

**Answer Sheet Cover Page
Final Examination Semester 2/2020**

(Readable handwriting and printed version are acceptable)

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Course ID EE 426 Course Title _____

Lecturer Assoc. prof. Dr. Tatre Jantarakolca

Exam date 28/5/21 Time 09.00-15.00

Total pages 45

***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 

Date 28/05/21

```

-----
name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\final\q1 new.log
log type: text
opened on: 28 May 2021, 13:14:39

```

```
. use "C:\Users\User\Desktop\EE 426 stata\final\Final_q1-1_5.dta", clear
```

a)

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

```

Multinomial logistic regression           Number of obs   =           170
                                           LR chi2(8)      =           87.68
                                           Prob > chi2     =           0.0000
Log likelihood = -106.80628                Pseudo R2       =           0.2910

```

```

-----
          y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
0          | (base outcome)
-----+-----
1          |
   x1      |  -.7655058   .6196616   -1.24   0.217   -1.98002   .4490086
   x2      |  -.7651638   .7706137   -0.99   0.321   -2.275539  .7452114
   x3      |  -.4346366   .6129129   -0.71   0.478   -1.635924  .7666506
   x4      |   .5772955   .247649    2.33   0.020   .0919124   1.062679
   _cons   |  -6.703481   3.535921   -1.90   0.058  -13.63376   .2267964
-----+-----
2          |
   x1      |  -.8269588   .6824567   -1.21   0.226   -2.164549  .5106317
   x2      |  -1.698946   .8042347   -2.11   0.035   -3.275217  -.1226749
   x3      |   .7452921   .6636072    1.12   0.261   -.5553541  2.045938
   x4      |   1.779832   .3057578    5.82   0.000   1.180558   2.379107
   _cons   |  -25.61276   4.575878   -5.60   0.000  -34.58132  -16.64421
-----

```

```
. est store m1
```

```
. mlogit y x* if y!=2, base(0) nolog
```

```

Multinomial logistic regression           Number of obs   =           63
                                           LR chi2(4)      =           6.49
                                           Prob > chi2     =           0.1655
Log likelihood = -35.324084                Pseudo R2       =           0.0841

```

```

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

```

```
1
```

x1	-.6041432	.601131	-1.01	0.315	-1.782338	.5740519
x2	-.5114184	.754524	-0.68	0.498	-1.990258	.9674213
x3	-.2692158	.6316639	-0.43	0.670	-1.507254	.9688226
x4	.5338047	.2465122	2.17	0.030	.0506496	1.01696
_cons	-6.4123	3.664639	-1.75	0.080	-13.59486	.7702618

```
-----
```

```
. est store m2
```

```
. hausman m1 m2, alleq constant
```

```
----- Coefficients -----
```

	(b) m1	(B) m2	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
x1	-.7655058	-.6041432	-.1613626	.1504061
x2	-.7651638	-.5114184	-.2537454	.1566497
x3	-.4346366	-.2692158	-.1654207	.
x4	.5772955	.5338047	.0434908	.0237006
_cons	-6.703481	-6.4123	-.2911813	.

```
-----
```

```
          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
```

```
          chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
```

```
                  =          0.78
```

```
          Prob>chi2 =          0.9784
```

```
          (V_b-V_B is not positive definite)
```

- Null hypothesis is rejected at 5% level, IIA is not violated. Multinomial Logit is appropriate in this case.
- IIA is importance because if it doesn't hold, then the comparison of the base case and other case will not exist.
- Multinomial Logit is inappropriate because it is an ordered data.

B)

```
. oprobit y x*, nolog
```

```
Ordered probit regression                  Number of obs      =          170
```

```
                                          LR chi2(4)          =          80.75
```

```
                                          Prob > chi2          =          0.0000
```

```
Log likelihood = -110.26907                Pseudo R2          =          0.2680
```

```
-----
```

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

x1	-.181094	.2298593	-0.79	0.431	-.63161	.269422
x2	-.5267477	.2384676	-2.21	0.027	-.9941357	-.0593597
x3	.5032115	.2162944	2.33	0.020	.0792822	.9271408
x4	.6737916	.092192	7.31	0.000	.4930986	.8544846
/cut1	9.217215	1.403268			6.466861	11.96757
/cut2	10.51401	1.455687			7.660915	13.3671

