

(a) Estimate the model using multinomial logit model using  $y_i=0$  is the base outcome. Make interpretation of your estimated results (sign & meaning (in term of rrr), overall test, goodness of fit, and individual test). Perform IIA test whether it is appropriated to apply multinomial logit in this case? Give explanation why IIA is important for multinomial logit. Determine whether multinomial logit is appropriated for this case? Why? (5 points).

1.

```
. mlogit y x1 x2 x3 x4, base(0) nolog
```

```
Multinomial logistic regression      Number of obs      =      170
                                      LR chi2(8)          =      94.19
                                      Prob > chi2        =      0.0000
Log likelihood = -100.73601          Pseudo R2          =      0.3186
```

```
-----
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
0		(base outcome)				
-----+-----						
1						
	x1	-.8716535	.6283126	-1.39	0.165	-2.103124 .3598166
	x2	-.5356032	.7697797	-0.70	0.487	-2.044344 .9731372
	x3	-.517283	.6320378	-0.82	0.413	-1.756054 .7214882
	x4	.5657851	.2625729	2.15	0.031	.0511516 1.080419
	_cons	-6.672078	3.719218	-1.79	0.073	-13.96161 .6174562
-----+-----						
2						
	x1	-.7377626	.7162596	-1.03	0.303	-2.141606 .6660804
	x2	-1.557584	.8090783	-1.93	0.054	-3.143348 .0281805
	x3	.6492327	.6826875	0.95	0.342	-.6888103 1.987276
	x4	1.886577	.3228789	5.84	0.000	1.253746 2.519408
	_cons	-27.46135	4.83019	-5.69	0.000	-36.92835 -17.99435

```
. est store m
```

```
. mlogit y x1 x2 x3 x4 if y!=2, base(0) nolog
```

```
Multinomial logistic regression      Number of obs      =      60
                                      LR chi2(4)          =      5.96
                                      Prob > chi2        =      0.2023
Log likelihood = -34.480553          Pseudo R2          =      0.0795
```

```
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```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						

```

0          | (base outcome)
-----+-----
1          |
      x1 | -.7497427   .6037771   -1.24   0.214   -1.933124   .4336386
      x2 | -.2864689   .7421089   -0.39   0.699   -1.740976   1.168038
      x3 | -.3366018   .640531    -0.53   0.599   -1.592019   .9188158
      x4 | .4928915    .257627    1.91   0.056   -.0120481   .9978311
      _cons | -5.928091  3.797311   -1.56   0.118   -13.37068   1.514502
-----+-----

```

```
. est store mno2
```

```
. hausman m mno2, alleqs constant
```

```

          ---- Coefficients ----
          |          (b)          (B)          (b-B)          sqrt(diag(V_b-V_B))
          |          m          mno2          Difference          S.E.
-----+-----
      x1 |  -.8716535  -.7497427  -.1219107  .1738677
      x2 |  -.5356032  -.2864689  -.2491343  .2045363
      x3 |  -.517283   -.3366018  -.1806812  .
      x4 |   .5657851   .4928915   .0728936  .0507236
      _cons | -6.672078  -5.928091  -.7439869  .
-----+-----

```

b = consistent under Ho and Ha; obtained from mlogit

B = inconsistent under Ha, efficient under Ho; obtained from mlogit

Test: Ho: difference in coefficients not systematic

$$\chi^2(5) = (b-B)'[(V_b-V_B)^{-1}](b-B)$$

$$= 1.05$$

$$\text{Prob} > \chi^2 = 0.9584$$

(V\_b-V\_B is not positive definite)

```
. mlogit y x1 x2 x3 x4, rrr base(0) nolog
```

```

Multinomial logistic regression          Number of obs   =          170
                                          LR chi2(8)       =          94.19
                                          Prob > chi2      =          0.0000
Log likelihood = -100.73601              Pseudo R2       =          0.3186
-----+-----

```

```

      y |          RRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
0          | (base outcome)

```

```

-----+-----
1      |
      x1 |  .4182594  .2627976  -1.39  0.165  .1220745  1.433067
      x2 |  .5853161  .4505644  -0.70  0.487  .1294651  2.646233
      x3 |  .596138  .3767818  -0.82  0.413  .172725  2.057493
      x4 |  1.76083  .4623462  2.15  0.031  1.052482  2.945912
      _cons | .0012658  .0047077  -1.79  0.073  8.64e-07  1.854205
-----+-----

```

```

2      |
      x1 |  .4781826  .3425029  -1.03  0.303  .1174661  1.946592
      x2 |  .2106444  .1704278  -1.93  0.054  .0431381  1.028581
      x3 |  1.914072  1.306713  0.95  0.342  .5021731  7.295631
      x4 |  6.596747  2.129951  5.84  0.000  3.503441  12.42124
      _cons | 1.18e-12  5.72e-12  -5.69  0.000  9.17e-17  1.53e-08
-----+-----

```

Ans. As we use y0 as the base case, the overall test is significant. Pseudo R2 is 0.3186. RRR of x1 x2 x3 in y1 is lower than 1, thus, they have negative impact on y. for x4, it has positive impact. In case of y2, RRR is lower than 1 only for x1 and x2, so only x3 and x4 have positive impact on y. However, the individual tests seem to be mostly insignificant. For x4 in both cases, it is significant under 95 percent confidence level.

After testing IIA, it turns out that we accept the null hypothesis. It means that IIA is valid, then we can use multinomial logit. If IIA is not satisfied and we use multinomial logit, the model will be biased as it is the most important assumption of mnlogit where decisions are independent of other alternatives.

**(b) Estimate the model using order probit model of yi. Make interpretation of your estimated results (sign & meaning, overall test, goodness of fit, and individual test). Perform the test to determine whether order probit is appropriated in this case? Give explanation why? (5 points).**

```

. oprobit y x1 x2 x3 x4, nolog

Ordered probit regression      Number of obs      =      170
                               LR chi2(4)                 =      84.22
                               Prob > chi2                 =      0.0000
Log likelihood = -105.72267    Pseudo R2           =      0.2848
-----+-----

```

```

-----+-----
      y |      Coef.  Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      x1 |  -.1825779  .2396318    -0.76  0.446   - .6522476   .2870919
      x2 |  -.489389   .2441328   -2.00  0.045   - .9678804  -.0108975
      x3 |  .4860257   .2228889    2.18  0.029    .0491715    .92288
      x4 |  .7169483   .0945822    7.58  0.000    .5315706    .902326
-----+-----

```

/cut1		9.935009	1.433907	7.124604 12.74542
/cut2		11.20764	1.492805	8.281792 14.13348

. tab y

y	Freq.	Percent	Cum.
0	19	11.18	11.18
1	41	24.12	35.29
2	110	64.71	100.00
Total	170	100.00	

. g y12=y>0

. g y2=y>1

. probit y12 x1 x2, nolog

```

Probit regression                               Number of obs   =       170
                                                LR chi2(2)      =         0.37
                                                Prob > chi2     =         0.8294
Log likelihood = -59.345062                    Pseudo R2       =         0.0031

```

y12	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	-.0227776	.2875784	-0.08	0.937	-.5864209 .5408658
x2	-.1670744	.281841	-0.59	0.553	-.7194726 .3853239
_cons	1.344802	.2666147	5.04	0.000	.8222469 1.867357

. est store p12

. probit y2 x1 x2, nolog

```

Probit regression                               Number of obs   =       170
                                                LR chi2(2)      =         7.58
                                                Prob > chi2     =         0.0226
Log likelihood = -106.58421                    Pseudo R2       =         0.0343

```

y2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.511485	.2233564	2.29	0.022	.0737145 .9492554
x2	-.3915635	.2199933	-1.78	0.075	-.8227425 .0396155
_cons	.4126665	.1989986	2.07	0.038	.0226365 .8026964

```

-----
. est store p2
. suest p12 p2

```

Simultaneous results for p12, p2

Number of obs = 170

```

-----
          |               Robust
          |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
p12_y12   |
          |
          | x1 |   -.0227776   .3181703   -0.07   0.943   - .64638   .6008249
          | x2 |  -.1670744   .2860756   -0.58   0.559   - .7277722 .3936235
          | _cons |  1.344802   .2586097    5.20   0.000   .8379364  1.851668
-----+-----
p2_y2     |
          |
          | x1 |    .511485   .2388239    2.14   0.032   .0433987  .9795712
          | x2 |   -.3915635   .2247024   -1.74   0.081   - .8319722  .0488452
          | _cons |  .4126665   .2000799    2.06   0.039   .020517  .8048159
-----

```

```

. test [p12_y12]x1=[p2_y2]x1
( 1) [p12_y12]x1 - [p2_y2]x1 = 0

```

```

          chi2( 1) =    3.30
          Prob > chi2 =    0.0693

```

```

. test [p12_y12]x2=[p2_y2]x2
( 1) [p12_y12]x2 - [p2_y2]x2 = 0

```

```

          chi2( 1) =    0.78
          Prob > chi2 =    0.3767

```

Ans. for the order probit model, the overall test is significant. Pseudo R2 is 0.2848, the higher the better. The individual test for x1 is insignificant, other Xs are significant under 95 percent confidence level. The cuts don't include zero in the confidence interval, they are significant; this can imply that there are differences for making decisions and the model may be ordered. From the test above, we run p12 and p2 simultaneously and test whether there are differences of the coefficients. Here we accept null hypothesis (pvalue greater than 0.5) that they are equal, thus, we have one set of beta so ordered probit should be used.

