

1) a)

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

```
Multinomial logistic regression      Number of obs      =      170
LR chi2(8)                          =      90.86
Prob > chi2                          =      0.0000
Log likelihood = -104.8068           Pseudo R2          =      0.3024
```

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

	y	RRR	Std. Err.	z	P> z	[95% Conf. Interval]
0	(base outcome)					
1						
	x1	.2599617	.1658795	-2.11	0.035	.0744329 .9079339
	x2	.3818281	.2992225	-1.23	0.219	.0821897 1.773857
	x3	.6644484	.4190852	-0.65	0.517	.1930127 2.287371
	x4	2.033882	.5337481	2.71	0.007	1.216036 3.401771
	_cons	.0001886	.0007014	-2.31	0.021	1.29e-07 .2763357
2						
	x1	.3193839	.2197084	-1.66	0.097	.0829393 1.229889
	x2	.1662242	.1344288	-2.22	0.026	.0340652 .8111065
	x3	2.072154	1.376082	1.10	0.273	.5638369 7.615361
	x4	6.282728	1.95573	5.90	0.000	3.413347 11.56421
	_cons	3.72e-12	1.72e-11	-5.70	0.000	4.40e-16 3.15e-08

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

```
est store my
```

```
fitstat
```

```
Measures of Fit for mlogit of y
```

```
Log-Lik Intercept Only:      -150.239      Log-Lik Full Model:      -104.807
D(155):                      209.614      LR(8):                  90.864
                              Prob > LR:          0.000
McFadden's R2:               0.302      McFadden's Adj R2:      0.203
Maximum Likelihood R2:       0.414      Cragg & Uhler's R2:     0.499
Count R2:                    0.259      Adj Count R2:           0.031
AIC:                          1.409      AIC*n:                  239.614
BIC:                          -586.435     BIC':                   -49.777
```

Variable x1 increases the probability that alternative 4 is chosen instead of the baseline alternative if RRR > 1

Variable x1 increases the probability that alternative 2 is chosen instead of the baseline alternative if RRR > 1

Variable x1 increases the probability that alternative 3 is chosen instead of the baseline alternative if RRR > 1

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

```
Multinomial logistic regression      Number of obs      =      61
LR chi2(4)                          =      10.66
Prob > chi2                          =      0.0307
Log likelihood = -33.945638           Pseudo R2          =      0.1357
```

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

y	RRR	Std. Err.	z	P> z	[95% Conf. Interval]	
0	(base outcome)					
1						
x1	.3234342	.1977792	-1.85	0.065	.0975614	1.072244
x2	.5219172	.3930008	-0.86	0.388	.119303	2.283241
x3	.8017844	.5258649	-0.34	0.736	.2217081	2.89957
x4	1.886394	.4854053	2.47	0.014	1.139205	3.123653
_cons	.000378	.0014383	-2.07	0.038	2.18e-07	.6552516

est store myno2

hausman my myno2, alleqs constant

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	my	myno2	Difference	S.E.
x1	-1.347221	-1.12876	-.2184611	.1822961
x2	-.9627847	-.6502463	-.3125384	.2170679
x3	-.408798	-.2209155	-.1878825	.
x4	.7099461	.6346669	.0752791	.0515311
_cons	-8.576009	-7.880673	-.6953359	.

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

$$\begin{aligned} \text{chi2}(5) &= (b-B)' [(V_b-V_B)^{-1}] (b-B) \\ &= 1.40 \\ \text{Prob}>\text{chi2} &= 0.9239 \\ &(\text{V}_b-\text{V}_B \text{ is not positive definite}) \end{aligned}$$

According to IIA (Hausman) test of y with p-value of 0.9239, which is greater than 0.05, IIA hypothesis is not rejected. Thus, IIA is satisfied in Model y

Independence of Irrelevant Alternatives (IIA) is the important assumption of Multinomial Logit Model It implies that the decision between two alternatives is independent from the existence of more alternatives

b)

oprobit y x1 x2 x3 x4, nolog

Ordered probit regression	Number of obs	=	170
	LR chi2(4)	=	82.32
	Prob > chi2	=	0.0000
Log likelihood = -109.07948	Pseudo R2	=	0.2740

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.2521765	.2334709	-1.08	0.280	-.7097711	.2054182
x2	-.5121066	.2373109	-2.16	0.031	-.9772274	-.0469858
x3	.5218909	.221538	2.36	0.018	.0876843	.9560974
x4	.6962484	.0932722	7.46	0.000	.5134383	.8790585

/cut1	9.656838	1.425278	6.863345	12.45033
/cut2	10.84958	1.47619	7.956298	13.74286

tab y

y	Freq.	Percent	Cum.
0	21	12.35	12.35
1	40	23.53	35.88
2	109	64.12	100.00
Total	170	100.00	

```
. g y01=y>0
. g y12=y>1
. qui probit y01 x*, nolog
. est store m01
. qui probit y12 x*, nolog
. est store m12
. suest m01 m12
```

Simultaneous results for m01, m12

Number of obs = 170

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

m01_y01						
x1	-.6851706	.3512494	-1.95	0.051	-1.373607	.0032655
x2	-.6845366	.3809002	-1.80	0.072	-1.431087	.0620141
x3	.1281714	.3167247	0.40	0.686	-.4925977	.7489404
x4	.6859726	.1150367	5.96	0.000	.4605049	.9114403
_cons	-8.921267	1.648028	-5.41	0.000	-12.15134	-5.691193

m12_y12						
x1	-.0894519	.279171	-0.32	0.749	-.6366171	.4577133
x2	-.5374584	.2915773	-1.84	0.065	-1.108939	.0340227
x3	.6475463	.2623226	2.47	0.014	.1334035	1.161689
x4	.7409548	.1229369	6.03	0.000	.5000028	.9819068
_cons	-11.72697	1.949461	-6.02	0.000	-15.54784	-7.906094

test [m01_y01]x1=[m12_y12]x1

(1) [m01_y01]x1 - [m12_y12]x1 = 0

 chi2(1) = 2.38
 Prob > chi2 = 0.1226

P-value > 0.05. Accept the null hypothesis implying that it is Ordered probit model is appropriated

```
test [m01_y01]x2=[m12_y12]x2
```

```
( 1) [m01_y01]x2 - [m12_y12]x2 = 0
```

```
      chi2( 1) =      0.12
      Prob > chi2 =     0.7251
```

P-value > 0.05. Accept the null hypothesis implying that it is Ordered probit model is appropriated

c)

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

```
Probit regression                               Number of obs   =       550
                                                LR chi2(4)      =       25.09
                                                Prob > chi2     =       0.0000
Log likelihood = -366.03158                    Pseudo R2      =       0.0331
```

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	1.188599	.3999831	2.97	0.003	.404647	1.972552
x2	-.6426085	.3842609	-1.67	0.094	-1.395746	.110529
x3	.6270111	.1774683	3.53	0.000	.2791796	.9748426
x4	.1931299	.1937898	1.00	0.319	-.1866911	.572951
_cons	-.7679513	.3042386	-2.52	0.012	-1.364248	-.1716547

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

```
Probit regression                               Number of obs   =       550
                                                LR chi2(4)      =       10.90
                                                Prob > chi2     =       0.0277
Log likelihood = -363.87855                    Pseudo R2      =       0.0148
```

y2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.4235012	.3884698	-1.09	0.276	-1.184888	.3378857
x2	-.7384116	.3799839	-1.94	0.052	-1.483166	.0063431
x3	-.2458996	.17666	-1.39	0.164	-.5921468	.1003475
x4	.5397564	.1996099	2.70	0.007	.1485281	.9309847
_cons	.296472	.3036155	0.98	0.329	-.2986034	.8915473

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

```
Probit regression                               Number of obs   =       550
                                                LR chi2(4)      =       10.52
                                                Prob > chi2     =       0.0325
Log likelihood = -328.13418                    Pseudo R2      =       0.0158
```

y3	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.6290106	.4029907	-1.56	0.119	-1.418858	.1608366
x2	.8205646	.3951429	2.08	0.038	.0460987	1.595031
x3	-.3849673	.1978462	-1.95	0.052	-.7727386	.0028041
x4	-.2225176	.1935093	-1.15	0.250	-.6017889	.1567537
_cons	-.482039	.3192918	-1.51	0.131	-1.107839	.1437615

Since p-value of LR test of $\rho_{ij}=0$ is less than 0.05, the hypothesis can be rejected. It implies that there are correlation among the disturbance terms of these three models. MV probit is appropriated and three separate probit models are not appropriated.

d)

mvprobit (y1 x1 x2 x3 x4) (y2 x1 x2 x3 x4) (y3 x1 x2 x3 x4)

