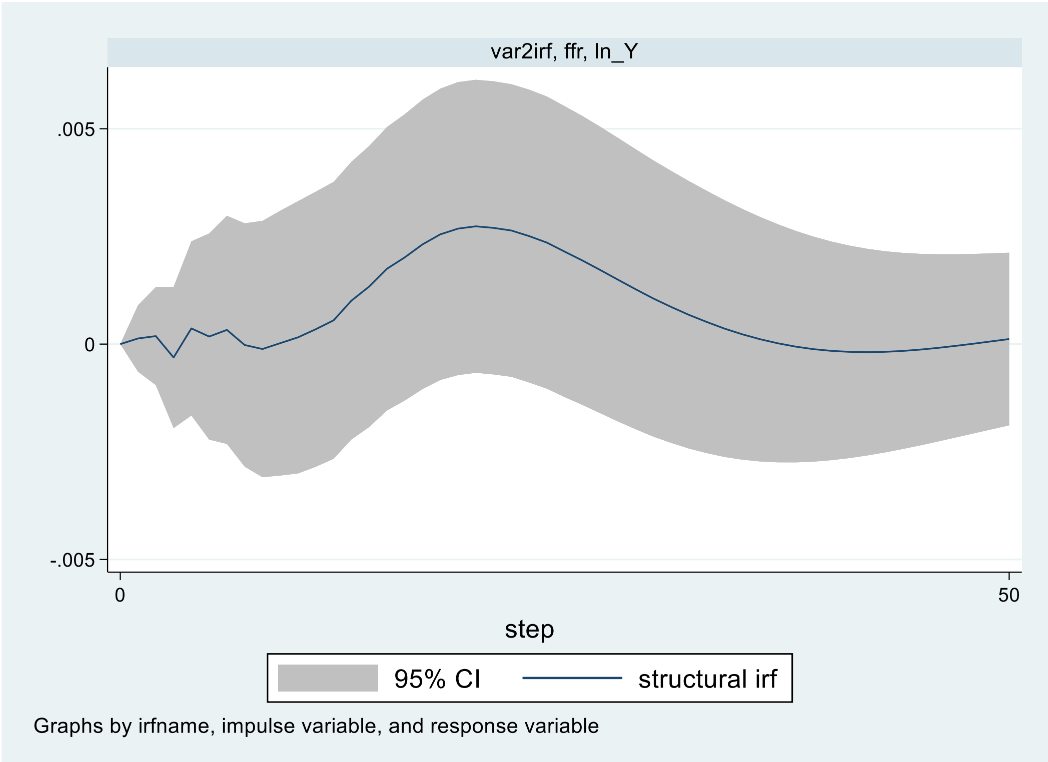
GRAPH 13



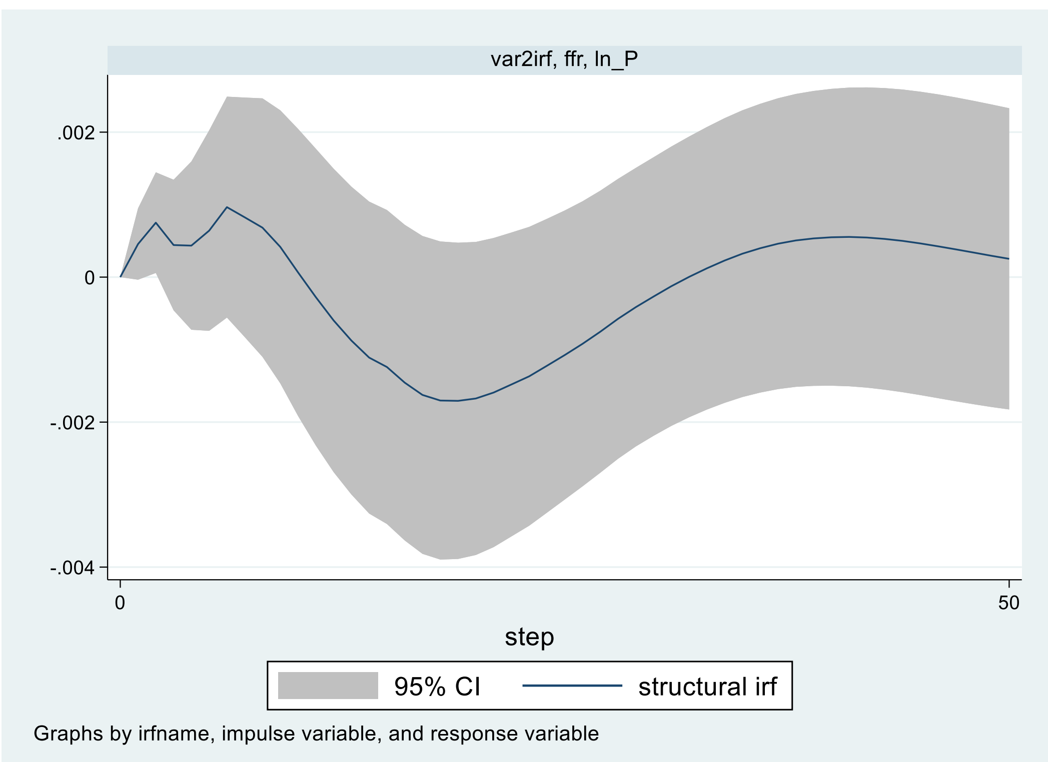
GRAPH 14



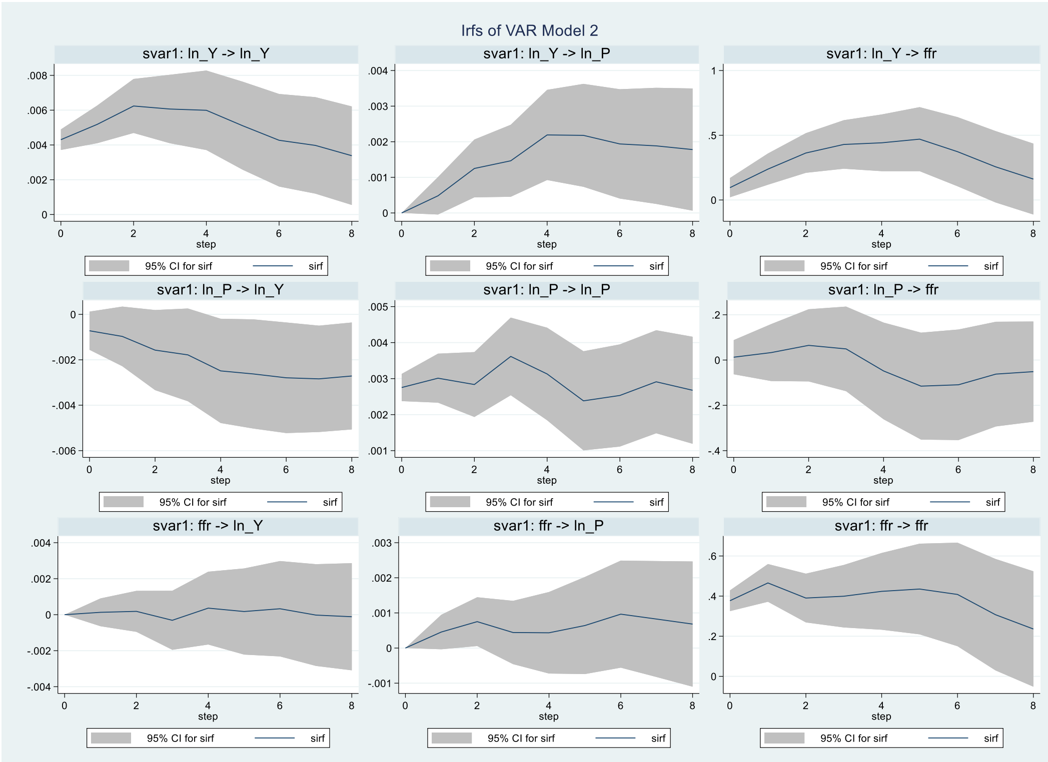
GRAPH 15