. tab y

y	Freq.	Percent	Cum.
0	19	11.18	11.18
1	44	25.88	37.06
2	107	62.94	100.00
Total	170	100.00	

. q y01=y>0
invalid syntax
r(198);

. g y01=y>0

. g y1=y>1

. g y12=y1

. tab y y01

y	y01		Total
	0	1	
0	19	0	19
1	0	44	44
2	0	107	107
Total	19	151	170

. tab y y12

y	y12		Total
	0	1	
0	19	0	19
1	44	0	44
2	0	107	107

```
-----+-----+-----
      Total |      63      107 |      170
```

```
. probit y01 x1 x2, nolog
```

```
Probit regression                               Number of obs   =      170
                                                LR chi2(2)      =       1.44
                                                Prob > chi2     =     0.4857
Log likelihood = -58.809916                    Pseudo R2      =     0.0121
```

```
-----+-----+-----+-----+-----+-----+-----
      y01 |      Coef.  Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----+-----+-----+-----+-----+-----
      x1 |   .1344467   .2763582     0.49   0.627   - .4072055   .6760989
      x2 |  -.3273367   .2948985    -1.11   0.267   - .9053272   .2506538
     _cons |  1.398929   .2705189     5.17   0.000    .8687213   1.929136
-----+-----+-----+-----+-----+-----+-----
```

```
. est store probit01
```

```
. probit y12 x1 x2, nolog
```

```
Probit regression                               Number of obs   =      170
                                                LR chi2(2)      =       9.07
                                                Prob > chi2     =     0.0107
Log likelihood = -107.541                      Pseudo R2      =     0.0405
```

```
-----+-----+-----+-----+-----+-----+-----
      y12 |      Coef.  Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----+-----+-----+-----+-----+-----
      x1 |   .530468   .2151251     2.47   0.014    .1088305   .9521055
      x2 |  -.436707   .2205912    -1.98   0.048   - .8690579  -.0043562
     _cons |  .4179719   .1950014     2.14   0.032    .0357761   .8001677
-----+-----+-----+-----+-----+-----+-----
```

```
. est store 12
12 invalid name
r(7);
```

```
. est store probit12
```

```
. suest probit01 probit12
```

```
Simultaneous results for probit01, probit12
```

```
Number of obs   =      170
```

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

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

probit01_y01						
x1	.1344467	.2920309	0.46	0.645	-.4379233	.7068168
x2	-.3273367	.3002285	-1.09	0.276	-.9157737	.2611002
_cons	1.398929	.2628876	5.32	0.000	.8836785	1.914179

probit12_y12						
x1	.530468	.2284481	2.32	0.020	.0827179	.9782181
x2	-.436707	.224271	-1.95	0.052	-.8762702	.0028561
_cons	.4179719	.1967748	2.12	0.034	.0323004	.8036434

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

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

 chi2(1) = 2.05
 Prob > chi2 = 0.1520

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

(1) [probit01_y01]x2 - [probit12_y12]x2 = 0

 chi2(1) = 0.16
 Prob > chi2 = 0.6919

According to the tesst, order logit model is inappropriated.

. use "C:\Users\User\Desktop\EE 426 stata\final\Final_q1-2_5.dta", clear

c) . probit y1 x*, nolog

```

Probit regression                               Number of obs   =          550
                                                LR chi2(4)      =          31.01
                                                Prob > chi2     =          0.0000
Log likelihood = -363.62871                    Pseudo R2      =          0.0409

```

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	

x1	1.445385	.4022585	3.59	0.000	.656973	2.233797
x2	-.8344805	.3854499	-2.16	0.030	-1.589949	-.0790125
x3	.6171441	.1770221	3.49	0.000	.2701872	.9641011
x4	.2509839	.1871514	1.34	0.180	-.115826	.6177939
_cons	-.8416628	.3033931	-2.77	0.006	-1.436302	-.2470233

. probit y2 x*, nolog

```

Probit regression                               Number of obs   =       550
                                                LR chi2(4)      =       15.15
                                                Prob > chi2     =       0.0044
Log likelihood = -359.55689                    Pseudo R2      =       0.0206

