

Answer Sheet Cover Page
Final Examination Semester 2/2020

(Readable handwriting and printed version are acceptable)

Student Name..... 6104640021

Student ID..... Thamchanok Pianmuan

Course ID..... EE426 Course Title..... Econometric 2

Lecturer..... Assoc. Prof. Dr. Tatre Santarakolica

Exam date..... May 28 Time..... 9.00 - 15.00

Total pages..... 30

***Students are responsible for checking the number of pages before submitting the answer sheets. Incomplete submissions caused by carelessness will not be accepted as an excuse for resubmission**

Student Signature..... Thamchanok

Date..... 28 May

1.)

a.)

. mlogit y x1 x2 x3 x4, 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	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
0		(base outcome)					
1							
	x1	-1.347221	.6380919	-2.11	0.035	-2.597858	-.0965837
	x2	-.9627847	.7836576	-1.23	0.219	-2.498725	.573156
	x3	-.408798	.6307265	-0.65	0.517	-1.644999	.8274031
	x4	.7099461	.2624283	2.71	0.007	.195596	1.224296
	_cons	-8.576009	3.71939	-2.31	0.021	-15.86588	-1.286139
2							
	x1	-1.141361	.6879132	-1.66	0.097	-2.489647	.2069238
	x2	-1.794418	.80872	-2.22	0.026	-3.37948	-.209356
	x3	.7285886	.664083	1.10	0.273	-.5729902	2.030167
	x4	1.837804	.3112868	5.90	0.000	1.227693	2.447915
	_cons	-26.3164	4.61453	-5.70	0.000	-35.36071	-17.27209

. est store m1

. mlogit y x1 x2 x3 x4 if y!=2, 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	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
0		(base outcome)					
1							
	x1	-1.12876	.6114976	-1.85	0.065	-2.327273	.0697537
	x2	-.6502463	.7529945	-0.86	0.388	-2.126088	.8255959
	x3	-.2209155	.6558682	-0.34	0.736	-1.506394	1.064563
	x4	.6346669	.2573192	2.47	0.014	.1303306	1.139003
	_cons	-7.880673	3.80514	-2.07	0.038	-15.33861	-.422736

. est store m3

. hausman m1 m3, alleqs constant

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	m1	m3	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

1	40	0	40
2	0	109	109

Total	61	109	170

. probit y01 x1 x2, nolog

```

Probit regression                               Number of obs   =       170
                                                LR chi2(2)      =         1.22
                                                Prob > chi2     =       0.5441
Log likelihood = -62.954181                    Pseudo R2      =       0.0096

```

y01	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.0418363	.271849	-0.15	0.878	-.5746505	.4909779
x2	-.2958165	.2766328	-1.07	0.285	-.8380068	.2463738
_cons	1.38165	.2601436	5.31	0.000	.8717783	1.891522

. est store probit01

. probit y12 x1 x2, nolog

```

Probit regression                               Number of obs   =       170
                                                LR chi2(2)      =         9.42
                                                Prob > chi2     =       0.0090
Log likelihood = -106.25363                    Pseudo R2      =       0.0425

```

y12	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.5566823	.2142879	2.60	0.009	.1366857	.9766789
x2	-.3878755	.2156422	-1.80	0.072	-.8105263	.0347754
_cons	.3975119	.1915046	2.08	0.038	.0221698	.7728541

. est store probit12

. suest probit01 probit12

Simultaneous results for probit01, probit12

Number of obs = 170

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

probit01_y01						
x1	-.0418363	.289243	-0.14	0.885	-.6087422	.5250696
x2	-.2958165	.2781781	-1.06	0.288	-.8410356	.2494026
_cons	1.38165	.2495808	5.54	0.000	.8924809	1.87082

probit12_y12						
x1	.5566823	.2297184	2.42	0.015	.1064425	1.006922
x2	-.3878755	.2198123	-1.76	0.078	-.8186997	.0429488
_cons	.3975119	.1930813	2.06	0.040	.0190795	.7759444

. test [probit01_y01]x1 - [probit12_y12]x1 = 0

(1) [probit01_y01]x1 - [probit12_y12]x1 = 0

```

        chi2( 1) =    5.12
        Prob > chi2 =    0.0236

```

. test [probit01_y01]x2 - [probit12_y12]x2 = 0

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	-.7005573	.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	-.269383 .9122902

y3					
x1	-.5286327	.3907745	-1.35	0.176	-1.294537 .2372713
x2	.6349395	.387475	1.64	0.101	-.1244976 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	.074836	-8.33	0.000	-.7697612 -.4764094

/atrho31	-.4021504	.0739358	-5.44	0.000	-.5470619 -.2572388

/atrho32	-.3327244	.0712365	-4.67	0.000	-.4723455 -.1931034

rho21	-.5532725	.0519279	-10.65	0.000	-.6467906 -.4433634

rho31	-.3817874	.0631588	-6.04	0.000	-.4983149 -.2517111

rho32	-.3209667	.0638978	-5.02	0.000	-.4400925 -.1907385

Likelihood ratio test of rho21 = rho31 = rho32 = 0:
chi2(3) = 247.471 Prob > chi2 = 0.0000

-mprobit is appropriated, because the null hypothesis is rejected at 0.05 level. Since correlation among the disturbance terms are existed, mprobit would be more appropriated.

-MV Probit model has limitation of dependent variables, discrete dependent variable, and limitation of the distribution, limitation of dependent variables. Probit models have binary choices.

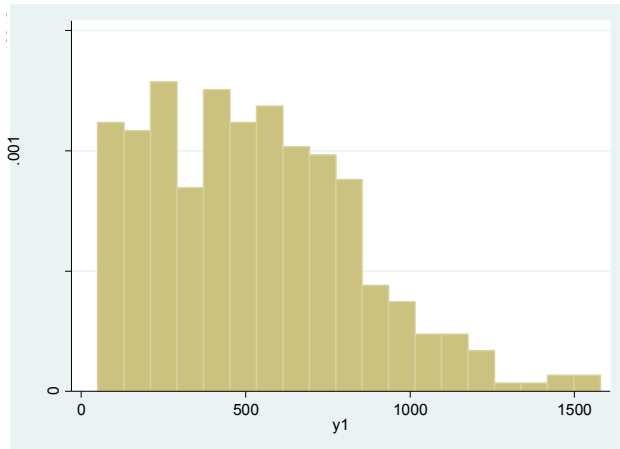
2.)

a.)