(c) Estimate models for Y1i, Y2i, and Y3i assuming that the probability functions follow separate normal distribution function. Should we use these three separate probit models? Why? (4 points)

```
. probit y1 x*, nolog
```

```
Probit regression                               Number of obs   =           550
                                                LR chi2(4)      =           33.87
                                                Prob > chi2     =           0.0000
Log likelihood = -361.4398                    Pseudo R2       =           0.0448
```

```
-----
```

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	1.473191	.4060376	3.63	0.000	.6773715 2.26901
x2	-.9429238	.3812976	-2.47	0.013	-1.690253 -.1955943
x3	.671879	.1790825	3.75	0.000	.3208837 1.022874
x4	.2561454	.1857917	1.38	0.168	-.1079996 .6202903
_cons	-.807743	.3058901	-2.64	0.008	-1.407277 -.2082095

```
-----
```

```
. probit y2 x*, nolog
```

```
Probit regression                               Number of obs   =           550
                                                LR chi2(4)      =           15.11
                                                Prob > chi2     =           0.0045
Log likelihood = -360.03405                    Pseudo R2       =           0.0205
```

```
-----
```

y2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	-.8482165	.3797737	-2.23	0.026	-1.592559 -.1038737
x2	-.4076769	.3663393	-1.11	0.266	-1.125689 .310335
x3	-.2409677	.1767855	-1.36	0.173	-.5874609 .1055255
x4	.6114268	.190396	3.21	0.001	.2382575 .9845961
_cons	.3242658	.3026141	1.07	0.284	-.268847 .9173786

```
-----
```

```
. probit y3 x*, nolog
```

```
Probit regression                               Number of obs   =           550
                                                LR chi2(4)      =           12.74
                                                Prob > chi2     =           0.0126
Log likelihood = -330.44911                    Pseudo R2       =           0.0189
```

```
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```

y3	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
----	-------	-----------	---	------	----------------------

```

-----+-----
      x1 |  -0.5264988   .3908551   -1.35   0.178   -1.292561   .2395631
      x2 |   .8452187   .3800049    2.22   0.026    .1004228   1.590014
      x3 |  -0.3860994   .1982681   -1.95   0.051   -0.7746977   .0024989
      x4 |  -0.3356344   .1826289   -1.84   0.066   -0.6935805   .0223118
    _cons |  -0.498158   .3167096   -1.57   0.116   -1.118897   .1225813
-----+-----

```

Ans. the models are significant in overall, however we need to look at the correlation among disturbances too. We can run them separately if the disturbances are not correlated to each other.

(d) Estimate models for Y1i, Y2i, and Y3i assuming that the probability functions follow multivariate normal probability distribution function (MV Probit models). Determine whether MVProbit is appropriated. Why? How does the MV Probit models differ from three separate probit models? (6 points)

```

. mvprobit (y1 x*) (y2 x*) (y3 x*), nolog
Multivariate probit (MSL, # draws = 5)          Number of obs   =          550
                                                Wald chi2(12)    =          45.91
Log likelihood = -931.74666                    Prob > chi2      =          0.0000
-----+-----

```

```

-----+-----
      |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
y1    |
      x1 |   1.312046   .3955406    3.32   0.001    .5368009   2.087292
      x2 |  -0.8140709  .3752078   -2.17   0.030   -1.549465  -0.0786772
      x3 |   .6494881   .1798034    3.61   0.000    .2970799   1.001896
      x4 |   .2353198   .1847334    1.27   0.203   -0.1267509  .5973906
    _cons |  -0.733309   .3074531   -2.39   0.017   -1.335906  -0.1307119
-----+-----

```

```

-----+-----
y2    |
      x1 |  -0.9163016  .3766512   -2.43   0.015   -1.654524  -0.1780789
      x2 |  -0.3409062  .3641912   -0.94   0.349   -1.054708  .3728954
      x3 |  -0.2596698  .1773654   -1.46   0.143   -0.6072996  .0879601
      x4 |   .5935985   .1895573    3.13   0.002    .222073   .965124
    _cons |   .3632508   .3014063    1.21   0.228   -0.2274946  .9539963
-----+-----

```

```

-----+-----
y3    |
      x1 |  -0.485328   .3837317   -1.26   0.206   -1.237428  .2667723
      x2 |   .6613654   .3751111    1.76   0.078   -0.0738389  1.39657
-----+-----

```

x3		-.2797045	.1860602	-1.50	0.133	-.6443757	.0849667
x4		-.2873432	.1862661	-1.54	0.123	-.6524182	.0777317
_cons		-.4278602	.3180921	-1.35	0.179	-1.051309	.1955888
-----+-----							
/atrho21		-.5589267	.07351	-7.60	0.000	-.7030036	-.4148498
-----+-----							
/atrho31		-.4436816	.0752587	-5.90	0.000	-.591186	-.2961772
-----+-----							
/atrho32		-.3496377	.0713966	-4.90	0.000	-.4895725	-.209703
-----+-----							
rho21		-.5071806	.0546008	-9.29	0.000	-.6062708	-.3925828
-----+-----							
rho31		-.4166914	.0621914	-6.70	0.000	-.530748	-.2878103
-----+-----							
rho32		-.3360542	.0633336	-5.31	0.000	-.453877	-.2066822
-----+-----							

Likelihood ratio test of rho21 = rho31 = rho32 = 0:

chi2(3) = 240.353 Prob > chi2 = 0.0000

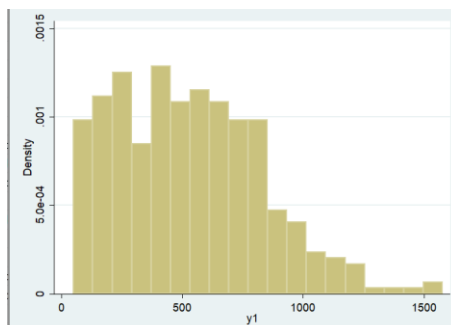
ans. the separate models seem to be significant in overall. However, from test of appropriateness of mvprobit model, it is better to use mvprobit because we reject the null hypothesis that rhos are zero. When rhos are not zero, it means that the disturbances are related and we cannot run them separately. When we run them separately, we assume no correlation among the disturbance terms from each models.

**2.(a) Plot histogram of  $y_{1i}$ ,  $y_{2i}$ ,  $y_{3i}$ , compute descriptive statistics of these three variables. Determine limitations of these three dependent variables. (5 points)**

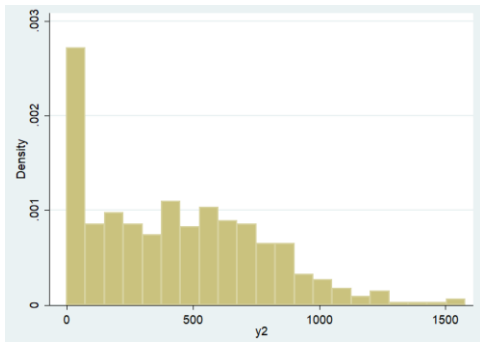
. sum y1 y2 y3

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	367	528.8534	302.314	50.21759	1578.51
y2	450	432.3137	340.3366	0	1578.51
y3	450	3344.719	14544.57	-466.0042	98951.63

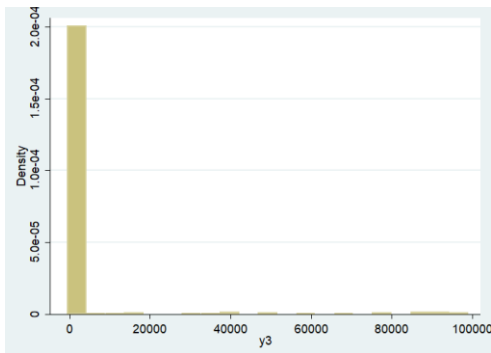
. histogram y1



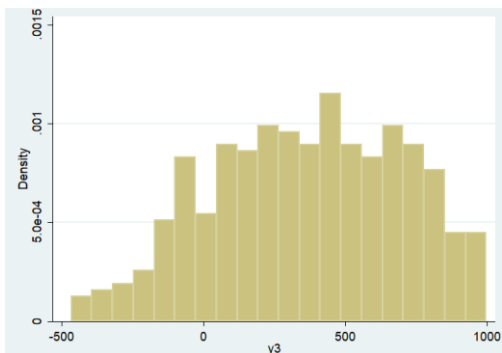
```
. histogram y2
```



```
. histogram y3
```



```
. histogram y3 if y3<2000
```



Ans. from descriptive stats of three variables and histograms, it may be concluded that  $y_1$  has truncated problem at its minimum,  $y_2$  has censored problem,  $y_3$  has outliers problem.

(b) Estimate the model (3) for  $y_{1i}$  using OLS and truncated regression model. Determine the most appropriated model in this case. Why? What is the major problem in this case? What will happen if we ignore the problem? (5 points)

```
. reg y1 x
```

Source	SS	df	MS	Number of obs	=	367
-----+-----				F(1, 365)	=	139.84
Model	9265666.01	1	9265666.01	Prob > F	=	0.0000
Residual	24184454.5	365	66258.7795	R-squared	=	0.2770
-----+-----				Adj R-squared	=	0.2750
Total	33450120.5	366	91393.7719	Root MSE	=	257.41

```
-----
```

y1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	166.2833	14.06151	11.83	0.000	138.6316	193.9351
_cons	-10.17282	47.52115	-0.21	0.831	-103.6224	83.27678

```
-----
```

```
. est store y1
. sum y1
```

```
-----
```

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	367	528.8534	302.314	50.21759	1578.51

```
-----
```

```
. scalar miny1=round(r(min))
. truncreg y1 x, ll(miny1) nolog
(note: 0 obs. truncated)
```

```
Truncated regression
Limit:  lower =      50                Number of obs   =      367
        upper =      +inf              Wald chi2(1)    =      106.88
Log likelihood = -2523.2473           Prob > chi2     =      0.0000
```

```
-----
```

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x	230.0903	22.25604	10.34	0.000	186.4693	273.7114
_cons	-293.0718	85.01096	-3.45	0.001	-459.6902	-126.4534
/sigma	304.355	16.61638	18.32	0.000	271.7875	336.9225