```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
y2						
x1	-.7662468	.3800725	-2.02	0.044	-1.511175	-.0213183
x2	-.5804844	.3723882	-1.56	0.119	-1.310352	.149383
x3	-.2515698	.1761122	-1.43	0.153	-.5967435	.0936038
x4	.6177622	.1929058	3.20	0.001	.2396738	.9958506
_cons	.3797781	.3020394	1.26	0.209	-.2122082	.9717644

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

```

Probit regression                               Number of obs   =       550
                                                LR chi2(4)      =       11.15
                                                Prob > chi2     =       0.0250
Log likelihood = -327.82122                    Pseudo R2      =       0.0167

```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
y3						
x1	-.5002966	.3908157	-1.28	0.200	-1.266281	.265688
x2	.7581937	.3864579	1.96	0.050	.0007502	1.515637
x3	-.3823911	.1975719	-1.94	0.053	-.7696248	.0048427
x4	-.3040029	.1853188	-1.64	0.101	-.6672211	.0592152
_cons	-.4916926	.3164181	-1.55	0.120	-1.111861	.1284755

- Since the correlation between the disturbance term is not zero, then these three separate probit models is inappropriate.

D)

```
. mvprobit (y1 x*) (y2 x*) (y3 x*), nolog
```

```

Multivariate probit (SML, # draws = 5)        Number of obs   =       550
                                                Wald chi2(12)   =       42.56
Log likelihood = -929.29773                    Prob > chi2     =       0.0000

```

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
y1						
x1	1.290919	.3922353	3.29	0.001	.5221516	2.059686
x2	-.7035317	.3795373	-1.85	0.064	-1.447411	.0403477
x3	.6018757	.1779435	3.38	0.001	.2531129	.9506384

	x4	.2327184	.1863713	1.25	0.212	-.1325626	.5979995
	_cons	-.7750348	.3054595	-2.54	0.011	-1.373724	-.1763452

y2							
	x1	-.8300746	.3752998	-2.21	0.027	-1.565649	-.0945005
	x2	-.4851346	.3706422	-1.31	0.191	-1.21158	.2413108
	x3	-.2658067	.1777109	-1.50	0.135	-.6141137	.0825004
	x4	.5833341	.1925894	3.03	0.002	.2058659	.9608023
	_cons	.4042966	.3002835	1.35	0.178	-.1842483	.9928416

y3							
	x1	-.4512174	.3845637	-1.17	0.241	-1.204949	.3025136
	x2	.6247652	.3814577	1.64	0.101	-.1228781	1.372409
	x3	-.2616852	.186518	-1.40	0.161	-.6272538	.1038833
	x4	-.2790318	.1887714	-1.48	0.139	-.6490169	.0909534
	_cons	-.4577304	.3188262	-1.44	0.151	-1.082618	.1671574

	/atrho21	-.6112249	.0745649	-8.20	0.000	-.7573693	-.4650804

	/atrho31	-.4256823	.0740828	-5.75	0.000	-.5708819	-.2804828

	/atrho32	-.3164979	.070872	-4.47	0.000	-.4554044	-.1775913

	rho21	-.5449888	.0524182	-10.40	0.000	-.6395248	-.4342158

	rho31	-.4017067	.0621282	-6.47	0.000	-.5160066	-.2733519

	rho32	-.3063368	.0642212	-4.77	0.000	-.4263313	-.1757475

Likelihood ratio test of $\rho_{21} = \rho_{31} = \rho_{32} = 0$:
 $\chi^2(3) = 243.418$ Prob > $\chi^2 = 0.0000$

MVprobit is appropriate due to the test that null hypothesis is rejected at 5% level. Since the correlation among the disturbance terms are existed, MVprobit is more appropriated

```
. log close
   name: <unnamed>
   log: C:\Users\User\Desktop\EE 426 stata\final\q1 new.log
  log type: text
closed on: 28 May 2021, 13:21:55
```