GRAPH 16



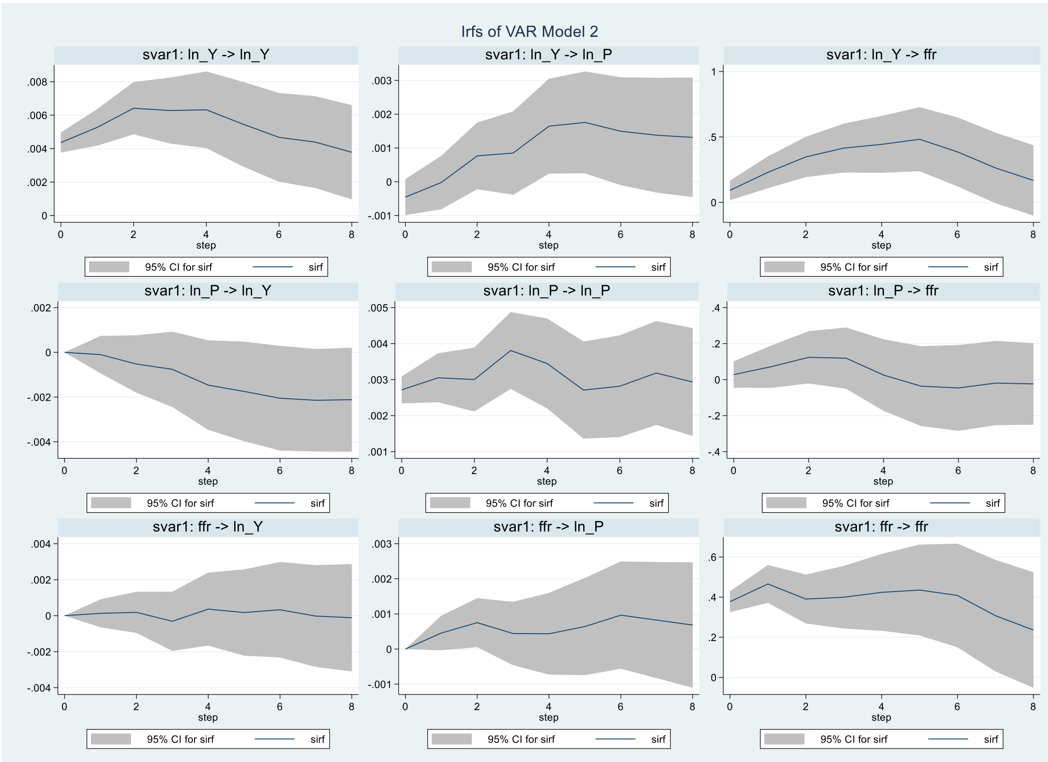
GRAPH 17



Irfs of VAR Model 2
svar1: ln_Y -> ln_Y
svar1: ln_Y -> ln_P
svar1: ln_Y -> ffr
svar1: ln_P -> ln_Y