Iteration 0: log likelihood = -1058.0443
 Warning: cannot do Cholesky factorization of rho matrix
 Warning: cannot do Cholesky factorization of rho matrix
 Iteration 1: log likelihood = -949.01698
 Iteration 2: log likelihood = -935.93086
 Iteration 3: log likelihood = -934.31518
 Iteration 4: log likelihood = -934.30894
 Iteration 5: log likelihood = -934.30894

Multivariate probit (SML, # draws = 5) Number of obs = 550
 Wald chi2(12) = 34.94
 Log likelihood = -934.30894 Prob > chi2 = 0.0005

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
y1						
x1	1.063387	.3921018	2.71	0.007	.294882	1.831893
x2	-.5473706	.3795919	-1.44	0.149	-1.291357	.1966158
x3	.6165159	.1787051	3.45	0.001	.2662604	.9667714
x4	.1801909	.192658	0.94	0.350	-.1974119	.5577937
_cons	-.7005574	.3065515	-2.29	0.022	-1.301387	-.0997274
-----+-----						
y2						
x1	-.4897698	.3831145	-1.28	0.201	-1.24066	.2611208
x2	-.636445	.3778582	-1.68	0.092	-1.377033	.1041434
x3	-.2634882	.178032	-1.48	0.139	-.6124246	.0854481
x4	.5059698	.1986647	2.55	0.011	.1165941	.8953454
_cons	.3214536	.3014528	1.07	0.286	-.2693829	.9122902
-----+-----						
y3						
x1	-.5286327	.3907745	-1.35	0.176	-1.294537	.2372713
x2	.6349395	.387475	1.64	0.101	-.1244975	1.394377
x3	-.2770804	.1869191	-1.48	0.138	-.6434351	.0892743
x4	-.1793495	.1961704	-0.91	0.361	-.5638365	.2051374
_cons	-.4569501	.3206043	-1.43	0.154	-1.085323	.1714229
-----+-----						
/atrho21	-.6230853	.0748361	-8.33	0.000	-.7697613	-.4764093
-----+-----						
/atrho31	-.4021503	.0739359	-5.44	0.000	-.5470621	-.2572386
-----+-----						
/atrho32	-.3327245	.0712366	-4.67	0.000	-.4723456	-.1931033
-----+-----						
rho21	-.5532726	.051928	-10.65	0.000	-.6467906	-.4433634
-----+-----						
rho31	-.3817873	.0631589	-6.04	0.000	-.498315	-.2517109
-----+-----						
rho32	-.3209667	.0638978	-5.02	0.000	-.4400926	-.1907384
-----+-----						

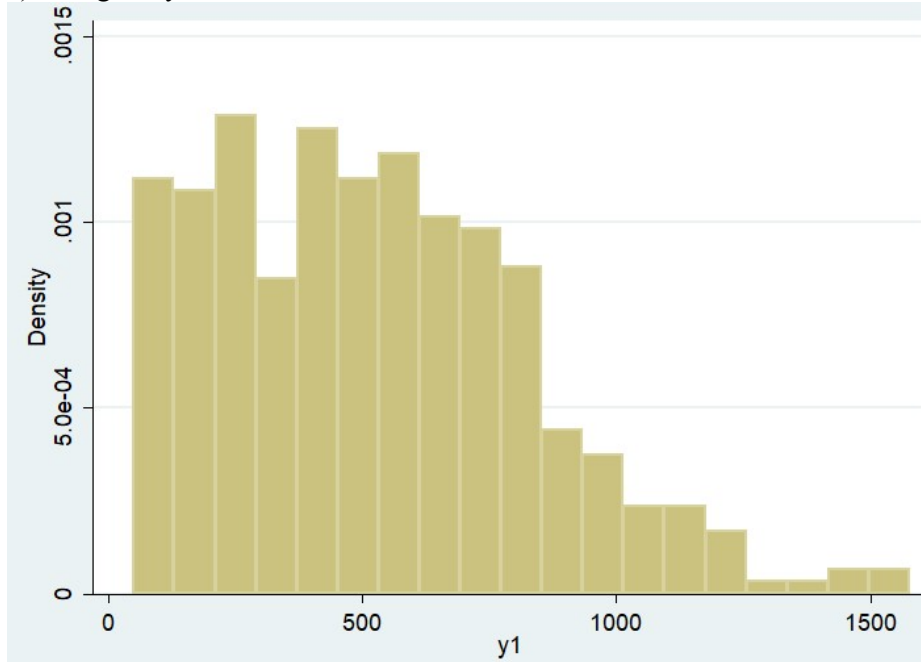
Likelihood ratio test of $\rho_{21} = \rho_{31} = \rho_{32} = 0$:
 chi2(3) = 247.471 Prob > chi2 = 0.0000

d)

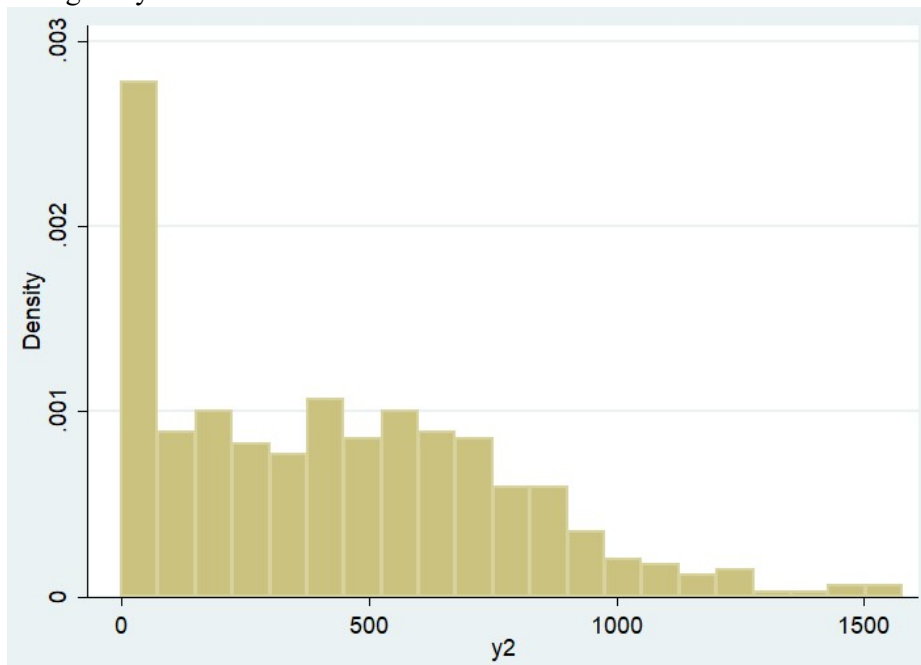
Since p-value of LR test of $\rho_{ij}=0$ is less than 0.05, the hypothesis can be rejected. It implies that there are correlation among the disturbance terms of these three models. MV probit is appropriated and three separate probit models are not appropriated.