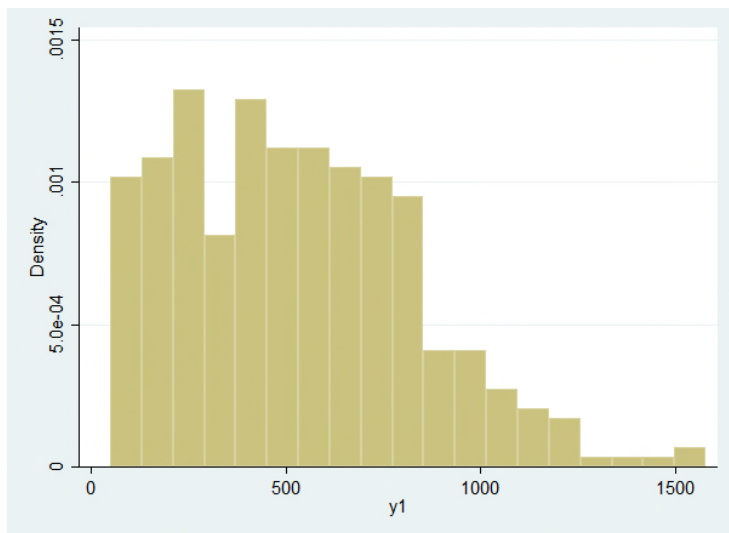
a2)

```
-----  
-----  
name: <unnamed>  
log: C:\Users\User\Desktop\EE 426 stata\final\q2.log  
log type: text  
opened on: 28 May 2021, 09:41:02
```

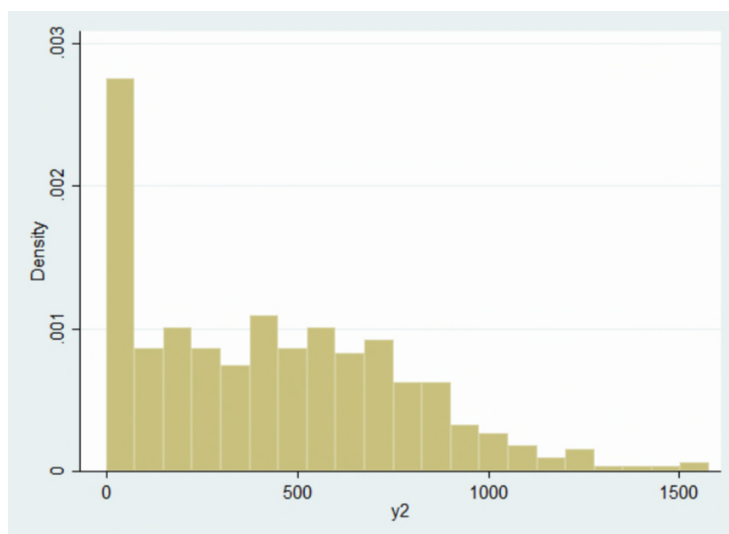
a) . use "C:\Users\User\Desktop\EE 426 stata\final\Final_q2_5.dta", clear
. sum y1 y2 y3

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	366	526.8888	302.9263	50.21759	1578.51
y2	450	429.5406	340.6001	0	1578.51
y3	450	3459.331	14741.52	-466.0042	98951.63

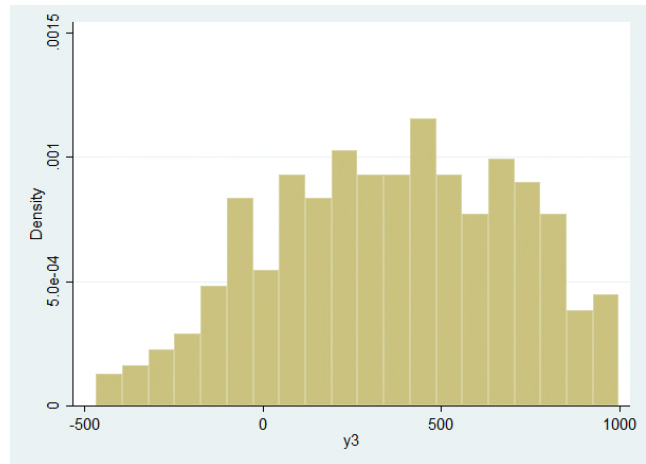
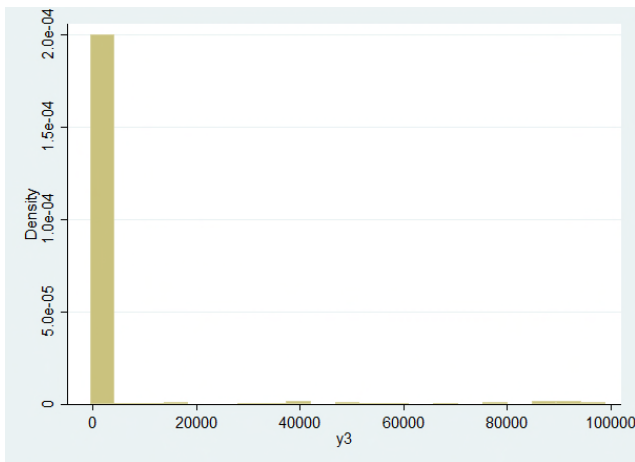
. histogram y1
(bin=19, start=50.217594, width=80.436449)