```
-----
```

```
. predict truncated, e(50,.)
. est store ylt
. lrtest y1 ylt, force
```

```
Likelihood-ratio test                LR chi2(1) =      67.19
(Assumption: y1 nested in ylt)       Prob > chi2 =      0.0000
```

Ans. from the test of appropriateness, truncated regression model should be used as we reject the null hypothesis. When we cannot observe the data but it does exists, we are facing truncated problem. If we ignore the truncated problem and run with only available data using ols linear regression model, it will be biased.

(c) Estimate the model (3) for  $y_{2i}$  using OLS and Tobit model. Determine the most appropriated model in this case. Why? What is the major problem in this case? What will happen if we ignore the problem? (5 points)

```
. reg y2 x
```

Source	SS	df	MS	Number of obs	=	450
-----+-----				F(1, 448)	=	253.69
Model	18802566.3	1	18802566.3	Prob > F	=	0.0000
Residual	33204659	448	74117.5425	R-squared	=	0.3615
-----+-----				Adj R-squared	=	0.3601
Total	52007225.3	449	115829.01	Root MSE	=	272.25

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
x	195.9104	12.30012	15.93	0.000	171.7373	220.0835
_cons	-161.8937	39.4527	-4.10	0.000	-239.429	-84.35833

```
. est store y2
. tobit y2 x, ll(0)
```

Tobit regression	Number of obs	=	450
	LR chi2(1)	=	211.53
	Prob > chi2	=	0.0000
Log likelihood = -2794.467	Pseudo R2	=	0.0365

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
x	232.3739	14.69983	15.81	0.000	203.4849	261.2629
_cons	-303.0343	47.96677	-6.32	0.000	-397.3016	-208.7671
-----+-----						
/sigma	305.08	11.30586			282.8611	327.299

```
67 left-censored observations at y2 <= 0
383 uncensored observations
0 right-censored observations
```

```
. est store y2tb
. lrtest y2 y2tb, force
```

Likelihood-ratio test	LR chi2(1)	=	732.14
(Assumption: y2 nested in y2tb)	Prob > chi2	=	0.0000

Ans. we reject the null hypothesis in the test, it means that tobit model should be used instead as we have the censored problem. When data is not available and we instead use zero as the information (however, it does not mean that it is zero but it means that it is not available), we have censored problem. If we ignore and run ols, the model will be biased because we got the wrong information.





```

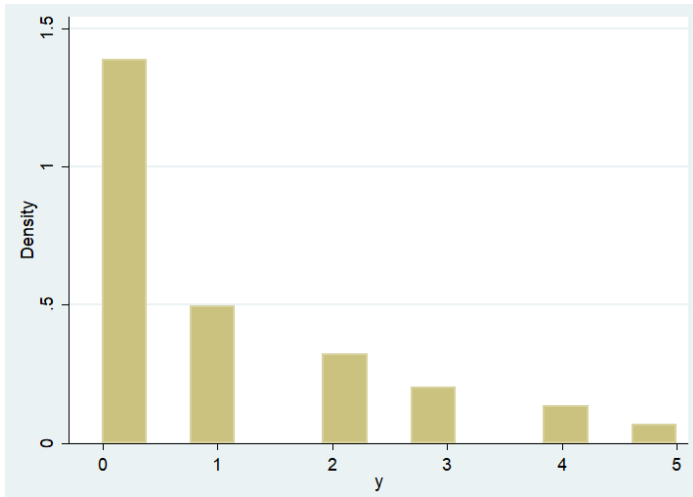
chi2 |          106.8811          211.52829
r2 | .27699948          .36153758          .07215367
r2_a | .27501866          .36011244          .07008259
-----
                                legend: * p<.1; ** p<.05; *** p<.01

-----
Variable |      y3ot
-----+-----
_      |
      x |
    _cons |
-----+-----
eq1    |
      x |
    _cons |
-----+-----
sigma  |
    _cons | 293.84115***
-----+-----
model  |
      x | 219.87524***
    _cons | -260.26928***
-----+-----
Statistics |
      N |      450
    rss |
    ll | -3056.8296
    rmse |
      F |
    chi2 | 212.4238
      r2 |
    r2_a |
-----
legend: * p<.1; ** p<.05; *** p<.01

```

ans. from the test we reject the null hypothesis which means tobit model should be used. we censored at 1000 for outliers, the model will be biased if we include all the actual outliers as the result will bend to the side of outliers.

3.(a) Estimate models for  $Y_i$  assuming that the model is traditional linear regression model. Create histogram for  $Y_i$ . Determine whether there is limitation of dependent variable in this case. If yes, what type of limitation is it? (3 points)



```
. reg y x1 x2 x3 x4
```

Source	SS	df	MS	Number of obs	=	195
-----+-----						
Model	34.7103145	4	8.67757863	F(4, 190)	=	5.10
Residual	323.289685	190	1.70152466	Prob > F	=	0.0006
-----+-----						
Total	358	194	1.84536082	R-squared	=	0.0970
-----+-----						
				Adj R-squared	=	0.0779
				Root MSE	=	1.3044

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
x1	.0782377	.0455503	1.72	0.087	-.0116115	.168087
x2	.135845	.0482593	2.81	0.005	.0406522	.2310378
x3	.1982819	.0696215	2.85	0.005	.0609515	.3356123
x4	-.0411306	.0493929	-0.83	0.406	-.1385595	.0562983
_cons	.9282072	.111482	8.33	0.000	.7083058	1.148109

```
. est store ols
```

Ans. although the ols model seems to be significant in overall, the actual distribution may not be normal as can be seen from the histogram. The distribution of dependent variable is likely to be poisson.

(b) Estimate models for  $Y_i$  assuming that the probability functions follow Poisson probability distribution. Perform GOF test and determine whether Poisson is appropriated in this case. Interpret the estimated result (sign and meaning (in term of incidence-rate ratios), overall test, individual test, pseudo  $R^2$ , marginal effects). (5 points)

```
. poisson y x1 x2 x3 x4, nolog
```

Poisson regression	Number of obs	=	195
	LR chi2(4)	=	35.29

```

Log likelihood = -276.58677
Prob > chi2 = 0.0000
Pseudo R2 = 0.0600

```

```

-----
      y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      x1 |   .0786569   .0342863     2.29   0.022     .011457   .1458569
      x2 |   .1355416   .0365243     3.71   0.000     .0639553   .2071279
      x3 |   .2110939   .0556809     3.79   0.000     .1019613   .3202265
      x4 |  -.0411834   .0379486    -1.09   0.278    -.1155614   .0331946
      _cons | -.1600951   .0940253    -1.70   0.089    -.3443813   .0241911
-----

```

```

. estat gof
      Deviance goodness-of-fit = 321.5064
      Prob > chi2(190) = 0.0000

      Pearson goodness-of-fit = 336.287
      Prob > chi2(190) = 0.0000

```

```

. poisson y x1 x2 x3 x4, ir nolog

```

```

Poisson regression
Number of obs = 195
LR chi2(4) = 35.29
Prob > chi2 = 0.0000
Log likelihood = -276.58677
Pseudo R2 = 0.0600

```

```

-----
      y |      IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      x1 |   1.081833   .0370921     2.29   0.022     1.011523   1.157031
      x2 |   1.145157   .0418261     3.71   0.000     1.066045   1.23014
      x3 |   1.235028   .0687675     3.79   0.000     1.107341   1.37744
      x4 |   .9596531   .0364175    -1.09   0.278     .8908659   1.033752
      _cons | .8520628   .0801155    -1.70   0.089     .7086587   1.024486
-----

```

```

. est store poi
. mfx
Marginal effects after poisson
      y = Predicted number of events (predict)
      = .91168981

```

```
-----
variable |      dy/dx      Std. Err.      z    P>|z|    [      95% C.I.      ]      X
-----+-----
      x1 |    .0717107      .0309      2.32    0.020    .011153    .132268    -.269757
      x2 |    .1235719      .03234      3.82    0.000    .060179    .186965     .878272
      x3 |    .1924522      .04891      3.93    0.000    .096583    .288322    -.297812
      x4 |   -.0375465      .0345     -1.09    0.276   -.105169    .030076   -.793566
-----
```

Ans. in this case we assume poisson distribution and perform the test of appropriateness, it turns out that we reject null hypothesis which means poisson model should not be used. The sign and meaning: x4 has negative impact on dependent variable according to  $IRR < 1$  and  $mf_x < 0$ . Overall test is significant, pseudo r2 is 0.06, not quite fit the data (we need higher pseudo r2 for better goodness of fit). Individual test for x4 is insignificant, others are significant.

**(c) Estimate models for  $Y_i$  assuming that the probability functions follow Negative Binomial probability distribution. Determine whether Negative Binomial regression model is appropriated in this case. Interpret your estimated result (sign and meaning (in term of incidence-rate ratios), overall test, individual test, pseudo R2 , marginal effects).**

```
. nbreg y x1 x2 x3 x4, nolog
Negative binomial regression              Number of obs   =           195
                                          LR chi2(4)       =           18.62
Dispersion = mean                        Prob > chi2      =           0.0009
Log likelihood = -260.81745              Pseudo R2       =           0.0345
-----
```

```
-----
      y |      Coef.      Std. Err.      z    P>|z|      [95% Conf. Interval]
-----+-----
      x1 |    .1048917      .0532951      1.97    0.049      .0004352      .2093482
      x2 |    .1525739      .0528768      2.89    0.004      .0489372      .2562105
      x3 |    .2032611      .0725929      2.80    0.005      .0609817      .3455405
      x4 |   -.0428056      .0512043     -0.84    0.403     -.1431641      .0575529
      _cons |  -.1783695      .1248751     -1.43    0.153     -.4231201      .0663812
-----+-----
      /lnalpha |  -.1410752      .2857036              -.7010441      .4188936
-----+-----
      alpha |    .868424      .2481119              .4960671      1.520279
-----
```

Likelihood-ratio test of alpha=0:  $\chi^2(01) = 31.54$  Prob>= $\chi^2 = 0.000$