svar1: ln_P -> ln_P
svar1: ln_P -> ffr
svar1: ffr -> ln_Y
svar1: ffr -> ln_P
svar1: ffr -> ffr
step
95% CI for sirf
sirf

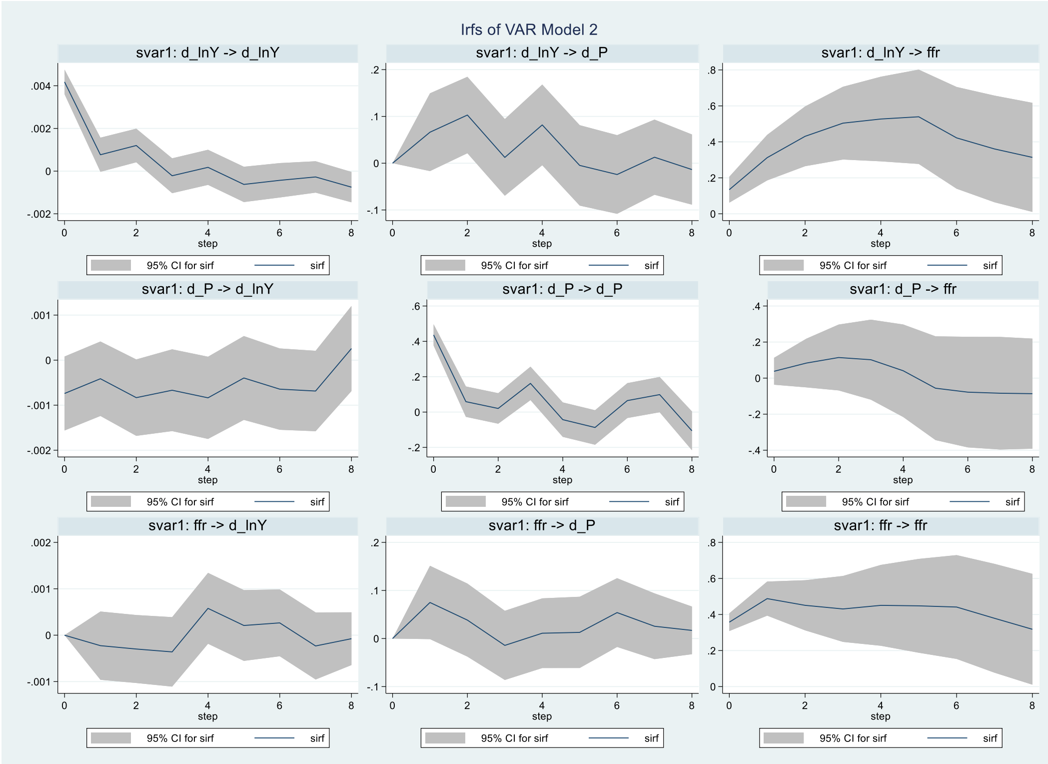
(G)