2) -

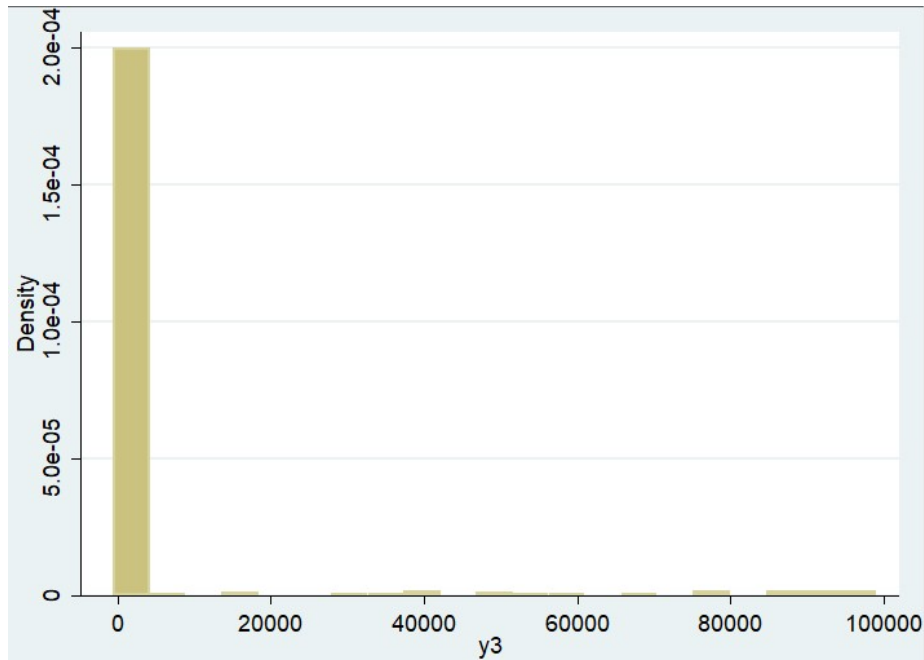
a) histogram y1



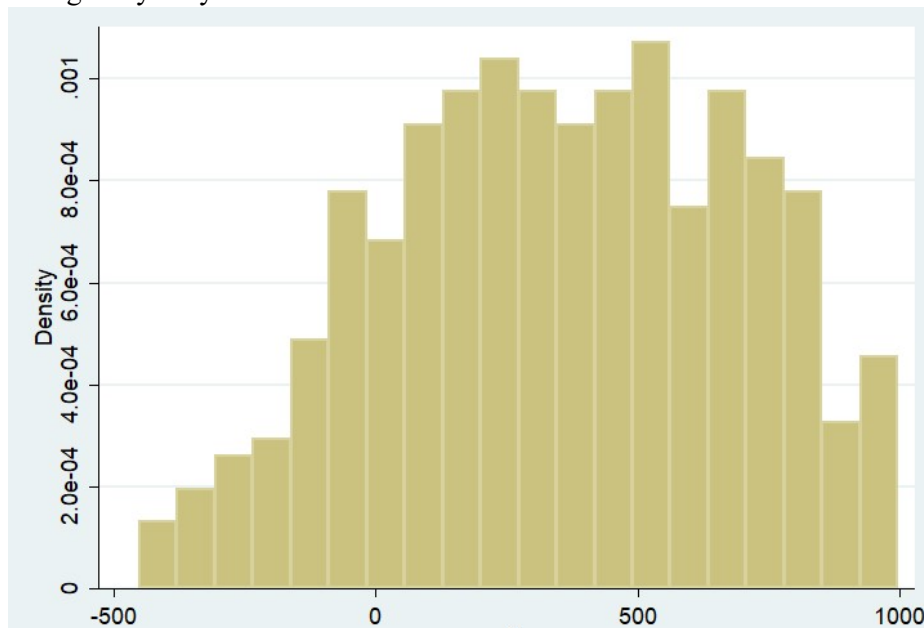
histogram y2



histogram y3



histogram y3 if y3 <=2000



sum y1 y2 y3 x

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	367	524.2029	308.2434	50.21759	1578.51
y2	450	428.525	343.5781	0	1578.51
y3	450	3815.157	15783.46	-450.6205	98951.63
x	450	3.008544	1.036395	.2858976	6.098752

On the y1, Some of obs are gone y1 (367 obs) which is implying that it is truncate sample. Sample is selected based only on value of y

On the y2 , many 0 is too huge which imply that it is censor sample

On Y3, it shows that is range between Min and Max is too large causing it to be outlier.

b)

reg y1 x

Source	SS	df	MS	Number of obs	=	367
Model	10122896.2	1	10122896.2	F(1, 365)	=	149.88
Residual	24652219	365	67540.3262	Prob > F	=	0.0000
				R-squared	=	0.2911
				Adj R-squared	=	0.2892
Total	34775115.2	366	95013.976	Root MSE	=	259.89

y1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	173.8049	14.19682	12.24	0.000	145.887	201.7227
_cons	-35.64063	47.69921	-0.75	0.455	-129.4404	58.15913

. est store m_y1

sum y1

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	367	524.2029	308.2434	50.21759	1578.51

. scalar miny1=round(r(min))

. scalar list miny1

miny1 = 50

truncreg y1 x, ll(miny1) nolog

(note: 0 obs. truncated)

Truncated regression

Limit: lower =	50	Number of obs	=	367
upper =	+inf	Wald chi2(1)	=	110.04
Log likelihood =	-2522.1932	Prob > chi2	=	0.0000

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x	248.761	23.71448	10.49	0.000	202.2815	295.2405
_cons	-365.4996	91.34527	-4.00	0.000	-544.533	-186.4661
/sigma	311.7764	17.43206	17.89	0.000	277.6102	345.9426

predict truncated, e(50,.)

est store m_y1t

. lrtest m_y1 m_y1t, force

Likelihood-ratio test LR chi2(1) = 76.33
 (Assumption: m_y1 nested in m_y1t) Prob > chi2 = 0.0000

P-value is less than 0.05 so reject the null hypothesis. According to significant LR-test between linear regression model and Truncated regression model, it can be concluded that Truncated regression model is a more appropriated model in this case.

In this case, some of data is truncated where Variable x and y can't be observed. If we ignore it, it will lead to bias since it is not normally distribution

c)
reg y2 x

Source	SS	df	MS	Number of obs	=	450
Model	20286305	1	20286305	F(1, 448)	=	277.79
Residual	32716310.8	448	73027.4794	Prob > F	=	0.0000
				R-squared	=	0.3827
				Adj R-squared	=	0.3814
Total	53002615.7	449	118045.915	Root MSE	=	270.24

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	205.0939	12.30536	16.67	0.000	180.9105	229.2773
_cons	-188.5091	39.15169	-4.81	0.000	-265.4529	-111.5653

. est store m_y

. tobit y2 x, ll(0)

Tobit regression	Number of obs	=	450
	LR chi2(1)	=	226.65
	Prob > chi2	=	0.0000
Log likelihood = -2789.8363	Pseudo R2	=	0.0390

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	242.0191	14.66612	16.50	0.000	213.1964	270.8419
_cons	-330.3892	47.49046	-6.96	0.000	-423.7204	-237.058
/sigma	302.3027	11.19031			280.3108	324.2946

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

. est store m_y2c
lrtest m_y m_y2c, force

Likelihood-ratio test	LR chi2(1)	=	734.73
(Assumption: m_y nested in m_y2c)	Prob > chi2	=	0.0000

P-value is less than 0.05 so reject the null hypothesis. According to significant LR-test between linear regression model and Tobit regression model, it can be concluded that Tobit regression model is a more appropriated model in this case.

In this case, some of data is censored based only on value of y. If we ignore it, it will lead to bias since it is not normally distribution.

d)
reg y3 x

Source	SS	df	MS	Number of obs	=	450
--------	----	----	----	---------------	---	-----

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-----+-----				F(1, 448)	=	41.34
Model		9.4500e+09	1	9.4500e+09	Prob > F	= 0.0000
Residual		1.0240e+11	448	228579849	R-squared	= 0.0845
-----+-----				Adj R-squared	=	0.0824
Total		1.1185e+11	449	249117556	Root MSE	= 15119

y3		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x		4426.571	688.4466	6.43	0.000	3073.585 5779.557
_cons		-9502.377	2190.414	-4.34	0.000	-13807.14 -5197.613

```
. predict y3_hat
(option xb assumed; fitted values)
```

```
. est store m_y3
```

```
. sum y3
```

Variable		Obs	Mean	Std. Dev.	Min	Max
y3		450	3815.157	15783.46	-450.6205	98951.63

```
. reg y3 x if y3<=2000
```

-----+-----				Number of obs	=	425
Model		15612930.7	1	15612930.7	F(1, 423)	= 210.21
Residual		31416934.1	423	74271.7118	Prob > F	= 0.0000
-----+-----				Adj R-squared	=	0.3320
Total		47029864.8	424	110919.492	Root MSE	= 272.53

y3		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x		195.0079	13.44998	14.50	0.000	168.5708 221.4451
_cons		-212.5701	41.48733	-5.12	0.000	-294.1171 -131.0231

```
. predict y3_hat_o
(option xb assumed; fitted values)
```

```
. est store m_y3o
```

```
. tobit y3 x, ul(2000) nolog
```

```
Tobit regression
Number of obs = 450
LR chi2(1) = 196.29
Prob > chi2 = 0.0000
Pseudo R2 = 0.0297
Log likelihood = -3207.5141
```

y3		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x		299.4023	19.17712	15.61	0.000	261.7142 337.0903
_cons		-444.6084	60.82021	-7.31	0.000	-564.136 -325.0808
-----+-----				/sigma		417.685 14.63844 388.9166 446.4534

```
-----
      0 left-censored observations
     425 uncensored observations
      25 right-censored observations at y3 >= 2000
```

```
. est store m_y3o_t
. lrtest m_y3 m_y3o_t, force
```

```
Likelihood-ratio test          LR chi2(1) = 3521.34
(Assumption: m_y3 nested in m_y3o_t)  Prob > chi2 = 0.0000
```

P-value is less than 0.05 so reject the null hypothesis. According to significant LR-test between linear regression model and Tobit regression model, it can be concluded that Tobit regression model is a more appropriated model in this case.