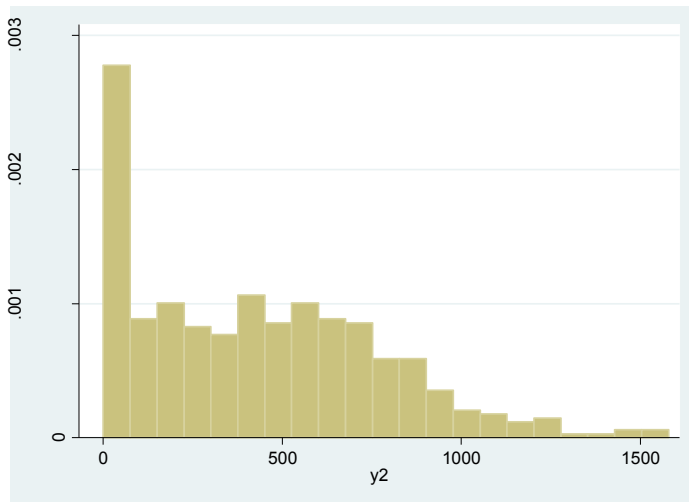
. sum y1 y2 y3

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

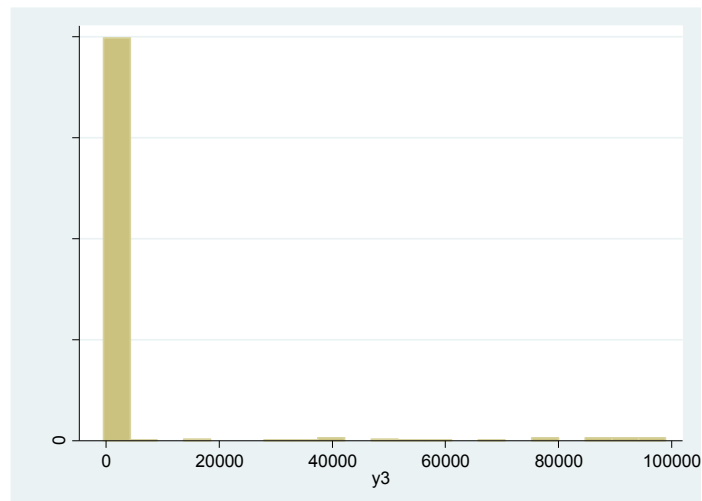
. histogram y1
(bin=19, start=50.217594, width=80.436449)



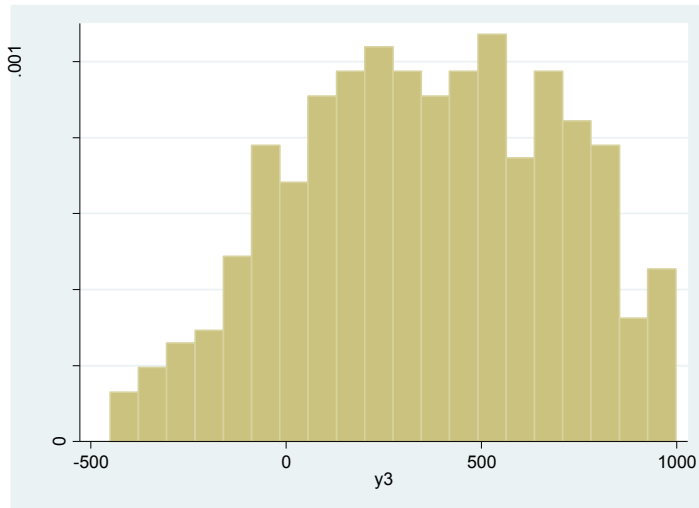
```
. histogram y2  
(bin=21, start=0, width=75.167149)
```



```
. histogram y3  
(bin=21, start=-450.62051, width=4733.4406)
```



```
. histogram y3 if y3<2000  
(bin=20, start=-450.62051, width=72.440572)
```



-According to data summarize and histogram, it might be concluded that y1 has truncated problem at approximately 50, y2 has censored problem at 0, y3 has outlier problem.

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 olsy1
```

```
. sum y1
```

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

```
. scalar miny=round(r(min))
```

```
. scalar lsit miny
varlist not allowed
r(101);
```

```
. scalar list miny
miny = 50
```

```
. truncreg y1 x, ll(miny) 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 ty1

. lrtest olsy1 ty1, force

```
Likelihood-ratio test                                LR chi2(1) =      76.33
(Assumption: olsy1 nested in ty1)                   Prob > chi2 =      0.0000
```

-According to significant LR-test between linear regression model and truncated model, it can be concluded that truncated regression model is more appropriated since null hypothesis of LR test is rejected. The major problem caused by sample is based only on value of y which will make OLS estimator biased.

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
-----+-----							
Total		53002615.7	449	118045.915	R-squared	=	0.3827
					Adj R-squared	=	0.3814
					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 olsy2

. sum y2

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

Variable		Obs	Mean	Std. Dev.	Min	Max
y2		450	428.525	343.5781	0	1578.51

. 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 tby2
. lrtest olsy2 tby2, force
```

```
Likelihood-ratio test                    LR chi2(1) =    734.73
(Assumption: olsy2 nested in tby2)      Prob > chi2 =    0.0000
```

-According to significant LR-test between OLS and tobit model, it can be concluded that tobit regression model is more appropriated since null hypothesis of LR-test is rejected. The major problem caused by sample is censored based only on value of y which will make OLS estimator be bias.

d.)

```
. reg y3 x if y3<1000
```

Source	SS	df	MS	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
				R-squared	=	0.3320
				Adj R-squared	=	0.3304
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

```
. reg y3 x
```

Source	SS	df	MS	Number of obs	=	450
Model	9.4500e+09	1	9.4500e+09	F(1, 448)	=	41.34
Residual	1.0240e+11	448	228579849	Prob > F	=	0.0000
				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

```
. est store olsy3
```

```
. sum y3
```

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

```
. tobit y3 x, ul(1000) nolog
```

```
Tobit regression                    Number of obs =    450
LR chi2(1)                          =    226.53
Prob > chi2                          =    0.0000
Log likelihood = -3038.746            Pseudo R2      =    0.0359
```

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x	227.9317	13.50702	16.88	0.000	201.3868 254.4765
_cons	-283.3561	42.60586	-6.65	0.000	-367.0878 -199.6244

```

/sigma | 289.9756 10.05253 270.2197 309.7314
-----
0 left-censored observations
425 uncensored observations
25 right-censored observations at y3 >= 1000

. est store tby3

. lrtest olsy3 tby3, force

Likelihood-ratio test                    LR chi2(1) = 3858.88
(Assumption: olsy3 nested in tby3)      Prob > chi2 = 0.0000

```

-According to significant LR-test between linear regression and tobit model, it can be concluded that tobit regression model is more appropriated since the null hypothesis of LR-test is rejected. The major problem caused by sample exist an outlier which will make OLS estimator to be biased

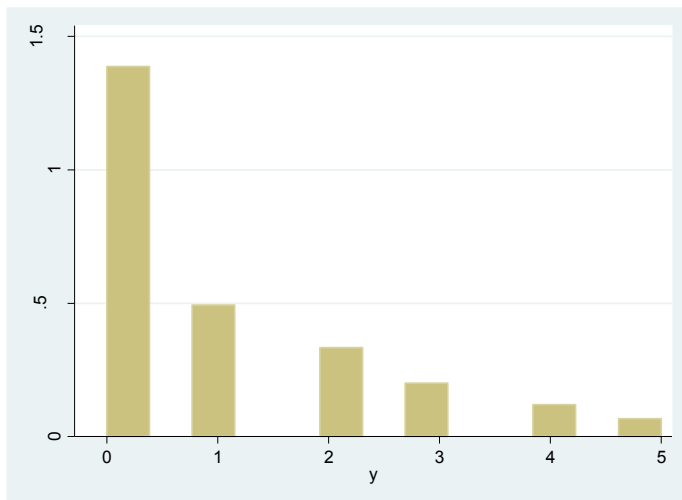
3.)

a.)