GRAPH 18

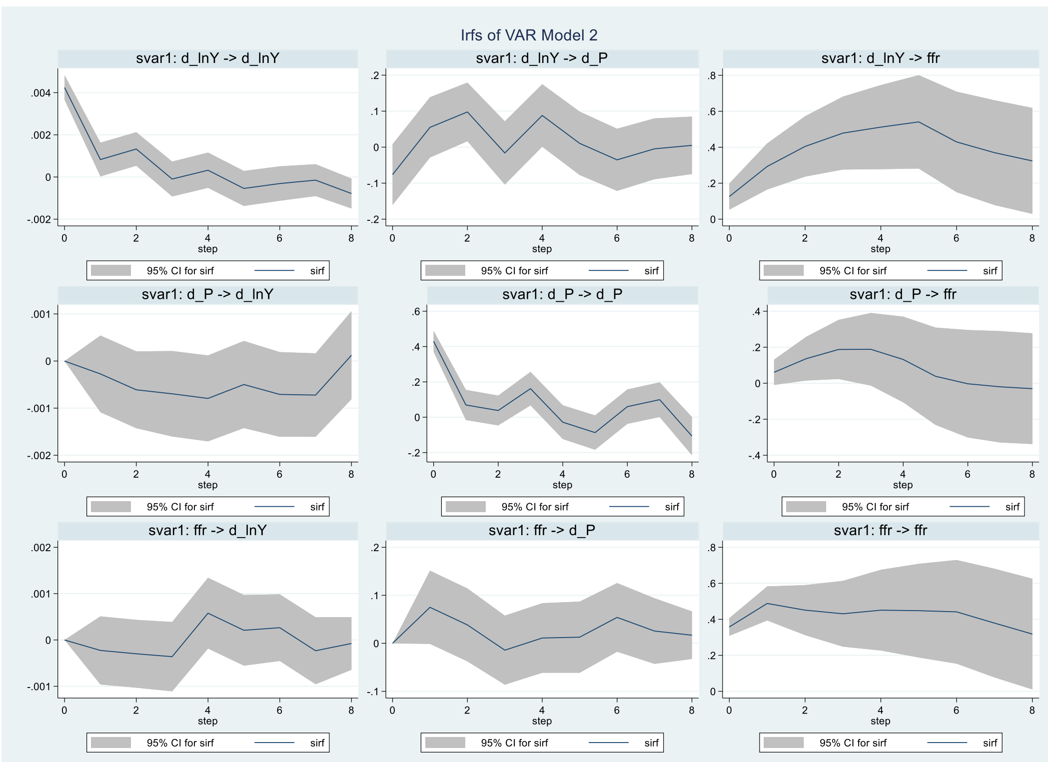


Irfs of VAR Model 2
svar1: ln_Y -> ln_Y
svar1: ln_Y -> ln_P
svar1: ln_Y -> ffr
svar1: ln_P -> ln_Y
svar1: ln_P -> ln_P
svar1: ln_P -> ffr
svar1: ffr -> ln_Y
svar1: ffr -> ln_P
svar1: ffr -> ffr
step
95% CI for sirf
sirf