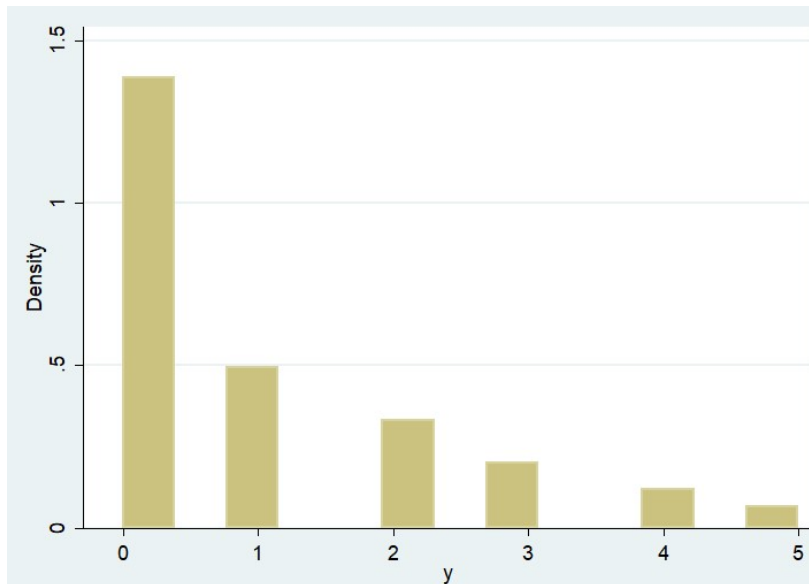
In this case, some of data is censored based only on value of y. If we ignore it, it will lead to bias since it is not normally distribution.

3) -
a)
reg y x1 x2 x3 x4

Source	SS	df	MS	Number of obs	=	195
-----+-----				F(4, 190)	=	5.01
Model	33.4104504	4	8.35261259	Prob > F	=	0.0007
Residual	316.569037	190	1.66615283	R-squared	=	0.0955
-----+-----				Adj R-squared	=	0.0764
Total	349.979487	194	1.80401798	Root MSE	=	1.2908

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----					
x1	.0793886	.0446285	1.78	0.077	-.0086424 .1674196
x2	.1390509	.0477181	2.91	0.004	.0449255 .2331763
x3	.1906963	.068193	2.80	0.006	.0561837 .3252089
x4	-.0240741	.0483414	-0.50	0.619	-.1194289 .0712806
_cons	.9293254	.1099856	8.45	0.000	.7123757 1.146275

```
. est store linear
. histogram y
```



a) Continued

According to Histogram, it looks like that the distribution of dependent variable follows Poisson distribution. It shows that the model is Poisson model

b)

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

```
Poisson regression              Number of obs   =          195
                                LR chi2(4)       =          34.23
                                Prob > chi2         =          0.0000
Log likelihood = -274.62075      Pseudo R2      =          0.0587
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
	x1	.0806329	.0343856	2.34	0.019	.0132383	.1480275
	x2	.1401445	.0367381	3.81	0.000	.0681392	.2121498
	x3	.2034995	.0551258	3.69	0.000	.0954549	.3115441
	x4	-.0243904	.0374602	-0.65	0.515	-.097811	.0490301
	_cons	-.1580224	.0935666	-1.69	0.091	-.3414097	.0253648

```
. estat gof
```

```
Deviance goodness-of-fit = 318.2264
Prob > chi2(190)         = 0.0000
```



```

LR chi2(4)          =      18.37
Dispersion    = mean    Prob > chi2        =      0.0010
Log likelihood = -259.61412 Pseudo R2           =      0.0342
    
```

```

-----+-----
          y |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      x1 |   .1087674   .0527511     2.06   0.039   .0053772   .2121576
      x2 |   .1549878   .052501     2.95   0.003   .0520877   .2578879
      x3 |   .1953154   .0712146     2.74   0.006   .0557373   .3348936
      x4 |  -.0280043   .0504403    -0.56   0.579  -.1268655   .0708569
    _cons |  -.1751075   .1234882    -1.42   0.156   -.41714    .066925
-----+-----
  /lnalpha |   -.16535   .2903142                -.7343554   .4036555
-----+-----
      alpha |   .847597   .2460695                .4798146   1.497288
-----+-----
    
```

Likelihood-ratio test of alpha=0: chibar2(01) = 30.01 Prob>=chibar2 = 0.000

According to LR test of alpha, null hypothesis of the test was rejected indicating that the distribution of dependent variable follows Negative Binomial distribution, thus, Negative Binomial regression model is more appropriated than Poisson regression model

```
nbreg y x1 x2 x3 x4, ir nolog
```

```

Negative binomial regression          Number of obs    =      195
LR chi2(4)                          =      18.37
Dispersion    = mean                 Prob > chi2       =      0.0010
Log likelihood = -259.61412          Pseudo R2        =      0.0342
    
```

```

-----+-----
          y |          IRR   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      x1 |   1.114903   .0588123     2.06   0.039   1.005392   1.236343
      x2 |   1.167644   .0613025     2.95   0.003   1.053468   1.294194
      x3 |   1.215694   .0865752     2.74   0.006   1.05732    1.397792
      x4 |   .9723842   .0490474    -0.56   0.579   .8808521   1.073428
    _cons |   .8393668   .1036519    -1.42   0.156   .6589286   1.069215
-----+-----
  /lnalpha |   -.16535   .2903142                -.7343554   .4036555
-----+-----
      alpha |   .847597   .2460695                .4798146   1.497288
-----+-----
    
```

Likelihood-ratio test of alpha=0: chibar2(01) = 30.01 Prob>=chibar2 = 0.000

```
. est store nb
```

```
. mfx
```


x3		.1304133	.05005	2.61	0.009	.03232	.228507	-.300421
x4		-.0072905	.03379	-0.22	0.829	-.073524	.058943	-.785193

According to the above estimated results, interpretation can be made concerning: sign and meaning of the estimated coefficient – correct sign (positive mfx sign for x1, x2, x3 and negative mfx sign for x4), Overall test LR-Chi-squared-test – significant, Individual test z-test –significant except x3.

est table linear poisson nb zip, star(.1 .05 .01) stat(N ll chi2 chi2_c vuong)

Variable	linear	poisson	nb	zip

–				
x1		.07938862*		
x2		.13905091***		
x3		.1906963***		
x4		-.02407411		
_cons		.92932537***		

y				
x1		.0806329**	.10876739**	.09108141**
x2		.1401445***	.15498784***	.12283434***
x3		.20349954***	.19531545***	.14362543**
x4		-.02439041	-.02800431	
_cons		-.15802244*	-.17510753	.32438125***

lnalpha				
_cons			-.16534997	

inflate				
x4				.02180894
_cons				-.52301075**

Statistics				
N		195	195	195
ll		-323.93584	-274.62075	-259.61412
chi2			34.227955	18.368828
chi2_c				30.013259
vuong				2.5787063

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

. According to GOF test, null hypothesis of the test was rejected, thus, Poisson regression model is more appropriated than linear regression model.

According to LR test of alpha, null hypothesis of the test was rejected indicating that the distribution of dependent variable follows Negative Binomial distribution, thus, Negative Binomial regression model is more appropriated than Poisson regression model.

According to Vuong test, null hypothesis of the test was rejected, thus, Zero Inflated Poisson regression model is more appropriated than Poisson regression model.

Also, Histogram illustrates zero inflated distribution of dependent variable, therefore, Zero Inflated Poisson regression model should be applied in this case.

4) -
a)

dfuller y, trend lag(1) regress

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

Test Statistic	----- Interpolated Dickey-Fuller -----		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-15.034	-3.980	-3.420

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

D.y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----					
y					
L1.	-.9728018	.0647089	-15.03	0.000	-1.09994 - .8456632
LD.	-.0592117	.0449927	-1.32	0.189	-.1476124 .0291891
_trend	.0012784	.0021013	0.61	0.543	-.0028501 .0054069
_cons	.9566398	.6100881	1.57	0.118	-.2420477 2.155327

reject the null hypothesis hence, there is no Unit Root

dfuller x, trend lag(1) regress

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

Test Statistic	----- Interpolated Dickey-Fuller -----		
	1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	-15.189	-3.980	-3.420

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

D.x	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----					
x					
L1.	-.9848987	.0648429	-15.19	0.000	-1.112301 - .8574967
LD.	-.0505535	.0449977	-1.12	0.262	-.138964 .037857
_trend	.0021181	.0030005	0.71	0.481	-.0037772 .0080135
_cons	.5922071	.8669077	0.68	0.495	-1.111074 2.295488

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```
. qui arima y, arima(3,0,3) nolog
. est store arima303
. qui arima y, arima(3,0,4) nolog
. est store arima304
. qui arima y, arima(4,0,1) nolog
. est store arima401
. qui arima y, arima(4,0,2) nolog
. est store arima402
. qui arima y, arima(4,0,3) nolog
. est store arima403
. qui arima y, arima(4,0,4) nolog
. est store arima404
```

```
est table arima10*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
```