```
. nbreg y x1 x2 x3 x4, ir nolog
Negative binomial regression              Number of obs   =           195
                                          LR chi2(4)       =           18.62
Dispersion = mean                        Prob > chi2      =           0.0009
```



Zero obs = 104

Inflation model = logit LR chi2(3) = 13.67

Log likelihood = -259.6744 Prob > chi2 = 0.0034

```
-----
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
y						
	x1	.0882506	.0438924	2.01	0.044	.0022231 .1742781
	x2	.1174633	.0406381	2.89	0.004	.0378141 .1971125
	x3	.1481343	.0569708	2.60	0.009	.0364735 .259795
	_cons	.3473148	.1169671	2.97	0.003	.1180636 .576566
-----+-----						
inflate						
	x4	.0307972	.1020081	0.30	0.763	-.1691351 .2307294
	_cons	-.4919609	.2559837	-1.92	0.055	-.9936799 .009758

Vuong test of zip vs. standard Poisson: z = 2.61 Pr>z = 0.0045

. mfx

Marginal effects after zip

y = Predicted number of events (predict)  
= .91818212

```
-----
```

variable	dy/dx	Std. Err.	z	P> z	[ 95% C.I. ]	X
-----+-----						
x1	.0810301	.04001	2.03	0.043	.002605 .159455	-.269757
x2	.1078527	.03659	2.95	0.003	.036132 .179574	.878272
x3	.1360142	.05122	2.66	0.008	.03562 .236409	-.297812
x4	-.0105671	.03513	-0.30	0.764	-.079421 .058287	-.793566

. est store zip

. est table ols poi nb zip, star(.1 .05 .01) stat(N ll chi2 chi2\_c vung)

```
-----
```

Variable	ols	poi	nb	zip
-----+-----				
x1	.07823774*			
x2	.135845***			

```

      x3 | .19828193***
      x4 | -.04113061
    _cons | .92820718***
-----+-----
y      |
      x1 | .07865693** .10489172** .08825059**
      x2 | .1355416*** .15257385*** .11746332***
      x3 | .2110939*** .20326108*** .14813427***
      x4 | -.04118338 -.04280564
    _cons | -.16009506* -.17836946 .3473148***
-----+-----
lnalpha |
    _cons | -.14107523
-----+-----
inflate |
      x4 | .03079715
    _cons | -.49196094*
-----+-----
Statistics |
      N | 195 195 195 195
      ll | -325.98406 -276.58677 -260.81745 -259.67438
      chi2 | 35.286302 18.62358 13.668238
      chi2_c | 31.538645
      vyoung |
-----+-----

```

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

Ans. from the test we reject null; thus, zip should be used. The overall test is significant, individual tests are sig. except for x4. From mfx and IRR, x4 has negative impact on y while other have positive.

From gof, we reject null; thus, poisson is inappropriate.

From test of alpha, the null is rejected; thus negative binomial should be used instead of poisson.

From vuong test, null is rejected; ZIP should be used instead of poisson.

As can be seen from histogram, there are many zeros of dependent variables; thus, ZIP is the most appropriated in this case.

**4.(a) Test whether the series yt and xt are stationary series and determine their order of integration. Give explanation of the process of the test. Why is testing equation important? Why is stationary property important to time series analysis?**

```

. tsset t
      time variable: t, 1 to 500

```

delta: 1 unit

. dfuller y, trend lags(1) regress

Augmented Dickey-Fuller test for unit root                    Number of obs =                    498

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-15.064	-3.980	-3.420
			-3.130

MacKinnon approximate p-value for Z(t) = 0.0000

D.y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
y						
L1.	-.9766545	.0648316	-15.06	0.000	-1.104034 - .8492748	
LD.	-.0591717	.0449902	-1.32	0.189	-.1475675 .0292241	
_trend	.001712	.0021085	0.81	0.417	-.0024307 .0058547	
_cons	.8158665	.6108936	1.34	0.182	-.3844037 2.016137	

. reg y x

Source	SS	df	MS	Number of obs	=	500
-----+-----				F(1, 498)	=	57414.60
Model	22599.9131	1	22599.9131	Prob > F	=	0.0000
Residual	196.026037	498	.39362658	R-squared	=	0.9914
-----+-----				Adj R-squared	=	0.9914
Total	22795.9391	499	45.6832448	Root MSE	=	.6274

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----					
x	.697591	.0029113	239.61	0.000	.691871 .703311
_cons	.5169709	.0282382	18.31	0.000	.4614903 .5724515

. dwstat

Durbin-Watson d-statistic( 2, 500) = 1.699397

Ans. from the test, we reject the null; thus, the series is already stationary and the order of integration is zero. The process is that firstly we test the unit root and in this case we reject the null hypothesis of there is unit root; thus, there is no unit root and series is stationary. If we did not reject null, we must test futher by dropping other terms in the equation. Before the analysis, we must make

sure that the series is stationary. If not, it will lead to spurious problem which is the false relationship of the variables. Moreover, from DWstat and r2, r2 is not greater than DW; thus, there is no spurious problem, supporting the fact that the series is already stationary.

(b) Estimate Autoregressive Integrated Moving Average (ARIMA(p,d,q)) model for yt – determine the most appropriated order for p, d, and q using SBIC given the maximum lag equals 4. Make dynamic forecast for period time = 501 to 505.

```
. est table a10*, star(.1 .05 .01) stat(N ll chi2 bic aic)
```

Variable	a101	a102	a103	a104
-----+-----				
y				
_cons	1.2783863***	1.281122***	1.2791531***	1.2796143***
-----+-----				
ARMA				
ar				
L1.	-.85046074***	.81947079***	-.85118368***	-.80777998***
ma				
L1.	.80613284***	-.85871207***	.81662977***	.77333988***
L2.		.07330406	.02669094	.02628038
L3.			.01786564	.04909843
L4.				.04871373
-----+-----				
sigma				
_cons	6.728622***	6.7288968***	6.7268756***	6.7195834***
-----+-----				
Statistics				
N	500	500	500	500
ll	-1662.6636	-1662.6768	-1662.5349	-1661.9889
chi2	50.079218	23.491264	50.136878	41.183747
bic	3350.1855	3356.4266	3362.3575	3367.4801
aic	3333.3271	3335.3536	3337.0699	3337.9778

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

```
. est table a20*, star(.1 .05 .01) stat(N ll chi2 bic aic)
```

Variable	a201	a202	a203	a204
-----+-----				
y				

```

      _cons |   1.281108***   1.280767***   1.2807996***   1.2807296***
-----+-----
ARMA      |
      ar |
      L1. |   .72953902***   .03547029   -.0062879   -.01786123
      L2. |   .07788416   .72197954***   .72251715***   .68062226**
      |
      ma |
      L1. |  -.77112068***  -.05929498   -.03103008   -.01852434
      L2. |                -.65277107**   -.6551612**   -.62767115**
      L3. |                                .0245666   .0231331
      L4. |                                .0257644
-----+-----
sigma      |
      _cons |   6.728009***   6.7172995***   6.7157424***   6.7140346***
-----+-----
Statistics  |
      N |           500           500           500           500
      ll |  -1662.6167   -1661.8255   -1661.7079   -1661.5797
      chi2 |   20.216544   20.405714   21.513034   20.14289
      bic |   3356.3064   3360.9386   3366.918   3372.8764
      aic |   3335.2334   3335.651   3337.4157   3339.1595
-----+-----

```

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

```
. est table a30*, star(.1 .05 .01) stat(N ll chi2 bic aic)
```

```

      Variable |      a301      a302      a303      a304
-----+-----
y            |
      _cons |   1.2791645***   1.2808262***   1.29709***   1.2970408***
-----+-----
ARMA      |
      ar |
      L1. |  -.84252296**   -.03735992   1.0737121***   1.0727138***
      L2. |   .02986665   .72407495***   .63880969**   .64085496
      L3. |   .01992436   .02515244   -.82793128***   -.82903352***
      |
      ma |

```

L1.		.80950138**	.00102216	-1.1331384	-1.1330084
L2.			-.65744142**	-.53811447	-.53964878
L3.				.79692477	.79950405
L4.					-.00126582

---

sigma					
_cons		6.7268367***	6.7158106***	6.6315795	6.6315672

---

Statistics					
N		500	500	500	500
ll		-1662.5223	-1661.7165	-1657.4839	-1657.4836
chi2		51.386274	22.059521	48896.509	49072.294
bic		3362.3322	3366.9352	3358.4701	3364.684
aic		3337.0446	3337.433	3328.9678	3330.9671

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

. est table a40\*, star(.1 .05 .01) stat(N ll chi2 bic aic)

---

Variable		a401	a402	a403	a404
y					
_cons		1.2798755***	1.281003***	1.2970437***	1.2807299***

---

ARMA					
ar					
L1.		-.76100779**	-.05304826	1.0711477***	-.35555204
L2.		.03093655	.64401144*	.642528	-.19846794
L3.		.05106124	.02542107	-.8280189***	.30260284
L4.		.05080673	.02793854	-.00130282	.6403234**
ma					
L1.		.72690001**	.01626353	-1.1314364***	.32593669
L2.			-.59171489	-.54141657	.24606498
L3.				.79863282***	-.28948366
L4.					-.55391935*

---

sigma					
_cons		6.7192073***	6.7138919***	6.6315723	6.7074171***

```
-----+-----
```

Statistics		500	500	500	500
N		500	500	500	500
ll		-1661.9674	-1661.5813	-1657.4836	-1661.1072
chi2		34.131091	19.371191	49155.273	31.137439
bic		3367.437	3372.8795	3364.684	3384.3604
aic		3337.9347	3339.1627	3330.9671	3342.2143

```
-----+-----
```

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

ans. Given max lags equal to 4, the most appropriated orders for(p,q,d) are (1,0,1) as the model has lowest BIC.