```

. histogram y
(bin=13, start=0, width=.38461538)

```



-According to histogram, it exist that the distribution of dependent variable follows Poission distribution, which mean the value is non-negative and also discrete, hence, Poission regression model should be applied.

```

. reg y x1 x2 x3 x4

```

Source	SS	df	MS	Number of obs	=	195
Model	33.4104504	4	8.35261259	F(4, 190)	=	5.01
Residual	316.569037	190	1.66615283	Prob > F	=	0.0007
				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 olsy

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

Pearson goodness-of-fit = 332.2892
Prob > chi2(190)         = 0.0000
```

. poisson y x1 x2 x3 x4, irr 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	IRR	Std. Err.	z	P> z	[95% Conf. Interval]
x1	1.083973	.0372731	2.34	0.019	1.013326 1.159545
x2	1.15044	.042265	3.81	0.000	1.070514 1.236333
x3	1.225685	.0675669	3.69	0.000	1.100159 1.365532
x4	.9759046	.0365575	-0.65	0.515	.9068203 1.050252
_cons	.8538306	.0798901	-1.69	0.091	.7107677 1.025689

. est store psy

. mfx

```
Marginal effects after poisson
y = Predicted number of events (predict)
= .90429488
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x1	.0729159	.03071	2.37	0.018	.012716 .133116	-.281682
x2	.126732	.0322	3.94	0.000	.063621 .189843	.871385
x3	.1840236	.04814	3.82	0.000	.08968 .278367	-.300421
x4	-.0220561	.03384	-0.65	0.515	-.088378 .044266	-.785193

-According to the above estimated result, interpretation can be made concerning sign and meaning of the estimated coefficient – positive mfx sign and irr>1 for x1, x2, and x3, and negative mfx sign and irr<1 for x4. Overall test LR-Chi-square-test, significant, Pseudo R-squared 0.0633, not quite fit the data. Individual z-test, all significant except x4.

c.)

```
. nbreg y x1 x2 x3 x4, 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	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
```

```
. est store nby
```

```
. mfx
```

```
Marginal effects after nbreg
y = Predicted number of events (predict)
= .89818493
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x1	.0976932	.04724	2.07	0.039	.005103 .190283	-.281682
x2	.1392077	.04697	2.96	0.003	.047148 .231268	.871385
x3	.1754294	.06369	2.75	0.006	.050608 .300251	-.300421
x4	-.025153	.0453	-0.56	0.579	-.113947 .063641	-.785193

-According to the above estimated result, interpretation can be made concerning sign and meaning of the estimated coefficient, positive mfx sign and irr>1 for x1, x2, and x3, and negative mfx sign and irr<1 for x4. For overall test, LR-Chi-squared-test is significant. Pseudo R-squared 0.0384, not quite fit the data. Individual z-tests are all significant except x4.

d.)

```
. zip y x1 x2 x3, inflate(x4) vuong nolog
```

```
Zero-inflated Poisson regression      Number of obs   =      195
Nonzero obs                          =      91
Zero obs                              =      104
```

```
Inflation model = logit              LR chi2(3)     =      14.28
Log likelihood = -258.0761           Prob > chi2    =      0.0025
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y					
x1	.0910814	.0438491	2.08	0.038	.0051388 .177024
x2	.1228343	.0405771	3.03	0.002	.0433047 .2023639
x3	.1436254	.0562275	2.55	0.011	.0334216 .2538293
_cons	.3243813	.1173574	2.76	0.006	.0943649 .5543976
inflate					
x4	.0218089	.1008201	0.22	0.829	-.1757948 .2194126
_cons	-.5230108	.259533	-2.02	0.044	-1.031686 -.0143354

Vuong test of zip vs. standard Poisson: z = 2.58 Pr>z = 0.0050

. mfx

Marginal effects after zip

y = Predicted number of events (predict)
= .90801003

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x1	.0827028	.03951	2.09	0.036	.005255 .16015	-.281682
x2	.1115348	.03615	3.09	0.002	.040688 .182381	.871385
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 result =, interpretation can be made concerning the sign and meaning of the estimated coefficient. Positive mfx sign and irr>1 for x1, x2, and x3, and negative mfx sign and irr<1 for x4. Overall test LR-Chi-Squared-test is significant. Individual z-test are all significant except x4.'

-According to GOF-test, we reject the null hypothesis of the test, Poisson regression model is more appropriated than linear regression model

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

-According to Vuong test, H null is rejected, zero inflated model is more appropriated than Poisson regression model

-Histogram illustrate zero inflated distribution of dependent variable, therefore, zero inflated regression model should be applied in this case.

4.)

a.)

. tsset t
time variable: t, 1 to 500
delta: 1 unit

. 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

. 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	-3.130

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

-y and x are stationary or I(0)

- The Unit root test is testing of the variable be stationary or nonstationary. If the data is stationary, OLS can still be used. But if the data is nonstationary, then the OLS estimator will be biased. Stationary is important to time-series due to the fact than most of the time-series data is high frequency and nonstationary which will lead OLS estimator to be biased.

b.)