Variable	arima101	arima102	arima103	arima104

Y				
_cons	1.3160732***	1.3164623***	1.3169246***	1.3196561***

ARMA				
ar				
L1.	-.85671231***	-.8407698***	-.85479005***	.79555112***
ma				
L1.	.81381586***	.81081395***	.82385933***	-.83063072***
L2.		.01776181	.02900763	.08192832
L3.			.01703608	-.04696028
L4.				.03883734

sigma				
_cons	6.7070643***	6.7062145***	6.7052679***	6.7033168***

Statistics				
N	500	500	500	500
ll	-1661.0562	-1660.9819	-1660.9152	-1660.7819
chi2	52.431996	48.538035	51.947118	20.004068
aic	3330.1124	3331.9639	3333.8305	3335.5639
bic	3346.9709	3353.0369	3359.1181	3365.0661

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

```
. est table arima20*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
```

Variable	arima201	arima202	arima203	arima204

Y				
_cons	1.3165966***	1.3193097***	1.3192028***	1.3190979***

ARMA				
ar				
L1.	-.81679808***	.02485091	-.00880392	-.01799803
L2.	.01965322	.72638325***	.72631603***	.68941508**
ma				
L1.	.78741991***	-.04728285	-.02454975	-.01490702
L2.		-.65937106**	-.66072222**	-.63706121**

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L3.				.01970127	.01889581
L4.					.02331994

sigma					
_cons		6.706091***	6.6966012***	6.695548***	6.6939821***

Statistics					
N		500	500	500	500
ll		-1660.9785	-1660.2724	-1660.1961	-1660.0893
chi2		46.275204	20.50189	21.61323	20.409942
aic		3331.957	3332.5449	3334.3921	3336.1786
bic		3353.0301	3357.8325	3363.8944	3369.8955

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

. est table arima30*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)

Variable		arima301	arima302	arima303	arima304

y					
_cons		1.3170214***	1.3192207***	1.3311023***	1.3312982***

ARMA					
ar					
L1.		-.84311244***	-.03418916	1.0641965***	1.0672402***
L2.		.03190832	.72699651***	.6530733**	.64680736*
L3.		.01910909	.02024337	-.83386019***	-.83047128***
ma					
L1.		.81339159***	.00153606	-1.1231676	-1.123462***
L2.			-.66194403**	-.55645796	-.55183321
L3.				.80656679	.79853444***
L4.					.00399858

sigma					
_cons		6.7050253***	6.6954461***	6.6128034	6.6127984

Statistics					
N		500	500	500	500
ll		-1660.9029	-1660.2011	-1656.0279	-1656.0246
chi2		52.888952	22.065233	44673.068	44570.467
aic		3333.8057	3334.4022	3326.0559	3328.0491
bic		3359.0934	3363.9044	3355.5581	3361.766

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

. est table arima40*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)

Variable		arima401	arima402	arima403	arima404

y					
_cons		1.3175059***	1.3190967***		1.3187605***

ARMA					
ar					
L1.		-.78144222**	-.0441011		.090027
L2.		.03235516	.65860818*		-.22996396

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L3.		.04475517	.02006821		-.05809939
L4.		.04099103	.02440356		.70709274***

ma					
L1.		.75091484**	.01110505		-.12463059
L2.			-.6062543		.31438256
L3.					.05252582
L4.					-.66037916**

sigma					
_cons		6.7000467***	6.694033***		6.6579737***

___000001					
L1.				-.06660543	
L2.				.045068	
L3.				.13149793	
L4.				.05926447	
___000002					
L1.				.04013471	
L2.				.01365599	
L3.				-.14130775	

Statistics					
N		500	500	466	500
ll		-1660.5409	-1660.0958	-1551.5332	-1657.6826
chi2		37.986475	19.683851		1491.758
aic		3335.0818	3336.1916	3117.0664	3335.3652
bic		3364.5841	3369.9085	3146.0757	3377.5113

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

The most appropriated order for yt is ARIMA(1,0,1)

Make dynamic forecast for period time = 501 to 505

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

ARIMA regression

Sample: 1 - 500

Number of obs = 500

Wald chi2(2) = 52.43

Log likelihood = -1661.056

Prob > chi2 = 0.0000

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

y						
_cons		1.316073	.2953446	4.46	0.000	.7372084 1.894938

ARMA						
ar						
L1.		-.8567123	.1648398	-5.20	0.000	-1.179792 -.5336322
ma						
L1.		.8138159	.1863522	4.37	0.000	.4485723 1.179059

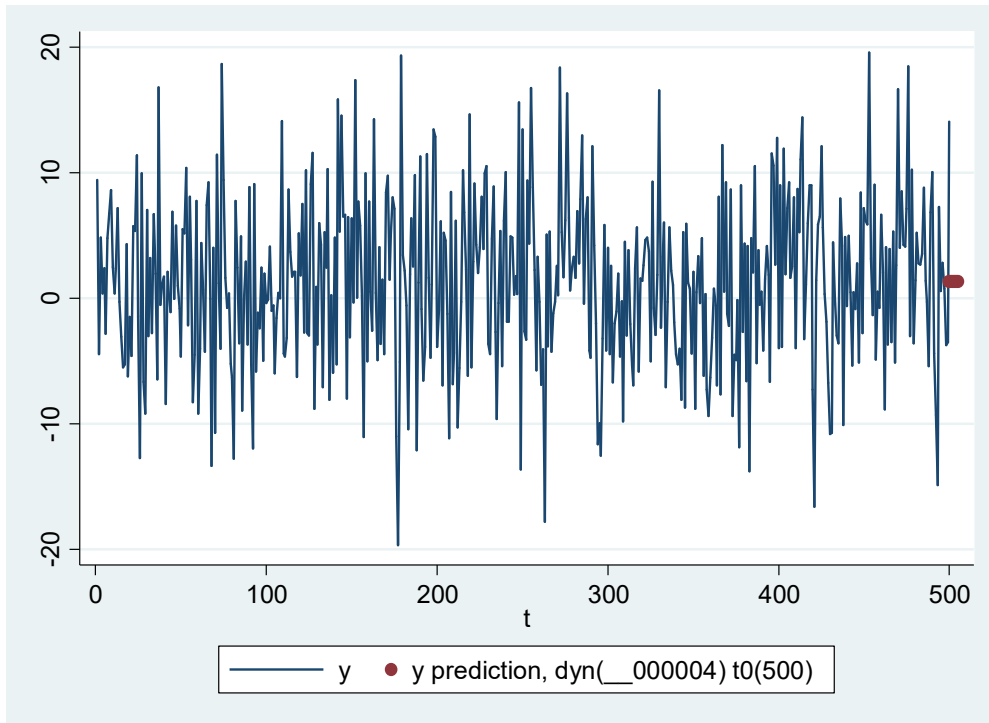
/sigma		6.707064	.2139816	31.34	0.000	6.287668 7.126461

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)
```



c)
reg y x

Source	SS	df	MS	Number of obs	=	500
Model	22448.3939	1	22448.3939	F(1, 498)	=	56889.89
Residual	196.507666	498	.394593706	Prob > F	=	0.0000
				R-squared	=	0.9913
				Adj R-squared	=	0.9913
Total	22644.9015	499	45.3805642	Root MSE	=	.62817

	y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
	x	.6976152	.0029248	238.52	0.000	.6918687 .7033617
	_cons	.5187858	.0282915	18.34	0.000	.4632004 .5743713

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

lags(p)	chi2	df	Prob > chi2
---------	------	----	-------------

1	38.784	1	0.0000
H0: no ARCH effects vs. H1: ARCH(p) disturbance			

. There exist significant ARCH effects since p-value of the ARCHLM-test is less than 0.05. The reason is that OLS is a restricted model.