. arima y, arima(1,0,1) nolog

ARIMA regression

Sample: 1 - 500	Number of obs	=	500
	Wald chi2(2)	=	50.08
Log likelihood = -1662.664	Prob > chi2	=	0.0000

```
-----+-----
```

		OPG				
y		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y						
_cons		1.278386	.2956659	4.32	0.000	.6988917 1.857881
ARMA						
ar						
L1.		-.8504607	.1673848	-5.08	0.000	-1.178529 -.5223925
ma						
L1.		.8061328	.1890731	4.26	0.000	.4355564 1.176709
/sigma		6.728622	.2147767	31.33	0.000	6.307667 7.149577

```
-----+-----
```

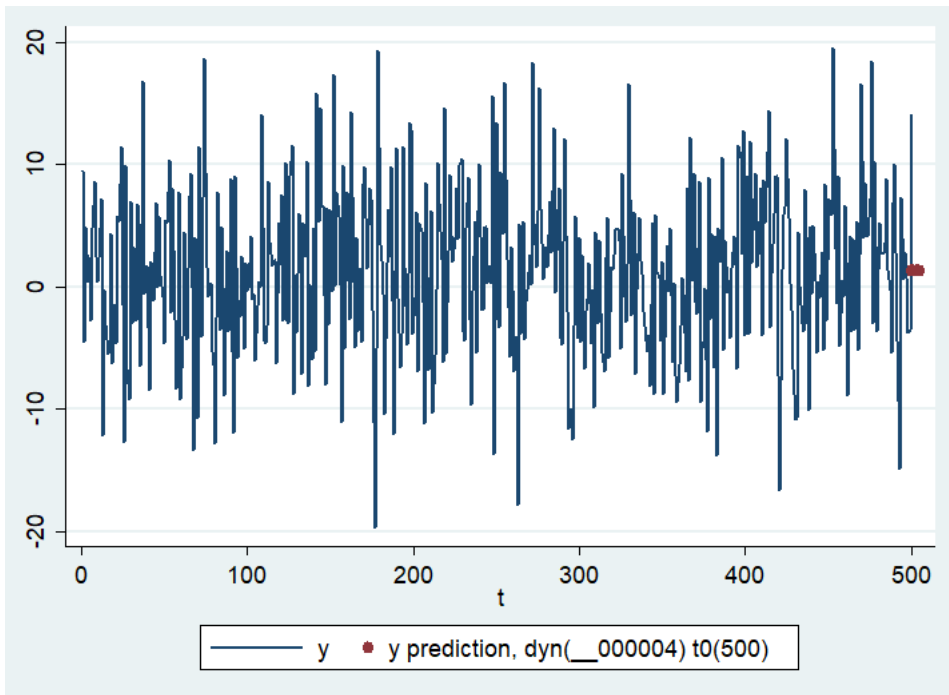
Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

. set obs 505

number of observations (\_N) was 500, now 505

. replace t=\_n

```
(5 real changes made)
. predict yhat, y dynamic(.) t0(500)
Note: beginning dynamic predictions in period      3.
(499 missing values generated)
. twoway (line y t, sort) (scatter yhat t, sort)
```



(c) Estimate model (5) using OLS by employing  $y_t$  as dependent variable and  $x_t$  as explanatory variable, determine whether ARCH-effect significantly occurs, and state null hypothesis of the test. Why the test is classified as LM test?

```
. reg y x
```

Source	SS	df	MS	Number of obs	=	500
-----+-----						
				F(1, 498)	=	57414.60
Model	22599.9131	1	22599.9131	Prob > F	=	0.0000
Residual	196.026037	498	.39362658	R-squared	=	0.9914
-----+-----						
				Adj R-squared	=	0.9914
Total	22795.9391	499	45.6832448	Root MSE	=	.6274
-----						
y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
x	.697591	.0029113	239.61	0.000	.691871	.703311
_cons	.5169709	.0282382	18.31	0.000	.4614903	.5724515
-----						

```
. estat archlm
LM test for autoregressive conditional heteroskedasticity (ARCH)
```

-----

lags (p)	chi2	df	Prob > chi2
1	38.569	1	0.0000

H0: no ARCH effects vs. H1: ARCH(p) disturbance

Ans. the null hypothesis is no arch effects. In this case we reject; thus, there is significant arch problem. Here for ols, it is a restricted model as we assume no arch effect in ols. So, the test will be LM test as the model is restricted.

(d) Estimate GARCH(p,q) for yt using xt as explanatory variable for mean equation (model (5) and (6)) – determine the most appropriated order p and q for variance equation using SBIC given the maximum lag equals to 2. Then, predict the variance of yt using the estimated result of GARCH(p,q) model with the most appropriated lag.

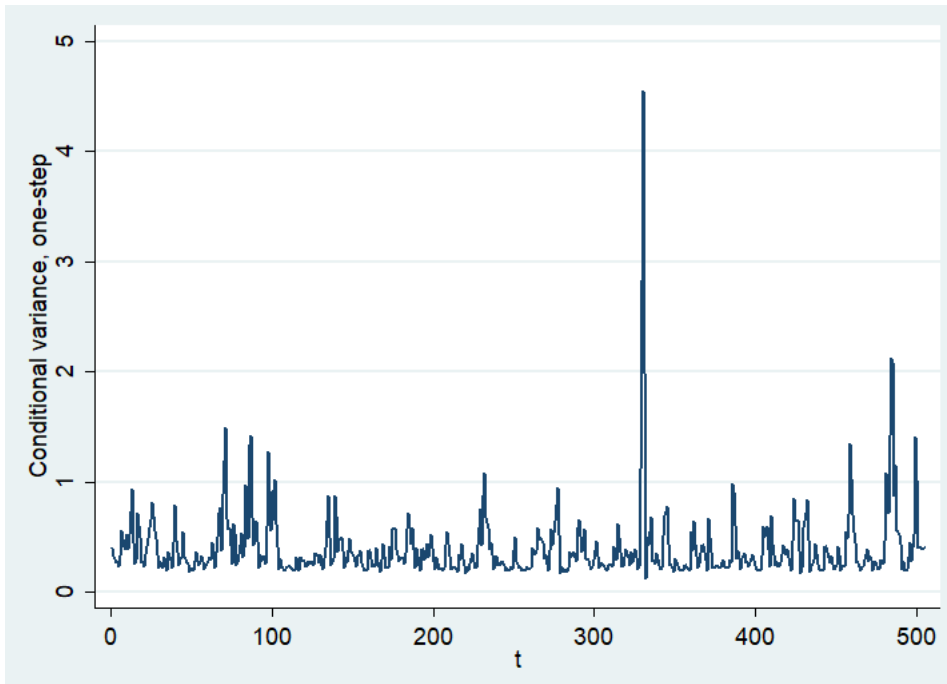
```
. est table g*, star(.1 .05 .01) stat(N ll chi2 bic aic)
```

Variable	g11	g12	g21	g22
<b>y</b>				
x	.69775812***	.69774139***	.69774644***	.69762642***
_cons	.51842966***	.51839207***	.51840685***	.51595866***
<b>ARCH</b>				
arch				
L1.	.36223733***	.36055372***	.36091784***	.37249344***
L2.		.015322		.30920474**
garch				
L1.	.31538419***	.28751012	.32622986*	-.39550084
L2.			-.0097377	.10865385
_cons	.128928***	.13460002*	.12900729***	.24612001***
<b>Statistics</b>				
N	500	500	500	500
ll	-443.6784	-443.67152	-443.67318	-442.8689
chi2	72792.196	72882.484	72850.286	74372.71
bic	918.42983	924.63069	924.63401	929.24006
aic	897.35679	899.34304	899.34636	899.7378

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

```
. predict sigmahat, v
```

```
. line sigmahat t
```



Ans. according to lowest BIC, garch(1,1) is the most appropriated one.

(e) Among these three models, ARCH(1), GARCH(1,1), or EGARCH(1,1,1), which model is the most appropriated in this case? Why? What are the differences among ARCH, GARCH, and EGARCH?

```
. arch y x, egarch(1/1) garch(1/1) arch(1/1) nolog
```

ARCH family regression

```
Sample: 1 - 500                               Number of obs   =           500
Distribution: Gaussian                         Wald chi2(1)    =       67004.12
Log likelihood = -447.1185                    Prob > chi2     =           0.0000
```

```
-----+-----
```

		OPG				
	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
y						
	x	.6979221	.0026962	258.85	0.000	.6926376 .7032066
	_cons	.5116238	.0250266	20.44	0.000	.4625726 .560675
-----+-----						
ARCH						
	egarch					
	L1.	.3619726	.1238794	2.92	0.003	.1191734 .6047719
	arch					
	L1.	.6726571	.0925512	7.27	0.000	.4912601 .8540541

```

      |
garch |
  L1. | -.0060473   .0106304   -0.57   0.569   -.0268825   .0147878
      |
  _cons | -.9232664   .1570025   -5.88   0.000   -1.230986   -.6155472
-----

```

```

. est store eg111
. est table eg111, star(.1 .05 .01) stat(N ll chi2 bic aic)
-----

```

```

Variable |      eg111
-----+-----
y        |
  x      | .69792214***
  _cons  | .51162381***
-----+-----

```

```

ARCH      |
egarch   |
  L1.    | .36197264***
      |
arch     |
  L1.    | .67265712***
      |
garch    |
  L1.    | -.00604733
      |
  _cons  | -.92326637***
-----+-----

```

```

Statistics |
  N        |      500
  ll       | -447.1185
  chi2     | 67004.123
  bic      | 931.52464
  aic      | 906.23699
-----+-----

```

legend: \* p<.1; \*\* p<.05; \*\*\* p<.01

Ans. from lowest BIC, garch(1,1) is most appropriated as it has the lowest value of BIC. Arch model is a process of weighted sum of lags of error terms or white noises. Garch is a model where we model the lags terms of variance. For egarch, it is when we have asymmetric model, the garch graph is not linear but kinked. In egarch, the exponential term is included to make the graph more smooth. Moreover,

in practice, we need high frequency data to detect the both arch and garch effect. But for garch effects, the frequency must be like daily data.