```
. *For y
. *specify order p d q
. forvalue d = 0(1)0 {
2. forvalue p = 1(1)4 {
3. forvalue q = 1(1)4 {
4. display "estimate arima`p'`d'`q'"
5. capture: qui arima y, arima(`q',`d',`p') nolog
6. if _rc~=0 {
7. display "flatlog when pdq =" `p'`d'`q'
8. continue
9. }
10. estimates store arima`p'`d'`q'
11. display "arima`p'`d'`q' already estimated"
12. }
13. }
14. estimates table arima1`d'1 arima1`d'2 arima1`d'3 arima1`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
15. estimates table arima2`d'1 arima2`d'2 arima2`d'3 arima2`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
16. estimates table arima3`d'1 arima3`d'2 arima3`d'3 arima3`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
17. estimates table arima4`d'1 arima4`d'2 arima4`d'3 arima4`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
18. }
estimate arima101
arima101 already estimated
estimate arima102
arima102 already estimated
estimate arima103
arima103 already estimated
estimate arima104
arima104 already estimated
estimate arima201
arima201 already estimated
estimate arima202
arima202 already estimated
estimate arima203
```

```

arima203 already estimated
estimate arima204
arima204 already estimated
estimate arima301
arima301 already estimated
estimate arima302
arima302 already estimated
estimate arima303
arima303 already estimated
estimate arima304
flatlog when pdq =304
estimate arima401
arima401 already estimated
estimate arima402
arima402 already estimated
estimate arima403
arima403 already estimated
estimate arima404
arima404 already estimated

```

Variable	arima101	arima102	arima103	arima104

Y				
_cons	1.3160732***	1.3165966***	1.3170214***	1.3175059***

ARMA				
ar				
L1.	-.85671231***	-.81679808***	-.84311244***	-.78144222**
L2.		.01965322	.03190832	.03235516
L3.			.01910909	.04475517
L4.				.04099103
ma				
L1.	.81381586***	.78741991***	.81339159***	.75091484**

sigma				
_cons	6.7070643***	6.706091***	6.7050253***	6.7000467***

Statistics				
aic	3330.1124	3331.957	3333.8057	3335.0818
bic	3346.9709	3353.0301	3359.0934	3364.5841
ll	-1661.0562	-1660.9785	-1660.9029	-1660.5409

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

Variable	arima201	arima202	arima203	arima204

Y				
_cons	1.3164623***	1.3193097***	1.3192207***	1.3190967***

ARMA				
ar				
L1.	-.8407698***	.02485091	-.03418916	-.0441011
L2.		.72638325***	.72699651***	.65860818*
L3.			.02024337	.02006821
L4.				.02440356
ma				
L1.	.81081395***	-.04728285	.00153606	.01110505
L2.	.01776181	-.65937106**	-.66194403**	-.6062543

sigma				
_cons	6.7062145***	6.6966012***	6.6954461***	6.694033***

Statistics				
aic	3331.9639	3332.5449	3334.4022	3336.1916
bic	3353.0369	3357.8325	3363.9044	3369.9085

	11	-1660.9819	-1660.2724	-1660.2011	-1660.0958

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

Variable		arima301	arima302	arima303	arima304

Y					
	_cons	1.3169246***	1.3192028***	1.3310897***	

ARMA					
	ar				
	L1.	-.85479005***	-.00880392	1.0641766***	-1.1197775***
	L2.		.72631603***	.65311363**	.60359466
	L3.			-.83388151***	.84850518***
	L4.				.05544077
	ma				
	L1.	.82385933***	-.02454975	-1.1231441***	1.0897361***
	L2.	.02900763	-.66072222**	-.55650296	-.59325463
	L3.	.01703608	.01970127	.80658953***	-.7687395***

sigma					
	_cons	6.7052679***	6.695548***	6.6127568	9.5277271***

x					
	_cons				1.1486373**

Statistics					
	aic	3333.8305	3334.3921	3326.0559	3691.346
	bic	3359.1181	3363.8944	3355.5581	3729.2774
	ll	-1660.9152	-1660.1961	-1656.0279	-1836.673

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

Variable		arima401	arima402	arima403	arima404

Y					
	_cons	1.3197063***	1.3190979***	1.3312903***	1.3187605***

ARMA					
	ar				
	L1.	.79554291***	-.01799803	1.0672528***	.090027
	L2.		.68941508**	.64678484*	-.22996396
	L3.			-.83046045***	-.05809939
	L4.				.70709274***
	ma				
	L1.	-.83063231***	-.01490702	-1.123474	-.12463059
	L2.	.08194831	-.63706121**	-.55181303	.31438256
	L3.	-.04699497	.01889581	.79852779	.05252582
	L4.	.03885793	.02331994	.00399586	-.66037916**

sigma					
	_cons	6.7032944***	6.6939821***	6.6127831	6.6579737***

Statistics					
	aic	3335.5639	3336.1786	3328.0491	3335.3652
	bic	3365.0661	3369.8955	3361.766	3377.5113
	ll	-1660.7819	-1660.0893	-1656.0246	-1657.6826

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

```

. *For x
. *specify order p d q
. forvalue d = 0(1)0 {
2. forvalue p = 1(1)4 {
3. forvalue q = 1(1)4 {
4. display "estimate arima`p`d`q'"

```

```

5. capture: qui arima x, arima(`q', `d', `p') nolog
6. if _rc~=0 {
7. display "flatlog when pdq =" `p' `d' `q'
8. continue
9. }
10. estimates store arima`p' `d' `q'
11. display "arima`p' `d' `q' already estimated"
12. }
13. }
14. estimates table arima1`d'1 arima1`d'2 arima1`d'3 arima1`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
15. estimates table arima2`d'1 arima2`d'2 arima2`d'3 arima2`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
16. estimates table arima3`d'1 arima3`d'2 arima3`d'3 arima3`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
17. estimates table arima4`d'1 arima4`d'2 arima4`d'3 arima4`d'4, star(0.1 0.05 0.01) stat( aic
bic ll)
18. }
estimate arima101
arima101 already estimated
estimate arima102
arima102 already estimated
estimate arima103
arima103 already estimated
estimate arima104
arima104 already estimated
estimate arima201
arima201 already estimated
estimate arima202
arima202 already estimated
estimate arima203
arima203 already estimated
estimate arima204
arima204 already estimated
estimate arima301
arima301 already estimated
estimate arima302
arima302 already estimated
estimate arima303
arima303 already estimated
estimate arima304
arima304 already estimated
estimate arima401
arima401 already estimated
estimate arima402
arima402 already estimated
estimate arima403
arima403 already estimated
estimate arima404
arima404 already estimated

```

Variable	arima101	arima102	arima103	arima104
x				
_cons	1.1429574***	1.1438648***	1.1435826***	1.144789**
ARMA				
ar				
L1.	-.87226788***	-.84813314***	-.85922478***	-.79064859***
L2.		.01339278	.02025562	.02132992
L3.			.00996172	.04351126
L4.				.05104355
ma				
L1.	.83034368***	.81593968***	.82688807***	.75769917***
sigma				
_cons	9.5703726***	9.5696168***	9.5694102***	9.5583281***

Statistics				
aic	3685.6274	3687.5528	3689.5106	3690.3884
bic	3702.4858	3708.6258	3714.7982	3719.8907
ll	-1838.8137	-1838.7764	-1838.7553	-1838.1942

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

Variable	arima201	arima202	arima203	arima204
x				
_cons	1.1434802***	1.1477731**	1.1481455**	1.1476833**
ARMA				
ar				
L1.	-.8637267***	.01984067	-.03979143	-.06877967
L2.		.75797154***	.75496418***	.65528076*
L3.			.02222992	.02359464
L4.				.03474976
ma				
L1.	.8313275***	-.0428149	.0045602	.03306671
L2.	.01248218	-.69472386***	-.69347266***	-.61275455*
sigma				
_cons	9.5696138***	9.5569958***	9.555084***	9.5512798***

Statistics				
aic	3687.5544	3688.2364	3690.0573	3691.6355
bic	3708.6274	3713.524	3719.5595	3725.3523
ll	-1838.7772	-1838.1182	-1838.0286	-1837.8177

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

Variable	arima301	arima302	arima303	arima304
x				
_cons	1.1437579***	1.1481262**	1.1692449**	1.1486373**
ARMA				
ar				
L1.	-.86931937***	-.01360873	1.0436082***	-1.1197775***
L2.		.7537429***	.68694475**	.60359466
L3.			-.84827425***	.84850518***
L4.				.05544077
ma				
L1.	.83624098***	-.02269915	-1.1034825***	1.0897361***
L2.	.01801232	-.6916531***	-.59313834*	-.59325463
L3.	.00837349	.0222733	.82577707***	-.7687395***
sigma				
_cons	9.5692441***	9.5549359***	9.4344997	9.5277271***

Statistics				
aic	3689.5218	3690.0407	3681.4935	3691.346
bic	3714.8095	3719.5429	3710.9958	3729.2774
ll	-1838.7609	-1838.0203	-1833.7468	-1836.673

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

Variable	arima401	arima402	arima403	arima404
x				
_cons	1.1445228**	1.1477398**	1.1486154**	1.149491**