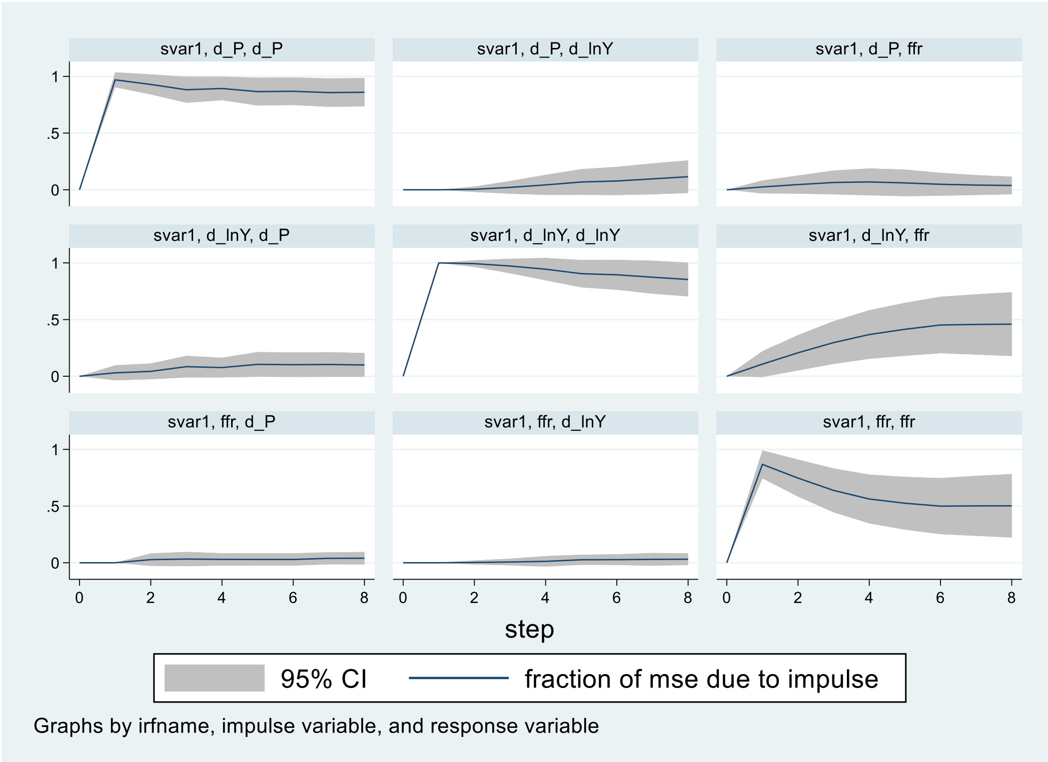
GRAPH 19



GRAPH 20



GRAPH 21



svar1, d_P, d_P
svar1, d_P, d_lnY
svar1, d_P, ffr
svar1, d_lnY, d_P
svar1, d_lnY, d_lnY
svar1, d_lnY, ffr
svar1, ffr, d_P
svar1, ffr, d_lnY
svar1, ffr, ffr
1
.5
0
0 2 4 6 8
step
95% CI
fraction of mse due to impulse
Graphs by irfname, impulse variable, and response variable

Question 2 (a). OLS's most crucial assumptions is that the regressors be exogenous—uncorrelated with the error term. Often with Macoeconomic data we are concerned with more than one variable. Those variables are often simultaneously determined. In other words, the variables simultaneously determine each other, and the causal effect is not completely clear. In such case, using a single-equation is not a very useful way of representing our model. On the other hand, if we have a structural model (e.g. supply/demand system) with endogenous explanatory variables, we must use instrumental variables. With VAR, because we use a reduced form, the problem of endogeneity does not arise. Hence, if we determine that endogeneity might be a potential problem for our macro data (which is often the case), the VAR method is the most convenient method to use.

Question 2 (d). We want to identify the exogenous effect of each one of the variables in question. In our case it is very likely that the shocks to demand affect price. Hence, price cannot generally be considered exogenous. Without sufficient exogeneity on the coefficients we want to estimate, we are likely to run into an identification problem. Hence, additional restrictions are necessary in order to get rid of the endogeneity problem.

Questions 2(e). We would use the Cholesky decomposition and assume that the beta inverse is a lower triangular. We would identify our model by imposing short-run restrictions. This would then 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 symmetric matrix into a lower triangular matrix. We use the Cholesky decomposition to make certain short-run assumptions on our variables of interest (price and demand). Through it we can assume that the contemporaneous effect of one of our variables is equal to zero. This, in turn, allows us to identify our model.