```
d)
qui arch y x, arch(1) garch(1) nolog
. est store garch11
. qui arch y x, arch(1) garch(1/2) nolog
. est store garch21
. qui arch y x, arch(1/2) garch(1) nolog
. est store garch12
. qui arch y x, arch(1/2) garch(1/2) nolog
. est store garch22
. est table garch*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
```

Variable	garch11	garch21	garch12	garch22
Y				
x	.69785097***	.69783869***	.69783972***	.69779147***
_cons	.51851398***	.51850973***	.51850887***	.51882531***
ARCH				
arch				
L1.	.36250292***	.36074245***	.36097359***	.36521493***
L2.			.00984107	.27444452
garch				
L1.	.3251895***	.33749919*	.30886518	-.35594504
L2.		-.00992983		.16076458
_cons	.12545535***	.125209***	.1286695*	.22454219**
Statistics				
N	500	500	500	500
ll	-443.95805	-443.95377	-443.95432	-443.79435
chi2	72868.369	72940.007	72933.849	73674.66
aic	897.9161	899.90755	899.90864	901.58871
bic	918.98914	925.1952	925.19629	931.09096

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

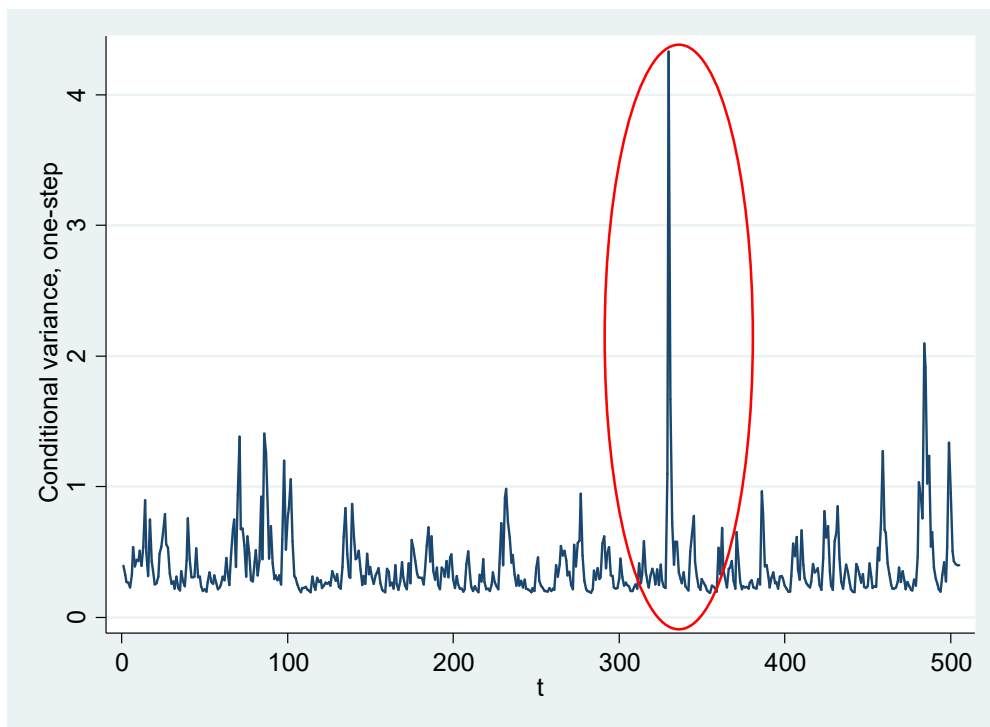
According to BIC, the most appropriated order for yt is GARCH(1,0,1)

```
arch y x, arch(1) garch(1) nolog
```

ARCH family regression

Sample: 1 - 500	Number of obs	=	500
Distribution: Gaussian	Wald chi2(1)	=	72868.37
Log likelihood = -443.958	Prob > chi2	=	0.0000

		OPG				
	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y	x	.697851	.0025852	269.94	0.000	.6927841 .7029179
	_cons	.518514	.0239007	21.69	0.000	.4716695 .5653585
ARCH	arch					
	L1.	.3625029	.0743235	4.88	0.000	.2168315 .5081743
	garch					
	L1.	.3251895	.1186414	2.74	0.006	.0926567 .5577223
	_cons	.1254554	.0357542	3.51	0.000	.0553784 .1955323



e)

arch y x, arch(1) nolog

ARCH family regression

Sample: 1 - 500	Number of obs =	500
Distribution: Gaussian	Wald chi2(1) =	66213.67
Log likelihood = -449.2639	Prob > chi2 =	0.0000

		OPG				
	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y	x	.697721	.0027115	257.32	0.000	.6924066 .7030354

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```

      arch |
      L1. |   .6732196   .0925378   7.28   0.000   .4918488   .8545903
      garch |
      L1. |  -.0060374   .0101859   -0.59   0.553   -.0260015   .0139267
      _cons |  -.9151576   .1550718   -5.90   0.000   -1.219093   -.6112225
  
```

```
. est store egarch111
```

```
. est table arch1 garch11 egarch111, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
```

```

-----+-----
Variable |      arch1      garch11      egarch111
-----+-----
y
  x      |  .69772101***  .69785097***  .69799216***
  _cons  |  .51458758***  .51851398***  .51195842***
  
```

ARCH			
arch	L1.	.38249114***	.36250292***
garch	L1.	.3251895***	-.0060374
egarch	L1.		.3694437***
_cons		.24182366***	.12545535***

```

-----+-----
Statistics |
N          |      500      500      500
ll         | -449.26385  -443.95805  -447.52473
chi2       | 66213.674   72868.369   66927.823
aic        |  906.5277   897.9161   907.04945
bic        |  923.38613   918.98914   932.3371
  
```

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

the most appropriated model is Garch(1,1) because it has lowest Bic
 Arch will only have epsilon(t) while Garch will have summation of error term-square. On the other hand, Egarch will have summation of ln(error term -square)

5)

```
a)
varsoc y x
```

```

Selection-order criteria
Sample: 5 - 500
Number of obs = 496
-----+-----
|lag |  LL      LR      df  p      FPE      AIC      HQIC      SBIC  |
-----+-----
| 0 | -1365.17          .849628  5.5128  5.51946  5.52976 |
| 1 | -1318.07   94.2*  4  0.000  .71409*  5.33901*  5.35898*  5.38989* |
| 2 | -1317.22  1.7068  4  0.789  .723209  5.3517   5.38499   5.43651 |
| 3 | -1315.98  2.4783  4  0.649  .731307  5.36283  5.40944   5.48156 |
  
```

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```
| 4 | -1313.81  4.3465    4  0.361  .736717   5.37019   5.43012   5.52285 |
+-----+
Endogenous:  y x
Exogenous:   _cons
```

According to SBIC, the most appropriated lag order is 1

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

Vector autoregression

```
Sample: 2 - 500                Number of obs   =      499
Log likelihood = -1328.195      AIC              =    5.347476
FPE           = .7201626        HQIC             =    5.367353
Det(Sigma_ml) = .7030505        SBIC            =    5.398128
```

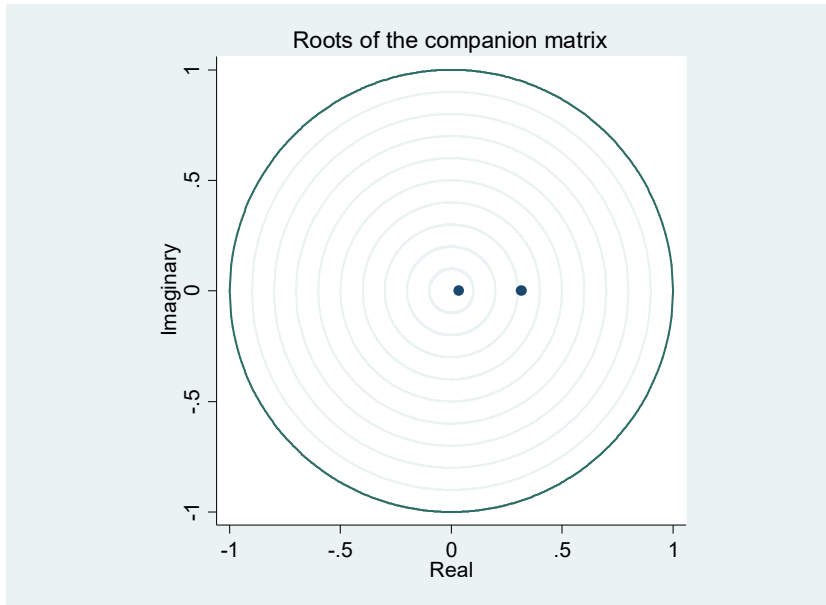
Equation	Parms	RMSE	R-sq	chi2	P>chi2
y	3	.994349	0.0148	7.487749	0.0237
x	3	.995147	0.0887	48.59594	0.0000

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y	y					
	L1.	.1368742	.0501021	2.73	0.006	.0386758 .2350726
	x					
	L1.	.0538789	.0481082	1.12	0.263	-.0404114 .1481691
	_cons	.3380393	.0544338	6.21	0.000	.2313511 .4447276
x	y					
	L1.	.342059	.0501424	6.82	0.000	.2437818 .4403362
	x					
	L1.	.212658	.0481468	4.42	0.000	.118292 .3070239
	_cons	.1205365	.0544775	2.21	0.027	.0137627 .2273104