```
ARMA
```

ar					
L1.	-.83159841***	-.0360773	-1.0556571***	-.43620697*	
L2.		.70081296**	.6665806	-.19060125	
L3.			.79635047***	.36572357	
L4.				.69806251***	
ma					
L1.	.79792245***	.00106843	1.0251578***	.41330159	
L2.	.01579383	-.65762305**	-.65682261	.23343208	
L3.	.04217276	.02139641	-.71845214***	-.3600084	
L4.	.05092146	.03206129	.05455814	-.61928398**	

```
sigma
```

_cons					
_cons	9.5581147***	9.5512942***	9.5276194***	9.5426163***	

```
Statistics
```

aic	3690.3703	3691.6363	3691.3316	3694.7701
bic	3719.8725	3725.3532	3729.263	3736.9162
ll	-1838.1851	-1837.8181	-1836.6658	-1837.3851

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

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

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

```
. 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
```

y		OPG				
	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
```

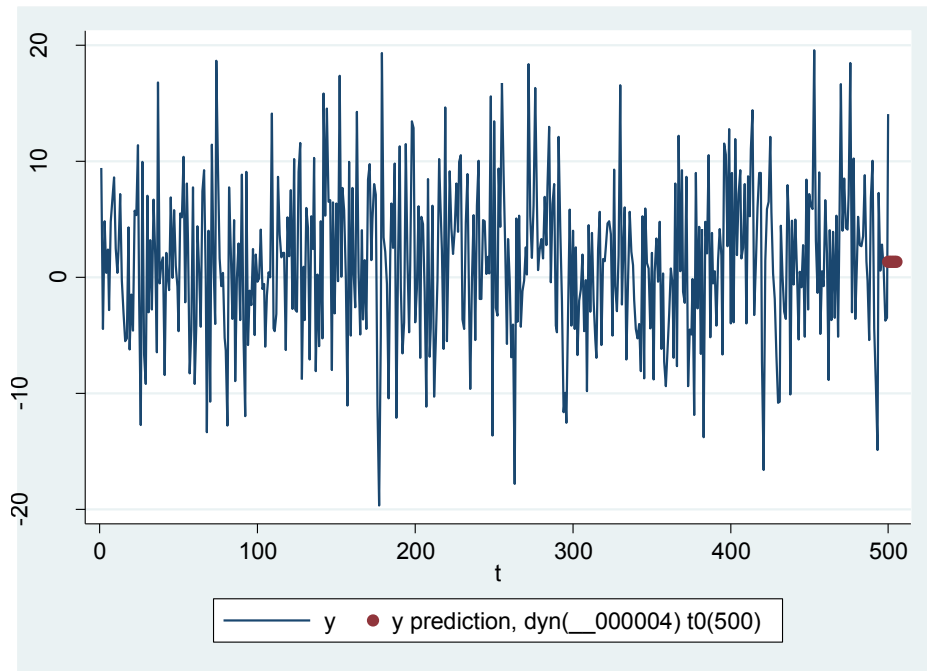
```
number of observations (_N) was 500, now 505
```

```
. replace t=_n
(5 real changes made)
```

```
. predict yhat, y dynamic(.) t0(500)
```

```
Note: beginning dynamic predictions in period      3.
(499 missing values generated)
```

```
. twoway (line y t, sort) (scatter yhat t, sort)
```



```
. arima x, arima(1,0,1) nolog
```

ARIMA regression

```
Sample: 1 - 500                Number of obs   =       500
                                Wald chi2(2)      =       66.85
Log likelihood = -1838.814      Prob > chi2     =       0.0000
```

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

x						
	_cons	1.142957	.422537	2.70	0.007	.3148001 1.971115

ARMA						
	ar					
	L1.	-.8722679	.1450005	-6.02	0.000	-1.156464 -.588072
	ma					
	L1.	.8303437	.1653247	5.02	0.000	.5063132 1.154374

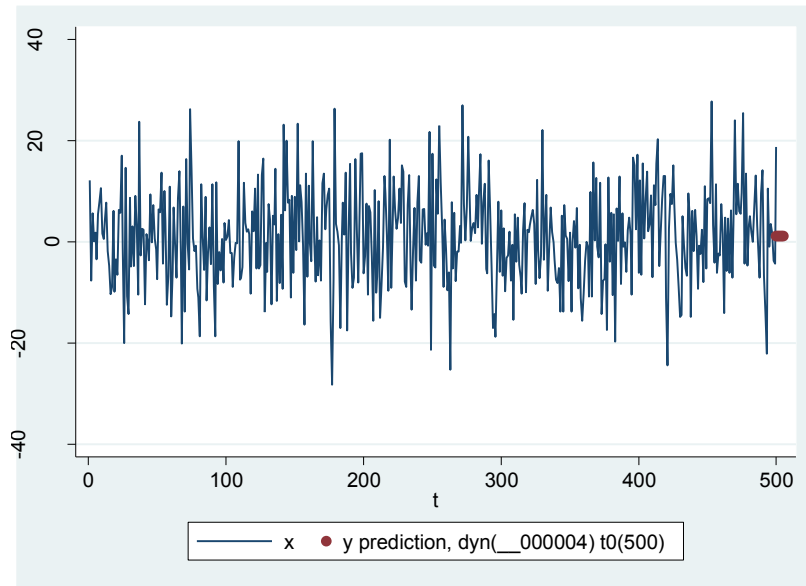
	/sigma	9.570373	.3051603	31.36	0.000	8.972269 10.16848

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

```
. predict yhat2, y dynamic(.) t0(500)
```

Note: beginning dynamic predictions in period 3.
(499 missing values generated)

```
. twoway (line x t, sort) (scatter yhat2 t, sort)
```



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
Total	22644.9015	499	45.3805642	R-squared	=	0.9913
				Adj R-squared	=	0.9913
				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. Reject the null hypothesis that all of alpha are equal to zero.