QUESTION 2 (b) :

2x2 macro model :

- price & demand equation as a system of equations :

$$Y_{1t} = \gamma_{10} + \beta_{12} Y_{2t} + \gamma_{11} Y_{1,t-1} + \gamma_{12} Y_{2,t-1} + \varepsilon_{1t}$$

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

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

IN MATRIX FORM: $B_{2x2} Y_{t\,2x1} = \Gamma_{0\,2x1} + \Gamma_{1\,2x2} Y_{t-1\,2x1} + \varepsilon_{t\,2x1}$

(c)

- The reduced-form VAR is used in order to reduce the number of unknown structural parameters to a number less than the number of estimated parameters. Our goal eventually is to move from a reduced-form VAR to estimating the structural model VAR. With reduced-form VAR we can apply the OLS technique.

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

$$Y_t = C_{2x1} + \Phi_{2x2} Y_{t-1} + e_t$$

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

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

The reduced-form essentially expresses every endogenous variable as a function of exogenous variables.

QUESTION 2. (f)

We would like to go from the structural parameters. However, we can only get the reduced ones.

As long as $\beta_{12} \neq \beta_{21} \neq |1|$, we know that B^{-1} exists.

So, we get a reduced form model of the form:

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

or

$$Y_t = C_{2\times1} + \Phi_{2\times2} Y_{t-1} + e_t$$

where

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

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

Letting B (and thus B^{-1}) be lower triangular, such that $\beta_{12} = 0$, we can now easily solve for ε_s from e_s.

That is,

$$e_{1t} = \varepsilon_{1t}$$
$$e_{2t} = \varepsilon_{2t} + \beta_{21}\varepsilon_{1t},$$

Hence, $\varepsilon_{1t} = e_{1t}$ and $\varepsilon_{2t} - e_{2t} - \beta_{21} e_{1t}$.

Through this we've been able to solve the identification issue.

QUESTION 2. (g)

The main purpose of an impulse response function is to describe the evolution of a model's variables in reaction to a shock in one or more variables. They give us the response of the endogenous variables to shocks.

The way the reduced form VAR can be related to the structural VAR is through an MA form with the B matrix.

The effect of e_t on Y_{t+s}, which we define as Ψ_s, is the effect of $B^{-1}\varepsilon_t$ on Y_{t+s}.

On a similar note, the effect of ε_t on Y_{t+s} is

$\theta_s = \Psi_s B^{-1}$, and $\theta_0 = B^{-1}$

We start by solving for the vector MA in terms of structural shocks.

$$Y = \mu + e_t + \Psi_1 e_{t-1} + \Psi_2 e_{t-2} + \dots$$

$$= \mu + B^{-1}\varepsilon_t + \Psi_1 B^{-1}\varepsilon_{t-1} + \Psi_2 B^{-1}\varepsilon_{t-2} + \dots$$

$$= \mu + \theta_0 \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots$$

To calculate the structural IRFs we need the reduced form IRFs and the identified matrix B, $\theta = \Psi_s B^{-1}$

$$\begin{bmatrix} \theta_{11,s} & \theta_{12,s} \\ \theta_{21,s} & \theta_{22,s} \end{bmatrix} = \Psi_s B^{-1} = \begin{bmatrix} \psi_{11,s} & \psi_{12,s} \\ \psi_{21,s} & \psi_{22,s} \end{bmatrix} \frac{1}{1-\beta_{12}\beta_{21}} \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix}$$

Continuation to Question 2. (g):

Structural MA form:

$$Y_t = \mu + \theta_0 \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_3 \varepsilon_{t-3} + \dots$$

In a 2x2 matrix form this becomes:

$$\begin{bmatrix} Y_{1t} \\ Y_{2t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \theta_{11,0} & \theta_{12,0} \\ \theta_{21,0} & \theta_{22,0} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} +$$

$$+ \begin{bmatrix} \theta_{11,1} & \theta_{12,1} \\ \theta_{21,1} & \theta_{22,1} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \end{bmatrix} +$$

$$+ \begin{bmatrix} \theta_{11,2} & \theta_{12,2} \\ \theta_{21,2} & \theta_{22,2} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-2} \\ \varepsilon_{2,t-2} \end{bmatrix} + \dots$$

where, $\theta_{21,3}$, for instance is equal to

$$\frac{\partial Y_{2,t}}{\partial \varepsilon_{1,t-3}} \left(= \frac{\partial Y_{2,t+3}}{\partial \varepsilon_{1,t}} \right).$$