```
. varstable, graph
```

```
Eigenvalue stability condition
+-----+
| Eigenvalue | Modulus |
+-----+
| .3157113   | .315711 |
| .0338209   | .033821 |
+-----+
```

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	1.2543	1	0.263
y	ALL	1.2543	1	0.263
x	y	46.536	1	0.000
x	ALL	46.536	1	0.000

According to stability test, the system is stable since all the eigenvalues lie inside the unit circle. According to Granger exogeneity, both x is endogenous variable since the tests are significant while y seems not to be endogenous.

If the stability is unsatisfied, It leads to divergence and unstationary.

c)

```
irf create order1, order(y x) step(5) set(xy)
(file xy.irf created)
(file xy.irf now active)
(file xy.irf updated)
```

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

Results from order1

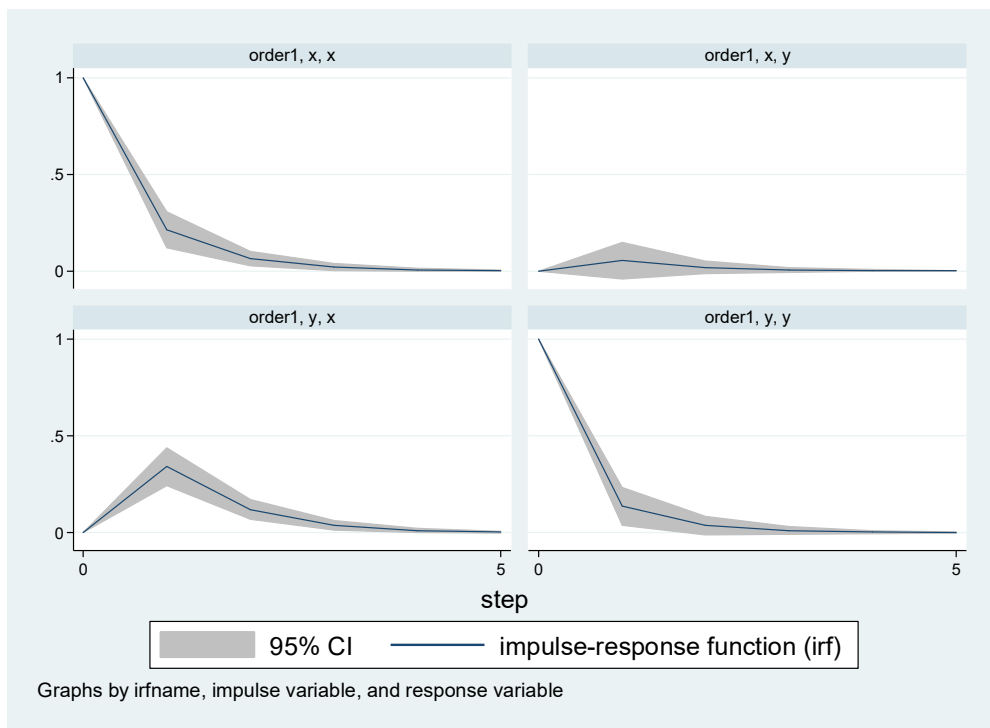
step	(1) irf	(1) Lower	(1) Upper	(2) irf	(2) Lower	(2) Upper
0	1	1	1	0	0	0
1	.136874	.038676	.235073	.342059	.243782	.440336
2	.037164	-.011403	.085732	.119561	.068148	.170974
3	.011529	-.008353	.03141	.038138	.013188	.063088
4	.003633	-.003911	.011176	.012054	.000586	.023522
5	.001147	-.001632	.003925	.003806	-.001076	.008688

step	(3) irf	(3) Lower	(3) Upper	(4) irf	(4) Lower	(4) Upper
0	0	0	0	1	1	1
1	.053879	-.040411	.148169	.212658	.118292	.307024
2	.018832	-.014523	.052188	.063653	.025715	.101591
3	.006007	-.006328	.018342	.019978	.001911	.038045
4	.001899	-.002639	.006437	.006303	-.001523	.014129
5	.000599	-.001043	.002242	.00199	-.001173	.005153

95% lower and upper bounds reported

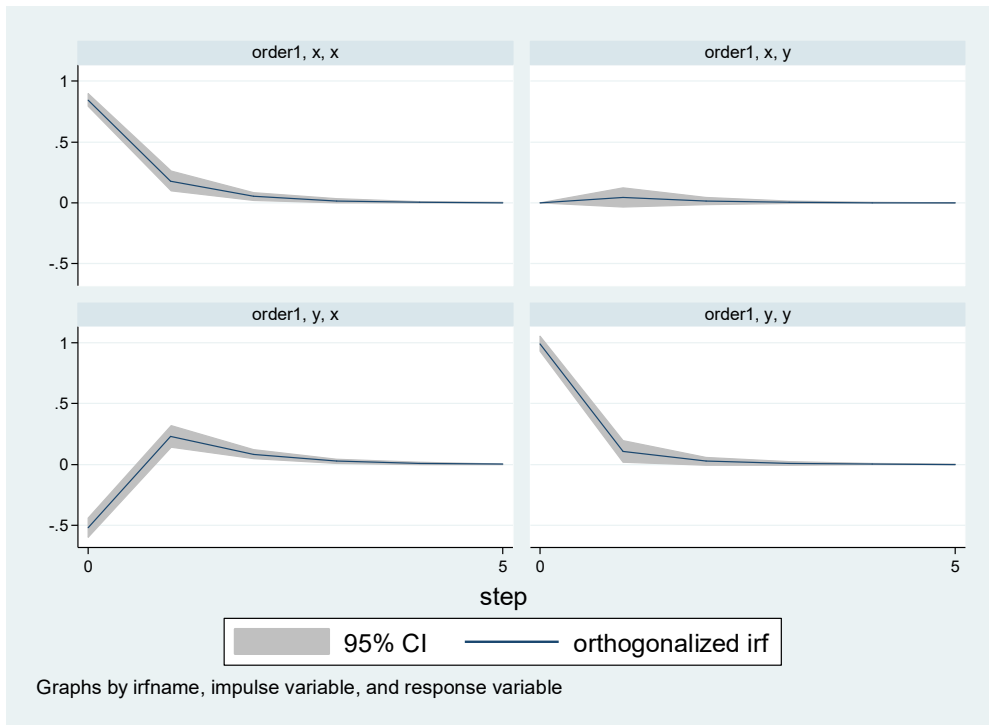
- (1) irfname = order1, impulse = y, and response = y
- (2) irfname = order1, impulse = y, and response = x
- (3) irfname = order1, impulse = x, and response = y
- (4) irfname = order1, impulse = x, and response = x

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

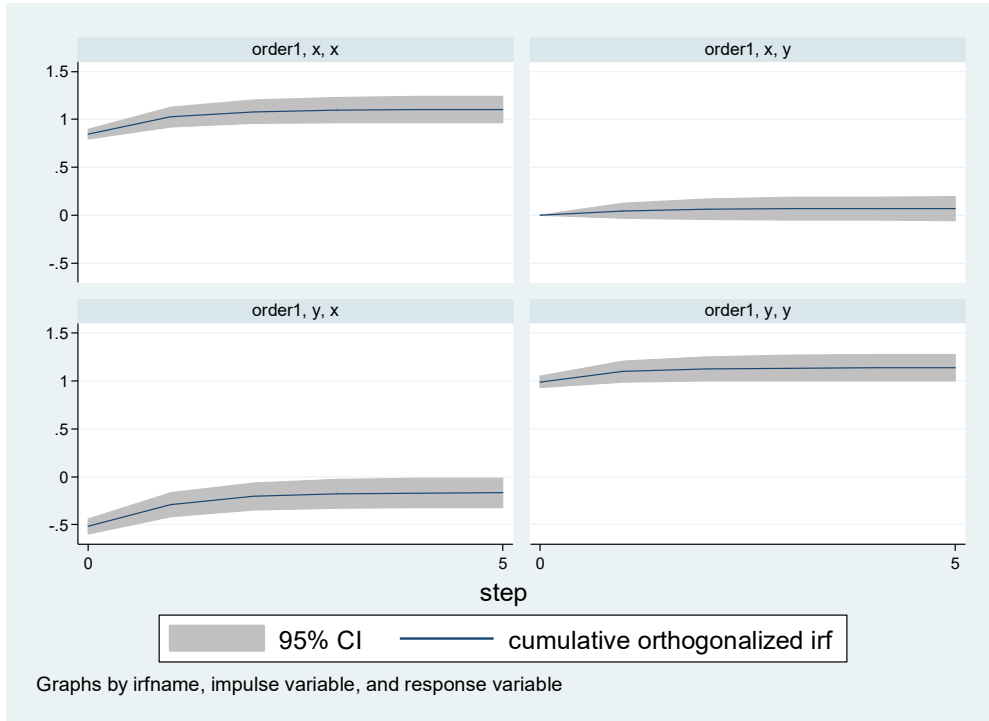


c) continued

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



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



According to IRF analysis, y has more impact on x.

d)

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

Results from order1

step	(1) fevd	(1) Lower	(1) Upper	(2) fevd	(2) Lower	(2) Upper