### 5.(a) Estimate VARs models using yt and xt as endogenous variables and determine the most appropriated lags models using SBIC

```
. varsoc y x

Selection-order criteria

Sample: 5 - 500                Number of obs   =           496

+-----+
|lag |    LL    LR    df    p    FPE    AIC    HQIC    SBIC    |
+-----+-----+
| 0 | -1366.52                .854238  5.51821  5.52487  5.53517 |
| 1 | -1320.19  92.648*    4  0.000  .720214*  5.34755*  5.36752*  5.39843* |
| 2 | -1319.33  1.7247    4  0.786  .729385  5.3602  5.39349  5.44501 |
| 3 | -1318.25  2.1559    4  0.707  .738031  5.37198  5.41859  5.49072 |
| 4 | -1316.13  4.2352    4  0.375  .743657  5.37957  5.43949  5.53223 |
+-----+

Endogenous:  y x

Exogenous:  _cons
```

Ans. according to lowest BIC, the most appropriated lag order is one.

### (b) Perform stability test and Granger exogeneity test. Determine whether assumptions of VARs are satisfied, explain your evaluation criteria. If the stability assumption is unsatisfied, what will happen?

```
. var y x, lag(1/1)

Vector autoregression

Sample: 2 - 500                Number of obs   =           499

Log likelihood = -1330.31      AIC              = 5.355953

FPE              = .7262936    HQIC            = 5.375831

Det(Sigma_ml)   = .7090358    SBIC           = 5.406605

Equation        Parms    RMSE    R-sq    chi2    P>chi2
-----
y                3      .994284  0.0148  7.496551  0.0236
```

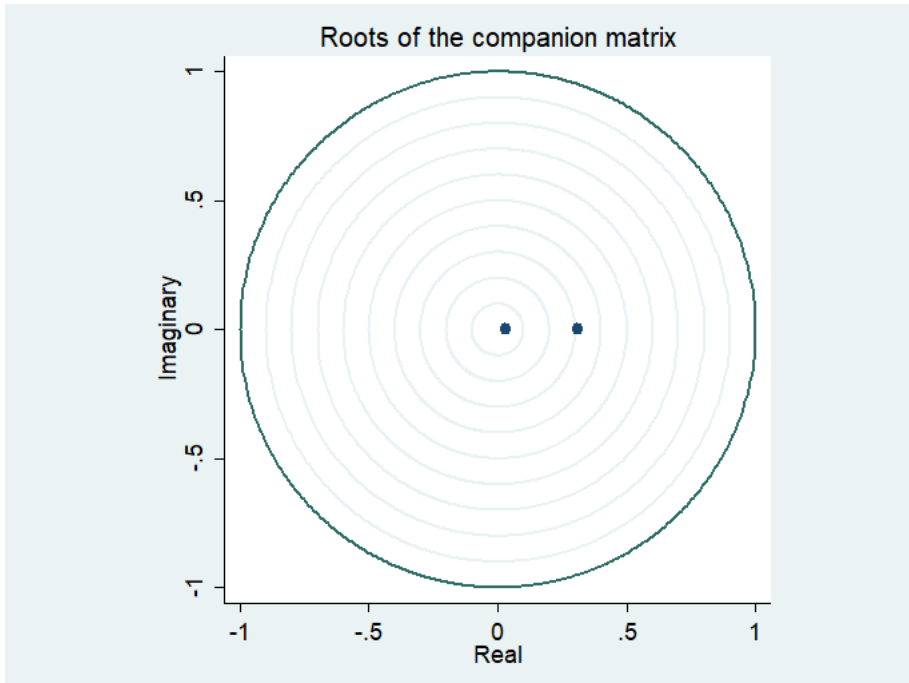


```
| .0328928          | .032893 |
```

```
+-----+
```

All the eigenvalues lie inside the unit circle.

VAR satisfies stability condition.



```
. vargranger
```

```
Granger causality Wald tests
```

```
+-----+
```

```
|          Equation          Excluded |  chi2    df Prob > chi2 |
```

```
|-----+-----|
```

```
|              y              x |  1.2618   1   0.261 |
```

```
|              y              ALL |  1.2618   1   0.261 |
```

```
|-----+-----|
```

```
|              x              y |  45.682   1   0.000 |
```

```
|              x              ALL |  45.682   1   0.000 |
```

```
+-----+
```

Ans. from stability test, all eigenvalues lie within unit circle; stability assumption is satisfied and the system is stable. According to granger test, the

variables will cause each other if both null hypotheses are rejected. In this case, only one is rejected; x seems not to be the endogenous variable but y is an endogenous variable. If the system is not stable, the impulse will not collapse into zero when we do IRF.

**(c) Perform Impulse response function analysis (irf), Orthogonal impulse response function analysis (oirf), Cumulative impulse response function analysis (coirf), make interpretation of the analysis, and determine which variable has more impact (using Cholesky order – yt xt).**

```
. irf create order1, o(y x) step(10) set(irf_1)
```

```
(file irf_1.irf created)
```

```
(file irf_1.irf now active)
```

```
(file irf_1.irf updated)
```

```
. irf table irf, impulse(y x) response(y x)
```

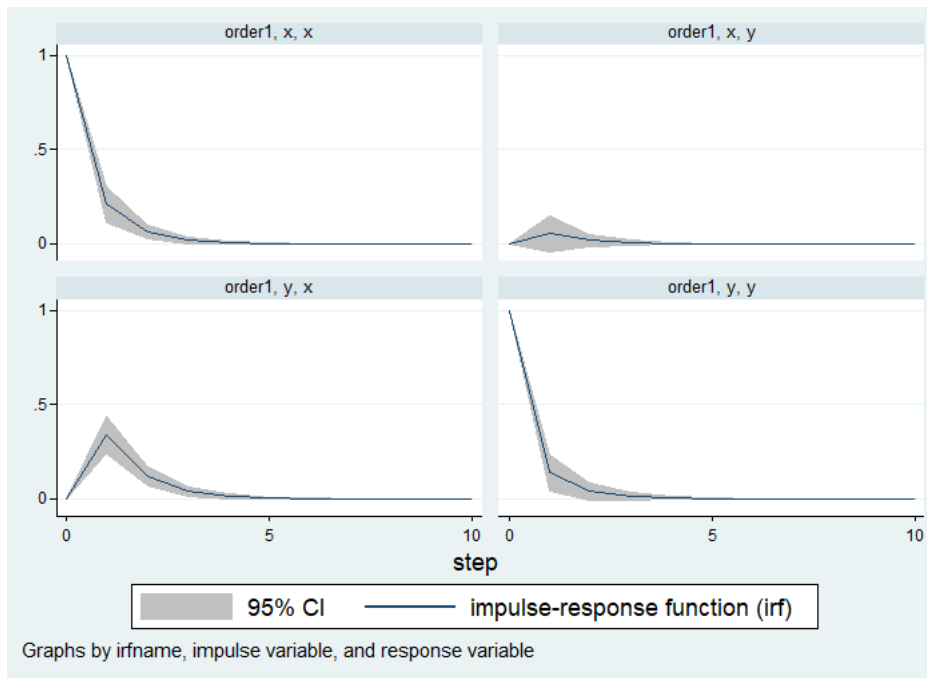
Results from order1

-----+							
	(1)	(1)	(1)	(2)	(2)	(2)	
step	irf	Lower	Upper	irf	Lower	Upper	
-----+							
0	1	1	1	0	0	0	
1	.136897	.038751	.235042	.339795	.24126	.43833	
2	.037052	-.011225	.085329	.117519	.066423	.168615	
3	.011405	-.008221	.031032	.037147	.012582	.061712	
4	.003563	-.003834	.01096	.011638	.000444	.022831	
5	.001115	-.001591	.00382	.003642	-.001081	.008366	
6	.000349	-.000621	.001319	.00114	-.000736	.003016	
7	.000109	-.000233	.000452	.000357	-.000357	.001071	
8	.000034	-.000085	.000154	.000112	-.000152	.000375	
9	.000011	-.000031	.000052	.000035	-.00006	.00013	
10	3.3e-06	-.000011	.000017	.000011	-.000023	.000045	
-----+							
-----+							
	(3)	(3)	(3)	(4)	(4)	(4)	

step	irf	Lower	Upper	irf	Lower	Upper
0	0	0	0	1	1	1
1	.05389	-.040138	.147918	.208957	.114556	.303359
2	.018638	-.014291	.051566	.061975	.024515	.099434
3	.005891	-.006206	.017989	.019283	.001614	.036952
4	.001846	-.002574	.006265	.006031	-.00155	.013612
5	.000578	-.00101	.002165	.001887	-.001149	.004923
6	.000181	-.000381	.000742	.000591	-.00057	.001752
7	.000057	-.000139	.000253	.000185	-.000245	.000615
8	.000018	-.00005	.000085	.000058	-.000098	.000213
9	5.5e-06	-.000018	.000029	.000018	-.000037	.000073
10	1.7e-06	-6.2e-06	9.6e-06	5.7e-06	-.000014	.000025

95% lower and upper bounds reported

- (1) irfname = order1, impulse = y, and response = y
  - (2) irfname = order1, impulse = y, and response = x
  - (3) irfname = order1, impulse = x, and response = y
  - (4) irfname = order1, impulse = x, and response = x
- . irf graph irf, impulse(y x) response(y x)



```
. irf table oirf, impulse(y x) response(y x)
```