-This test is classified as LM test because, it computed bases on Restricted Model.

d.)

```
. *GARCH
. forvalue p=1(1)2 {
. 2. forvalue q=1(1)2 {
. 3. display "estimate garch`p'`q'"
. 4. qui arch y x, garch(1/`p') arch(1/`q') nolog
. 5. qui est store garch`p'`q'
```

```

6. }
7. est table garch*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
8. }
estimate garch11
estimate garch12

```

Variable	garch11	garch12
Y		
x	.69785097***	.69783972***
_cons	.51851398***	.51850887***
ARCH		
arch		
L1.	.36250292***	.36097359***
L2.		.00984107
garch		
L1.	.3251895***	.30886518
_cons	.12545535***	.1286695*
Statistics		
N	500	500
ll	-443.95805	-443.95432
chi2	72868.369	72933.849
aic	897.9161	899.90864
bic	918.98914	925.19629

```

legend: * p<.1; ** p<.05; *** p<.01
estimate garch21
estimate garch22

```

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

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

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

ARCH family regression

```

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

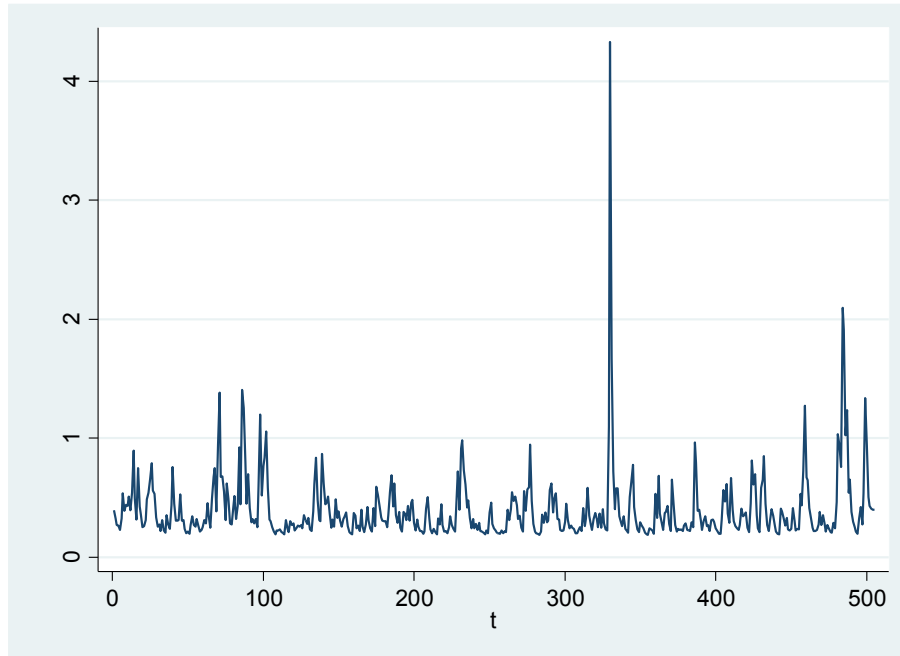
```

		OPG				[95% Conf. Interval]	
y		Coef.	Std. Err.	z	P> z		
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
	L1.	.3251895	.1186414	2.74	0.006	.0926567	.5577223
garch	L1.	.1254554	.0357542	3.51	0.000	.0553784	.1955323
	_cons						

-According to BIC, the most appropriated lags order in this case is GARCH(1,1)

```
. predict sigmahat, v
. line sigmahat t
```



e.)

Among three models, the most appropriated in this case is GARCH, because it is the generalized of ARCH and we have p and q. GARCH is extended from ARCH and EGARCH is an asymmetric GARCH model, we react to shock asymmetrically, good for fluctuation period.

5.)

a.)

```
. tsset t
   time variable: t, 1 to 500
      delta: 1 unit
```

. varsoc y x, maxlag(5)

Selection-order criteria
Sample: 6 - 500

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-1363.76				.854259	5.51823	5.5249	5.53522
1	-1316.78	93.956*	4	0.000	.718084*	5.34458*	5.36459*	5.39555*
2	-1316.03	1.5085	4	0.825	.727564	5.3577	5.39104	5.44264
3	-1315.1	1.8666	4	0.760	.736636	5.37009	5.41677	5.48901
4	-1313.08	4.0355	4	0.401	.742563	5.3781	5.43812	5.53099
5	-1311.42	3.3226	4	0.505	.749618	5.38755	5.46091	5.57442

Endogenous: y x
Exogenous: _cons

-According to SBIC, the most appropriated lag order is 1.

b.)

. var y x, lag(1/1)

Vector autoregression

Sample:	2 - 500	Number of obs	=	499
Log likelihood	= -1329.966	AIC	=	5.354573
FPE	= .7252923	HQIC	=	5.374451
Det(Sigma_ml)	= .7080582	SBIC	=	5.405226

Equation	Parms	RMSE	R-sq	chi2	P>chi2
y	3	.994217	0.0148	7.510069	0.0234
x	3	.99826	0.0877	47.99154	0.0000