0	0	0	0	0	0	0
1	1	1	1	.273273	.206608	.339938
2	.997916	.990626	1.00521	.300591	.235783	.3654
3	.997664	.989501	1.00583	.304523	.240271	.368775
4	.997638	.989374	1.0059	.304927	.24074	.369115
5	.997635	.98936	1.00591	.304968	.240787	.369148

step	(3) fevd	(3) Lower	(3) Upper	(4) fevd	(4) Lower	(4) Upper
0	0	0	0	0	0	0
1	0	0	0	.726727	.660062	.793392
2	.002084	-.005206	.009374	.699409	.6346	.764217
3	.002336	-.005826	.010499	.695477	.631225	.759729
4	.002362	-.005902	.010626	.695073	.630885	.75926
5	.002365	-.005911	.01064	.695032	.630852	.759213

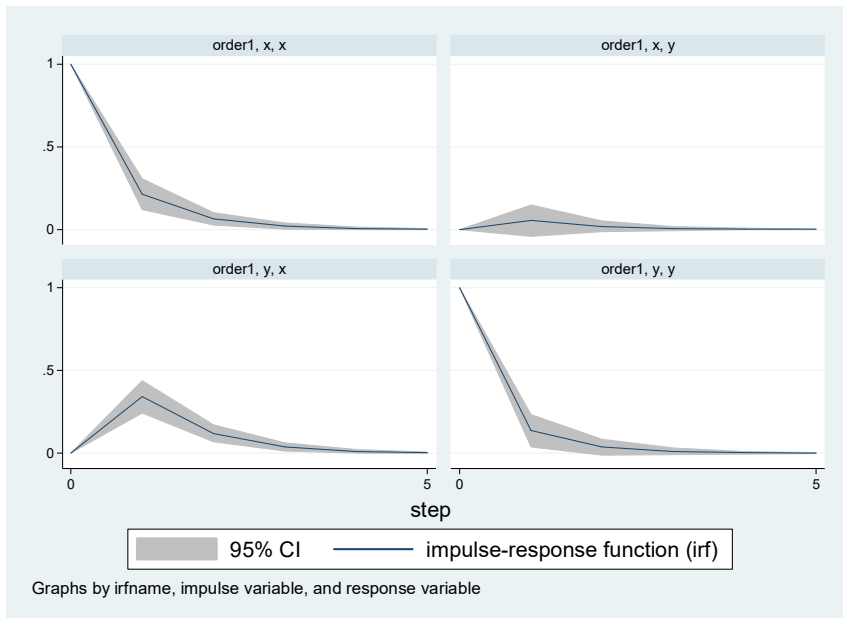
95% lower and upper bounds reported

- (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

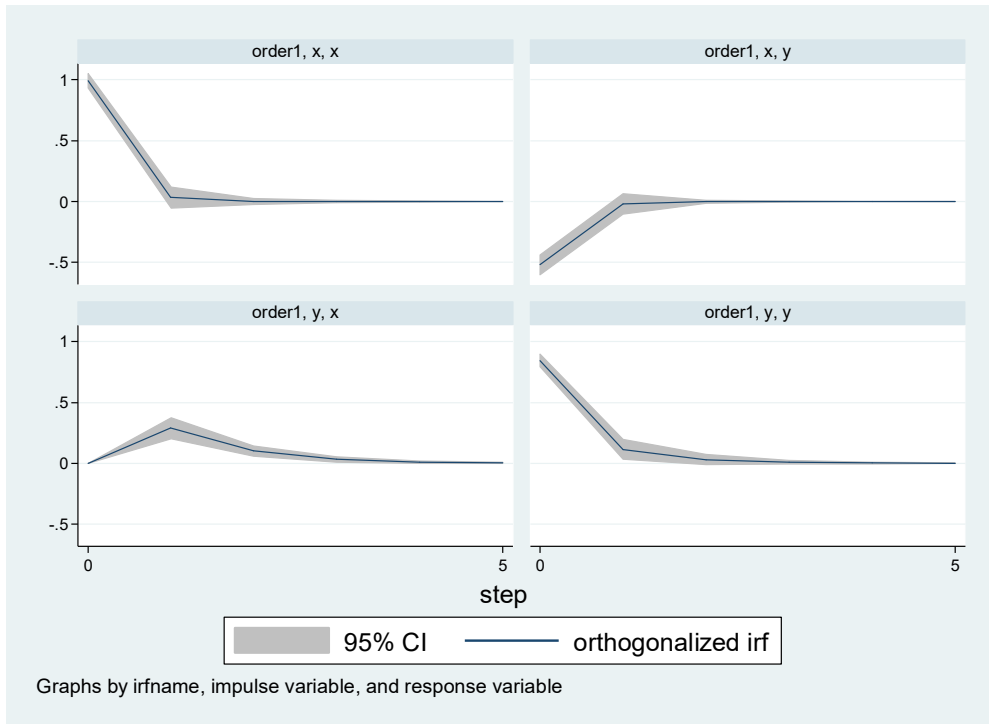
According to Forecast error variance decomposition, y has more impact on x.

e)

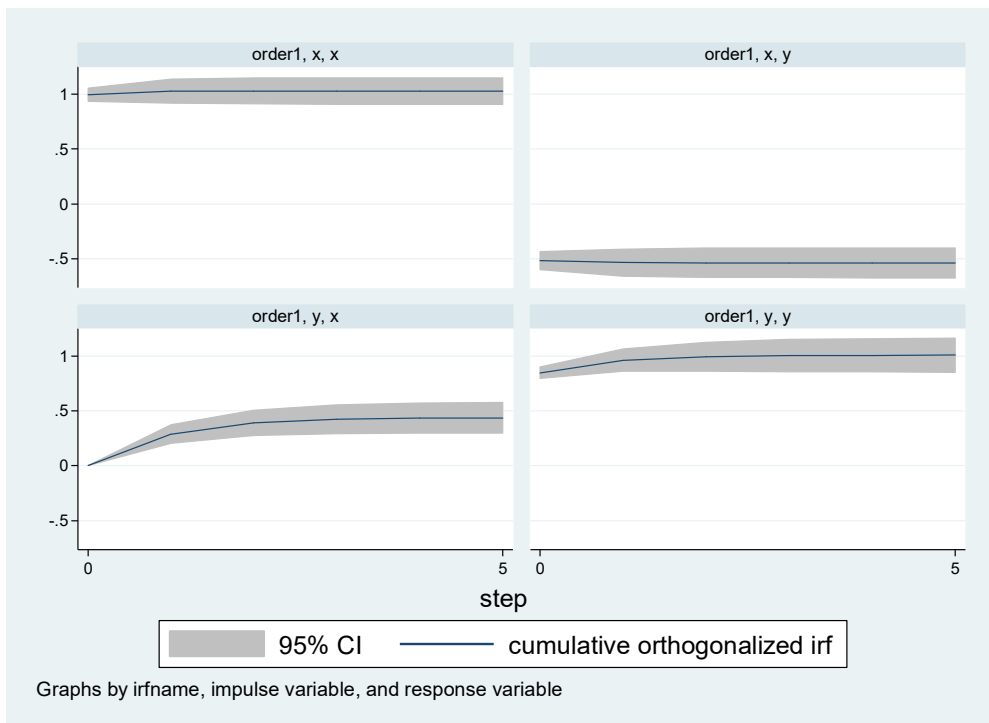
```
irf create order1, order(x y) step(5) set(xy2)
irf graph irf, impulse(x y) response(y x)
```



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



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



```
irf table fevd, impulse(x y) response(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	.273273	.206608	.339938	.726727	.660062	.793392
2	.269826	.203301	.336352	.730174	.663648	.796699
3	.26956	.203015	.336104	.73044	.663896	.796985
4	.269534	.202986	.336082	.730466	.663918	.797014
5	.269531	.202983	.33608	.730469	.66392	.797017

95% lower and upper bounds reported

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

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

```
irf table fevd, impulse(x y) response(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	0	0	0
2	.921832	.8785	.965165	.078168	.034835	.1215
3	.913112	.865451	.960773	.086888	.039227	.134549
4	.912234	.864064	.960404	.087766	.039596	.135936
5	.912147	.86392	.960374	.087853	.039626	.13608

95% lower and upper bounds reported

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

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

According to Forecast error variance decomposition, x has more impact on y.

The result changes as the order changes. The reason is that it changes theoretical framework and lead to the different values.