Results from order1

-----+-----							
	(1)	(1)	(1)	(2)	(2)	(2)	
step	oirf	Lower	Upper	oirf	Lower	Upper	
-----+-----							
0	.99129	.929789	1.05279	-.518579	-.599757	-.437401	
1	.107758	.02092	.194597	.228474	.139126	.317822	
2	.027064	-.005259	.059387	.084357	.04536	.123355	
3	.008251	-.005158	.02166	.026823	.009633	.044014	
4	.002575	-.002519	.007669	.008409	.000835	.015982	
5	.000806	-.001067	.002678	.002632	-.000565	.005829	
6	.000252	-.000422	.000926	.000824	-.000455	.002102	
7	.000079	-.00016	.000318	.000258	-.000232	.000748	
8	.000025	-.000059	.000108	.000081	-.000101	.000263	
9	7.7e-06	-.000021	.000037	.000025	-.000041	.000091	
10	2.4e-06	-7.5e-06	.000012	7.9e-06	-.000016	.000031	
-----+-----							

	(3)	(3)	(3)	(4)	(4)	(4)
step	oirf	Lower	Upper	oirf	Lower	Upper
0	0	0	0	.849441	.79674	.902142
1	.045776	-.034146	.125698	.177497	.096556	.258438
2	.015832	-.012156	.04382	.052644	.020657	.084631
3	.005004	-.005277	.015285	.01638	.001337	.031423
4	.001568	-.002188	.005323	.005123	-.001324	.01157
5	.000491	-.000858	.001839	.001603	-.000978	.004184
6	.000154	-.000323	.00063	.000502	-.000485	.001489
7	.000048	-.000118	.000215	.000157	-.000208	.000522
8	.000015	-.000043	.000073	.000049	-.000083	.000181
9	4.7e-06	-.000015	.000024	.000015	-.000032	.000062
10	1.5e-06	-5.2e-06	8.2e-06	4.8e-06	-.000012	.000021

95% lower and upper bounds reported

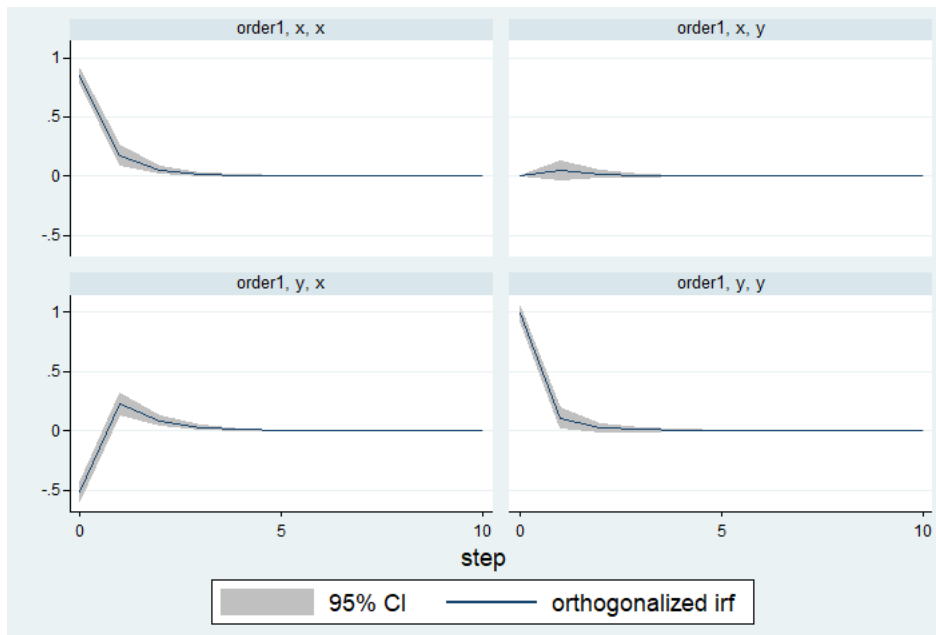
(1) irfname = order1, impulse = y, and response = y

(2) irfname = order1, impulse = y, and response = x

(3) irfname = order1, impulse = x, and response = y

(4) irfname = order1, impulse = x, and response = x

. irf graph oirf, impulse(y x) response(y x)



```
. irf table coirf, impulse(y x) response(y x)
```

Results from order1

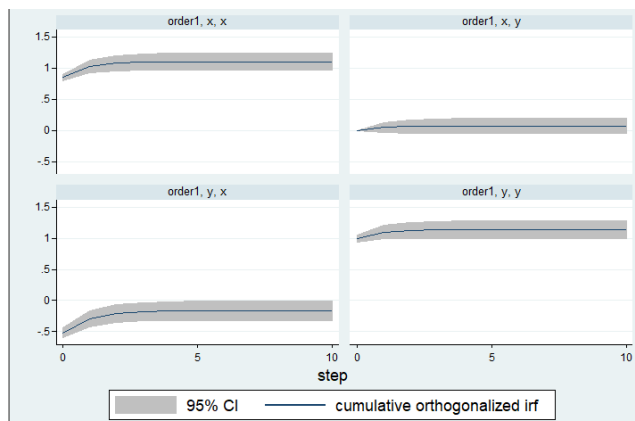
-----+						
	(1)	(1)	(1)	(2)	(2)	(2)
step	coirf	Lower	Upper	coirf	Lower	Upper
-----+						
0	.99129	.929789	1.05279	-.518579	-.599757	-.437401
1	1.09905	.988841	1.20926	-.290105	-.416525	-.163684
2	1.12611	.997787	1.25444	-.205747	-.347383	-.064112
3	1.13436	.998474	1.27025	-.178924	-.327699	-.030149
4	1.13694	.99813	1.27575	-.170516	-.322242	-.01879
5	1.13774	.997874	1.27761	-.167884	-.320744	-.015023
6	1.138	.997752	1.27824	-.16706	-.320336	-.013784
7	1.13808	.9977	1.27845	-.166802	-.320226	-.013379
8	1.1381	.997681	1.27852	-.166721	-.320196	-.013247
9	1.13811	.997673	1.27854	-.166696	-.320189	-.013204
10	1.13811	.99767	1.27855	-.166688	-.320187	-.01319
-----+						

	(3)			(4)		
step	coirf	Lower	Upper	coirf	Lower	Upper
0	0	0	0	.849441	.79674	.902142
1	.045776	-.034146	.125698	1.02694	.92452	1.12936
2	.061608	-.045907	.169123	1.07958	.955614	1.20355
3	.066612	-.050942	.184167	1.09596	.963061	1.22886
4	.06818	-.053012	.189371	1.10108	.964611	1.23756
5	.068671	-.053817	.191158	1.10269	.964865	1.24051
6	.068824	-.054118	.191766	1.10319	.964877	1.2415
7	.068872	-.054227	.191972	1.10335	.96486	1.24183
8	.068887	-.054266	.192041	1.1034	.964849	1.24194
9	.068892	-.05428	.192064	1.10341	.964844	1.24198
10	.068893	-.054285	.192072	1.10342	.964842	1.24199

95% lower and upper bounds reported

- (1) irfname = order1, impulse = y, and response = y
- (2) irfname = order1, impulse = y, and response = x
- (3) irfname = order1, impulse = x, and response = y
- (4) irfname = order1, impulse = x, and response = x

. irf graph coirf, impulse(y x) response(y x)



Ans. from all the graphs, it seems that there is positive impact. From the coirf graph, it can be seen that the magnitude of impact y on x is larger than x on y; thus, y has more impact on x. Moreover, the impact of x on y mostly insignificant as almost all of them cover zero in the interval.

**(d) Perform Forecast error variance decomposition (fevd) and determine variable that has more impact on each endogenous variable**

```
. irf table fevd, impulse(y x) response(y x)
```

Results from order1

-----+							
	(1)	(1)	(1)	(2)	(2)	(2)	
step	fevd	Lower	Upper	fevd	Lower	Upper	
-----+							
0	0	0	0	0	0	0	
1	1	1	1	.27151	.2049	.338121	
2	.997897	.990562	1.00523	.298949	.234118	.363779	
3	.997648	.989454	1.00584	.302786	.238493	.36708	
4	.997623	.989331	1.00591	.303174	.238941	.367406	
5	.99762	.989317	1.00592	.303212	.238985	.367438	
6	.99762	.989316	1.00592	.303216	.23899	.367441	
7	.99762	.989316	1.00592	.303216	.23899	.367442	
8	.99762	.989316	1.00592	.303216	.23899	.367442	
9	.99762	.989316	1.00592	.303216	.23899	.367442	
10	.99762	.989316	1.00592	.303216	.23899	.367442	
-----+							
-----+							
	(3)	(3)	(3)	(4)	(4)	(4)	
step	fevd	Lower	Upper	fevd	Lower	Upper	
-----+							
0	0	0	0	0	0	0	
1	0	0	0	.72849	.661879	.7951	
2	.002103	-.005232	.009438	.701051	.636221	.765882	

3		.002352	-	.005842	.010546		.697214	.63292	.761507	
4		.002377	-	.005915	.010669		.696826	.632594	.761059	
5		.00238	-	.005923	.010683		.696788	.632562	.761015	
6		.00238	-	.005924	.010684		.696784	.632559	.76101	
7		.00238	-	.005925	.010684		.696784	.632558	.76101	
8		.00238	-	.005925	.010684		.696784	.632558	.76101	
9		.00238	-	.005925	.010684		.696784	.632558	.76101	
10		.00238	-	.005925	.010684		.696784	.632558	.76101	

+-----+

95% lower and upper bounds reported

(1) irfname = order1, impulse = y, and response = y

(2) irfname = order1, impulse = y, and response = x

(3) irfname = order1, impulse = x, and response = y

(4) irfname = order1, impulse = x, and response = x

Ans. according to Fevd, y has more impact on x.