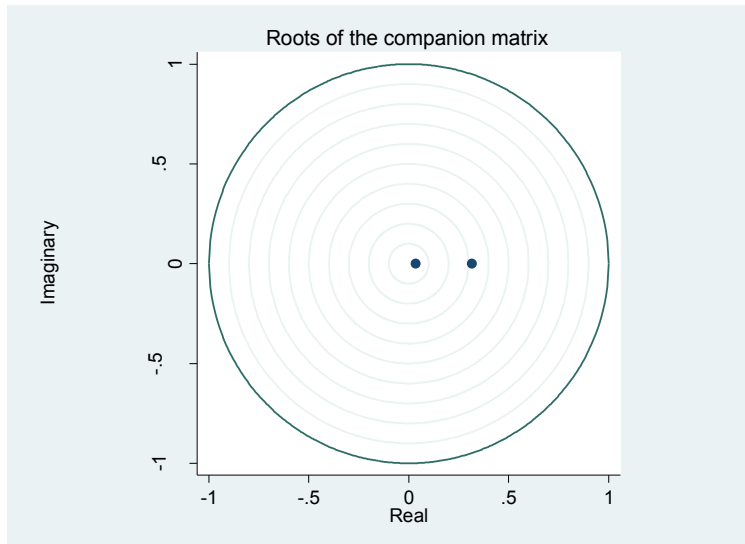
		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y	y					
	L1.	.1370087	.0500719	2.74	0.006	.0388696 .2351478
	x					
	L1.	.0538854	.0479496	1.12	0.261	-.0400941 .1478649
	_cons	.3367878	.0544732	6.18	0.000	.2300223 .4435534
x	y					
	L1.	.3405712	.0502755	6.77	0.000	.242033 .4391095
	x					
	L1.	.2120147	.0481446	4.40	0.000	.117653 .3063764
	_cons	.1231797	.0546947	2.25	0.024	.0159799 .2303794

. varstable, graph

Eigenvalue stability condition

Eigenvalue	Modulus
.3150759	.315076
.0339475	.033948

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	1.2629	1	0.261
y	ALL	1.2629	1	0.261
x	y	45.888	1	0.000
x	ALL	45.888	1	0.000

-According to stability test, the system is stable since all the eigenvalue lie inside the unit circle.

-According to Granger exogeneity, x is endogenous since the test is significant, while y is not endogenous.

-If the stability assumption is unsatisfied, the IRF won't get back to the equilibrium.

c.)

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

Results from order1

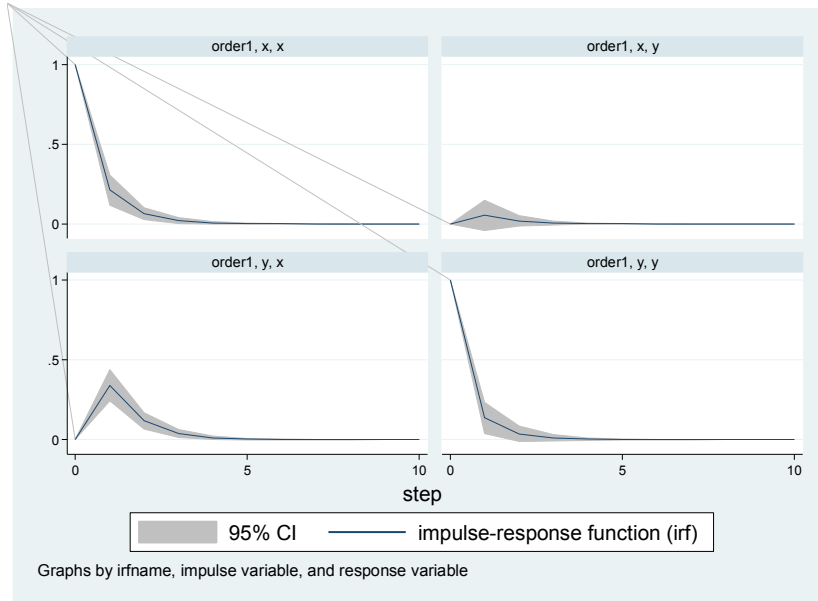
step	(1)			(2)		
	irf	Lower	Upper	irf	Lower	Upper
0	1	1	1	0	0	0
1	.137009	.03887	.235148	.340571	.242033	.439109
2	.037123	-.011219	.085465	.118867	.067548	.170187
3	.011491	-.008261	.031244	.037845	.013023	.062667
4	.003614	-.003868	.011095	.011937	.000566	.023308
5	.001138	-.001613	.003889	.003762	-.001066	.008589
6	.000359	-.000633	.001351	.001185	-.000745	.003115
7	.000113	-.000239	.000465	.000373	-.000366	.001113
8	.000036	-.000088	.000159	.000118	-.000157	.000392
9	.000011	-.000032	.000054	.000037	-.000063	.000137
10	3.5e-06	-.000011	.000018	.000012	-.000024	.000047

step	(3) irf	(3) Lower	(3) Upper	(4) irf	(4) Lower	(4) Upper
0	0	0	0	1	1	1
1	.053885	-.040094	.147865	.212015	.117653	.306376
2	.018807	-.014393	.052008	.063302	.02548	.101124
3	.005988	-.006268	.018244	.019826	.001882	.03777
4	.001889	-.002612	.006389	.006243	-.001509	.013994
5	.000595	-.00103	.002221	.001967	-.001159	.005092
6	.000188	-.000391	.000766	.00062	-.000584	.001823
7	.000059	-.000144	.000262	.000195	-.000254	.000644
8	.000019	-.000052	.000089	.000062	-.000102	.000225
9	5.9e-06	-.000018	.00003	.000019	-.000039	.000078
10	1.8e-06	-6.5e-06	.00001	6.1e-06	-.000015	.000027

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

step	(1) oirf	(1) Lower	(1) Upper	(2) oirf	(2) Lower	(2) Upper
0	.991224	.929727	1.05272	-.519501	-.600659	-.438343
1	.107813	.02099	.194635	.227441	.138072	.316809
2	.027027	-.005211	.059265	.084939	.045912	.123965
3	.00828	-.005161	.021721	.027213	.009891	.044535
4	.002601	-.002531	.007732	.008589	.000924	.016255

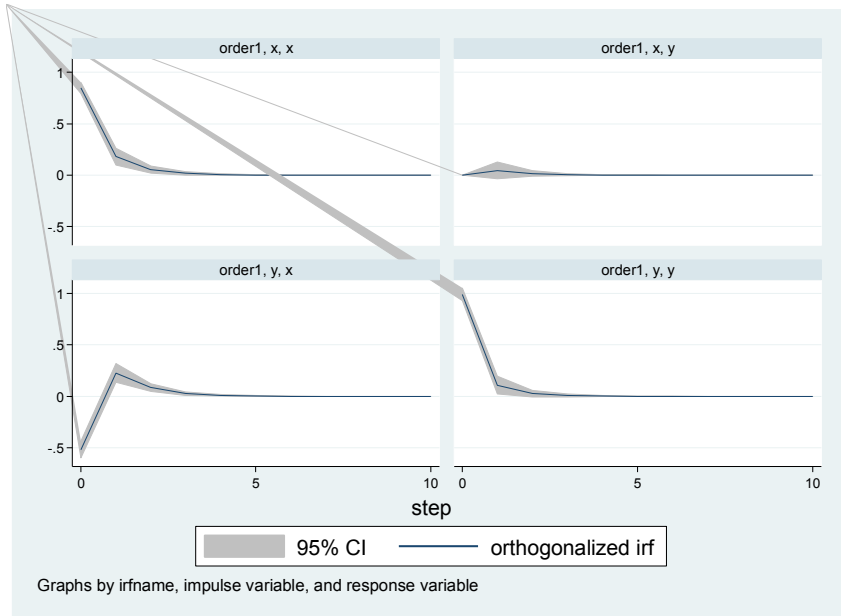
5	.000819	- .001077	.002715	.002707	- .000547	.005961	
6	.000258	- .000429	.000945	.000853	- .000457	.002162	
7	.000081	- .000163	.000326	.000269	- .000236	.000774	
8	.000026	- .000061	.000112	.000085	- .000104	.000274	
9	8.1e-06	- .000022	.000038	.000027	- .000042	.000096	
10	2.5e-06	-7.8e-06	.000013	8.4e-06	- .000016	.000033	