QUESTION 2. (h)

COMPUTE THE FOLLOWING IRFs :

① CALCULATING THE EFFECT OF STRUCTURAL SHOCKS ON EQUATION 1 ON THE LEFT HAND SIDE VARIABLE OF EQUATION 1, 3 PERIODS AHEAD.

We have $\Theta_s = \Psi_s B^{-1}$

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

Therefore, we have : $\theta_{11,s} = \frac{1}{1-\beta_{12}\beta_{21}} (\psi_{11,s} + \beta_{21}\psi_{21,s})$

We are interested in $\frac{\partial Y_{1,t}}{\partial \varepsilon_{1,t}}$.

Specifically, we want to know : $\frac{\partial Y_{1,t+1}}{\partial \varepsilon_{1,t}}$, $\frac{\partial Y_{1,t+2}}{\partial \varepsilon_{1,t}}$, $\frac{\partial Y_{1,t+3}}{\partial \varepsilon_{1,t}}$

Employing stationarity and backward-looking IRFs, we obtain :

$$\frac{\partial Y_{1,t+1}}{\partial \varepsilon_{1,t}} = \frac{\partial Y_{1,t}}{\partial \varepsilon_{1,t-1}};$$

$$\frac{\partial Y_{1,t+2}}{\partial \varepsilon_{1,t}} = \frac{\partial Y_{1,t}}{\partial \varepsilon_{1,t-2}};$$

$$\frac{\partial Y_{1,t+3}}{\partial \varepsilon_{1,t}} = \frac{\partial Y_{1,t}}{\partial \varepsilon_{1,t-3}}.$$

Then,

$$\Theta_3 = \begin{bmatrix} \theta_{11,3} & \theta_{12,3} \\ \theta_{21,3} & \theta_{22,3} \end{bmatrix} = \Psi_3 B^{-1}$$

$$= \begin{bmatrix} \psi_{11,3} & \psi_{12,3} \\ \psi_{21,3} & \psi_{22,3} \end{bmatrix} \frac{1}{1-\beta_{12}\beta_{21}} \begin{bmatrix} 1 & \beta_{12} \\ \beta_{21} & 1 \end{bmatrix}$$

Hence, $\theta_{11,3} = \frac{1}{1-\beta_{12}\beta_{21}} (\psi_{11,3} + \beta_{12}\psi_{21,3})$

And, $\theta_{11,3} = \frac{\partial Y_{1,t}}{\partial \varepsilon_{1,t-3}} \left(= \frac{\partial Y_{1,t+3}}{\partial \varepsilon_{1,t}} \right)$.

Continuation to Question 2. (h):

COMPUTE THE IRFs FOR:

2 CALCULATING THE EFFECT OF THE STRUCTURAL SHOCK IN EQUATION 2 ON THE LEFT-HAND SIDE OF EQUATION 1, 3 PERIODS AHEAD:

Here we are interested in $\frac{\partial Y_{1,t}}{\partial \varepsilon_{2,t}}$.

Specifically, we want to find: $\frac{\partial Y_{1,t+1}}{\partial \varepsilon_{2,t}}$, $\frac{\partial Y_{1,t+2}}{\partial \varepsilon_{2,t}}$, $\frac{\partial Y_{1,t+3}}{\partial \varepsilon_{2,t}}$.

Employing stationarity & a backward-looking IRF, we get:

$$\frac{\partial Y_{1,t+1}}{\partial \varepsilon_{2,t}} = \frac{\partial Y_{1,t}}{\partial \varepsilon_{2,t-1}};$$

$$\frac{\partial Y_{1,t+2}}{\partial \varepsilon_{2,t}} = \frac{\partial Y_{,t}}{\partial \varepsilon_{2,t-2}};$$

$$\frac{\partial Y_{1,t+3}}{\partial \varepsilon_{2,t}} = \frac{\partial Y_{,t}}{\partial \varepsilon_{2,t-3}}.$$