**(e) Determine whether changing Cholesky order from – “yt xt” to “xt yt” will change the results of irf, oirf, coirf, and fevd.**

```
. irf create order1, o(x y) step(10) set(irf_2)
```

```
(file irf_2.irf created)
```

```
(file irf_2.irf now active)
```

```
(file irf_2.irf updated)
```

```
. irf table irf, impulse(x y) response(x y)
```

Results from order1

+-----+									
		(1)	(1)	(1)		(2)	(2)	(2)	
	step	irf	Lower	Upper		irf	Lower	Upper	
+-----+									
0		1	1	1		0	0	0	
1		.208957	.114556	.303359		.05389	-.040138	.147918	

2		.061975	.024515	.099434		.018638	-.014291	.051566	
3		.019283	.001614	.036952		.005891	-.006206	.017989	
4		.006031	-.00155	.013612		.001846	-.002574	.006265	
5		.001887	-.001149	.004923		.000578	-.00101	.002165	
6		.000591	-.00057	.001752		.000181	-.000381	.000742	
7		.000185	-.000245	.000615		.000057	-.000139	.000253	
8		.000058	-.000098	.000213		.000018	-.00005	.000085	
9		.000018	-.000037	.000073		5.5e-06	-.000018	.000029	
10		5.7e-06	-.000014	.000025		1.7e-06	-6.2e-06	9.6e-06	

-----+

-----+

	(3)	(3)	(3)	(4)	(4)	(4)
--	-----	-----	-----	-----	-----	-----

step	irf	Lower	Upper	irf	Lower	Upper
------	-----	-------	-------	-----	-------	-------

-----+

0		0	0	0		1	1	1	
1		.339795	.24126	.43833		.136897	.038751	.235042	
2		.117519	.066423	.168615		.037052	-.011225	.085329	
3		.037147	.012582	.061712		.011405	-.008221	.031032	
4		.011638	.000444	.022831		.003563	-.003834	.01096	
5		.003642	-.001081	.008366		.001115	-.001591	.00382	
6		.00114	-.000736	.003016		.000349	-.000621	.001319	
7		.000357	-.000357	.001071		.000109	-.000233	.000452	
8		.000112	-.000152	.000375		.000034	-.000085	.000154	
9		.000035	-.00006	.00013		.000011	-.000031	.000052	
10		.000011	-.000023	.000045		3.3e-06	-.000011	.000017	

-----+

95% lower and upper bounds reported

(1) irfname = order1, impulse = x, and response = x

(2) irfname = order1, impulse = x, and response = y

(3) irfname = order1, impulse = y, and response = x

(4) irfname = order1, impulse = y, and response = y

. irf table oirf, impulse(x y) response(x y)

Results from order1

```
+-----+
|      |      (1)      (1)      (1)  |      (2)      (2)      (2)  |
| step | oirf   Lower   Upper  | oirf   Lower   Upper  |
|-----+-----+-----+-----+-----+
| 0     | .995226  .93348  1.05697 | -.516528  -.597385  -.435671 |
| 1     | .032446  -.055074 .119966  | -.017079  -.101153  .066995  |
| 2     | .000977  -.025324 .027278  | -.00059   -.013299  .01212   |
| 3     | 3.8e-06  -.009566 .009573  | -.000028  -.003175  .003119  |
| 4     | -8.8e-06 -.003076 .003058  | -3.6e-06  -.00095   .000943  |
| 5     | -3.1e-06 -.000966 .000959  | -9.7e-07  -.000295  .000293  |
| 6     | -9.7e-07 -.000302 .0003   | -3.0e-07  -.000092  .000092  |
| 7     | -3.0e-07 -.000094 .000094  | -9.3e-08  -.000029  .000029  |
| 8     | -9.5e-08 -.00003   .000029  | -2.9e-08  -9.0e-06  9.0e-06  |
| 9     | -3.0e-08 -9.2e-06  9.2e-06  | -9.1e-09  -2.8e-06  2.8e-06  |
| 10    | -9.3e-09 -2.9e-06  2.9e-06  | -2.9e-09  -8.8e-07  8.8e-07  |
+-----+
+-----+
```

```
+-----+
|      |      (3)      (3)      (3)  |      (4)      (4)      (4)  |
| step | oirf   Lower   Upper  | oirf   Lower   Upper  |
|-----+-----+-----+-----+-----+
| 0     | 0       0       0       | .846082  .79359   .898574  |
| 1     | .287494 .202239  .37275   | .115826  .032477  .199175  |
| 2     | .099431 .055762  .1431    | .031349  -.009544  .072242  |
| 3     | .031429 .010554  .052304  | .00965   -.006967  .026266  |
| 4     | .009846 .000356  .019336  | .003015  -.003247  .009276  |
+-----+
```

5		.003082	-.000919	.007083		.000943	-.001346	.003233	
6		.000965	-.000624	.002553		.000295	-.000526	.001116	
7		.000302	-.000303	.000906		.000092	-.000198	.000382	
8		.000094	-.000129	.000318		.000029	-.000072	.00013	
9		.00003	-.000051	.00011		9.0e-06	-.000026	.000044	
10		9.3e-06	-.000019	.000038		2.8e-06	-9.1e-06	.000015	

+-----+

95% lower and upper bounds reported

- (1) irfname = order1, impulse = x, and response = x
- (2) irfname = order1, impulse = x, and response = y
- (3) irfname = order1, impulse = y, and response = x
- (4) irfname = order1, impulse = y, and response = y

. irf table coirf, impulse(x y) response(x y)

Results from order1

+-----+									
	(1)	(1)	(1)	(2)	(2)	(2)			
step	coirf	Lower	Upper	coirf	Lower	Upper			
+-----+									
0		.995226	.93348	1.05697		-.516528	-.597385	-.435671	
1		1.02767	.919409	1.13593		-.533607	-.656826	-.410388	
2		1.02865	.911276	1.14602		-.534197	-.667537	-.400856	
3		1.02865	.908054	1.14925		-.534225	-.670073	-.398376	
4		1.02864	.90693	1.15036		-.534228	-.670828	-.397628	
5		1.02864	.906566	1.15071		-.534229	-.671063	-.397395	
6		1.02864	.906451	1.15083		-.534229	-.671137	-.397322	
7		1.02864	.906415	1.15086		-.53423	-.67116	-.397299	
8		1.02864	.906403	1.15087		-.53423	-.671167	-.397292	
9		1.02864	.9064	1.15088		-.53423	-.671169	-.39729	
10		1.02864	.906399	1.15088		-.53423	-.67117	-.397289	

```

+-----+
+-----+
|      |      (3)      (3)      (3) |      (4)      (4)      (4) |
| step | coirf      Lower      Upper | coirf      Lower      Upper |
+-----+-----+-----+-----+-----+-----+
|0      | 0          0          0      | .846082     .79359     .898574    |
|1      | .287494    .202239    .37275     | .961908     .859649    1.06417    |
|2      | .386925    .269313    .504537    | .993257     .859792    1.12672    |
|3      | .418354    .286622    .550087    | 1.00291     .856144    1.14967    |
|4      | .428201    .290687    .565714    | 1.00592     .854101    1.15774    |
|5      | .431282    .29153     .571035    | 1.00687     .853205    1.16052    |
|6      | .432247    .291665    .572829    | 1.00716     .852848    1.16147    |
|7      | .432549    .291669    .573428    | 1.00725     .852713    1.16179    |
|8      | .432643    .291659    .573627    | 1.00728     .852663    1.1619     |
|9      | .432673    .291652    .573693    | 1.00729     .852645    1.16194    |
|10     | .432682    .291649    .573715    | 1.00729     .852639    1.16195    |
+-----+

```

95% lower and upper bounds reported

- (1) irfname = order1, impulse = x, and response = x
  - (2) irfname = order1, impulse = x, and response = y
  - (3) irfname = order1, impulse = y, and response = x
  - (4) irfname = order1, impulse = y, and response = y
- . irf graph coirf, impulse(x y) response(x y)
- . irf table fevd, impulse(x y) response(x y)

Results from order1

```

+-----+
|      |      (1)      (1)      (1) |      (2)      (2)      (2) |
| step | fevd      Lower      Upper | fevd      Lower      Upper |
+-----+-----+-----+-----+-----+-----+

```

0	0	0	0	0	0	0	
1	1	1	1	.27151	.2049	.338121	
2	.923055	.879983	.966127	.268068	.201606	.33453	
3	.914637	.867335	.961939	.267804	.201324	.334284	
4	.913804	.866015	.961594	.267779	.201296	.334262	
5	.913723	.86588	.961565	.267777	.201293	.33426	
6	.913715	.865866	.961563	.267776	.201292	.33426	
7	.913714	.865865	.961563	.267776	.201292	.33426	
8	.913714	.865865	.961563	.267776	.201292	.33426	
9	.913714	.865865	.961563	.267776	.201292	.33426	
10	.913714	.865865	.961563	.267776	.201292	.33426	

-----+  
-----+

	(3)	(3)	(3)	(4)	(4)	(4)	
step	fevd	Lower	Upper	fevd	Lower	Upper	

0	0	0	0	0	0	0	
1	0	0	0	.72849	.661879	.7951	
2	.076945	.033873	.120017	.731932	.66547	.798394	
3	.085363	.038061	.132665	.732196	.665716	.798676	
4	.086196	.038406	.133985	.732221	.665738	.798704	
5	.086277	.038435	.13412	.732223	.66574	.798707	
6	.086285	.038437	.134134	.732224	.66574	.798708	
7	.086286	.038437	.134135	.732224	.66574	.798708	
8	.086286	.038437	.134135	.732224	.66574	.798708	
9	.086286	.038437	.134135	.732224	.66574	.798708	
10	.086286	.038437	.134135	.732224	.66574	.798708	

-----+

95% lower and upper bounds reported

(1) irfname = order1, impulse = x, and response = x

(2) irfname = order1, impulse = x, and response = y

(3) irfname = order1, impulse = y, and response = x

(4) irfname = order1, impulse = y, and response = y

Ans. yes, it will change the result if we change the order. As a result, we need to make sure the order first. In this case, the impact of x on y is larger (previous case is impact on y is larger) when we change the order from (y x) to (x y).