step	(3) oirf	(3) Lower	(3) Upper	(4) oirf	(4) Lower	(4) Upper	
0	0	0	0	.848912	.796244	.90158	
1	.045744	- .034087	.125575	.179982	.099103	.260861	
2	.015966	- .012236	.044168	.053738	.021458	.086018	
3	.005083	- .005326	.015492	.016831	.001562	.032099	
4	.001603	- .002219	.005425	.0053	- .001289	.011888	
5	.000505	- .000875	.001886	.00167	- .000986	.004325	
6	.000159	- .000332	.00065	.000526	- .000496	.001548	
7	.00005	- .000122	.000223	.000166	- .000215	.000547	
8	.000016	- .000044	.000076	.000052	- .000087	.000191	
9	5.0e-06	- .000016	.000026	.000016	- .000033	.000066	
10	1.6e-06	-5.5e-06	8.6e-06	5.2e-06	- .000012	.000023	

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

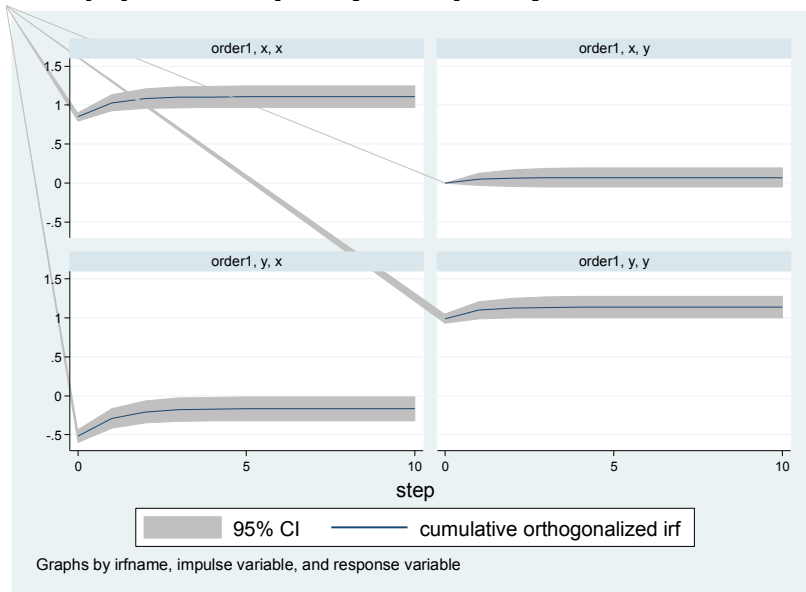
step	(1) coirf	(1) Lower	(1) Upper	(2) coirf	(2) Lower	(2) Upper
0	.991224	.929727	1.05272	-.519501	-.600659	-.438343
1	1.09904	.988843	1.20923	-.29206	-.418616	-.165505
2	1.12606	.997777	1.25435	-.207122	-.349063	-.065181
3	1.13434	.9985	1.27019	-.179909	-.329085	-.030733
4	1.13694	.99817	1.27572	-.171319	-.323504	-.019135
5	1.13776	.997917	1.27761	-.168613	-.321961	-.015264
6	1.13802	.997794	1.27825	-.16776	-.321537	-.013982
7	1.1381	.997743	1.27846	-.167491	-.321422	-.01356
8	1.13813	.997723	1.27853	-.167406	-.321391	-.013421
9	1.13814	.997715	1.27856	-.16738	-.321383	-.013376
10	1.13814	.997712	1.27857	-.167371	-.321381	-.013361

step	(3) coirf	(3) Lower	(3) Upper	(4) coirf	(4) Lower	(4) Upper
0	0	0	0	.848912	.796244	.90158
1	.045744	-.034087	.125575	1.02889	.926465	1.13132
2	.06171	-.045933	.169352	1.08263	.958289	1.20697
3	.066793	-.051017	.184603	1.09946	.965973	1.23295
4	.068396	-.053116	.189909	1.10476	.967587	1.24194
5	.068901	-.053937	.19174	1.10643	.967855	1.24501
6	.069061	-.054246	.192368	1.10696	.967868	1.24605
7	.069111	-.05436	.192581	1.10712	.967851	1.2464
8	.069127	-.0544	.192653	1.10718	.967839	1.24651
9	.069132	-.054415	.192678	1.10719	.967833	1.24655
10	.069133	-.05442	.192686	1.1072	.967831	1.24656

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)



-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	.272461	.20582	.339101
2	.9979	.990577	1.00522	.299268	.234485	.364052
3	.997646	.98945	1.00584	.303132	.238893	.367371
4	.99762	.989324	1.00592	.303528	.239353	.367704
5	.997618	.989309	1.00593	.303568	.239398	.367737
6	.997618	.989308	1.00593	.303572	.239403	.367741
7	.997618	.989308	1.00593	.303572	.239403	.367741
8	.997618	.989308	1.00593	.303572	.239403	.367741
9	.997618	.989308	1.00593	.303572	.239403	.367741
10	.997618	.989308	1.00593	.303572	.239403	.367741

step	(3) fevd	(3) Lower	(3) Upper	(4) fevd	(4) Lower	(4) Upper
0	0	0	0	0	0	0
1	0	0	0	.727539	.660899	.79418
2	.0021	-.005222	.009423	.700732	.635948	.765515
3	.002354	-.005842	.01055	.696868	.632629	.761107
4	.00238	-.005917	.010676	.696472	.632296	.760647
5	.002382	-.005926	.010691	.696432	.632263	.760602
6	.002382	-.005927	.010692	.696428	.632259	.760597
7	.002382	-.005927	.010692	.696428	.632259	.760597
8	.002382	-.005927	.010692	.696428	.632259	.760597
9	.002382	-.005927	.010692	.696428	.632259	.760597
10	.002382	-.005927	.010692	.696428	.632259	.760597

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.)

Yes, because if we change the order, the matrix that we begin with will be different.