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



```
. histogram y3
(bin=21, start=-466.00415, width=4734.1732)
```



```
. histogram y3 if y3<2000
(bin=20, start=-466.00415, width=73.209753)
```

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

b) . reg y1 x

Source	SS	df	MS	Number of obs	=	366
Model	9223755.7	1	9223755.7	F(1, 364)	=	138.34
Residual	24270234.4	364	66676.468	Prob > F	=	0.0000
-----				R-squared	=	0.2754
-----				Adj R-squared	=	0.2734
Total	33493990.1	365	91764.3563	Root MSE	=	258.22

y1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x	165.8019	14.09684	11.76	0.000	138.0804 193.5234
_cons	-6.366052	47.30493	-0.13	0.893	-99.39132 86.65922

```
. est store olsy1
```

```
. sum y1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	366	526.8888	302.9263	50.21759	1578.51

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

```
. scalar list miny
```

```
miny = 50
```

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

```
(note: 0 obs. truncated)
```

Truncated regression

```
Limit: lower = 50 Number of obs = 366
       upper = +inf Wald chi2(1) = 105.05
Log likelihood = -2516.5699 Prob > chi2 = 0.0000
```

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x	231.6383	22.60014	10.25	0.000	187.3428 275.9338
_cons	-297.2026	86.1017	-3.45	0.001	-465.9588 -128.4463
/sigma	306.6324	16.90108	18.14	0.000	273.5069 339.7579

```
. predict truncated, e(50,.)
```

```
. est store ty1
```

```
. lrtest olsy1 ty1, force
```

```
Likelihood-ratio test LR chi2(1) = 68.90
(Assumption: olsy1 nested in ty1) Prob > chi2 = 0.0000
```

- According to significant LR-test between linear regression model and truncated model, it can be conclude 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 be bias.

② . reg y2 x

Source	SS	df	MS	Number of obs	=	450
Model	19329293.7	1	19329293.7	F(1, 448)	=	264.34
Residual	32758500.4	448	73121.6526	Prob > F	=	0.0000
				R-squared	=	0.3711
				Adj R-squared	=	0.3697

Source	SS	df	MS	Number of obs	=	450
Model	8.0481e+09	1	8.0481e+09	F(1, 448)	=	40.27
Residual	8.9525e+10	448	199833170	Prob > F	=	0.0000
				R-squared	=	0.0825
				Adj R-squared	=	0.0804
Total	9.7573e+10	449	217312520	Root MSE	=	14136

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	4073.721	641.9178	6.35	0.000	2812.177	5335.264
_cons	-8768.09	2038.725	-4.30	0.000	-12774.74	-4761.438

. reg y3 x if y3<1000

Source	SS	df	MS	Number of obs	=	426
Model	15508914.9	1	15508914.9	F(1, 424)	=	202.22
Residual	32517971.8	424	76693.3298	Prob > F	=	0.0000
				R-squared	=	0.3229
				Adj R-squared	=	0.3213
Total	48026886.7	425	113004.439	Root MSE	=	276.94

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	193.1476	13.58243	14.22	0.000	166.4503	219.8449
_cons	-203.3899	41.8601	-4.86	0.000	-285.6691	-121.1108

. reg y3 x

Source	SS	df	MS	Number of obs	=	450
Model	8.0481e+09	1	8.0481e+09	F(1, 448)	=	40.27
Residual	8.9525e+10	448	199833170	Prob > F	=	0.0000
				R-squared	=	0.0825
				Adj R-squared	=	0.0804
Total	9.7573e+10	449	217312520	Root MSE	=	14136

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	4073.721	641.9178	6.35	0.000	2812.177	5335.264
_cons	-8768.09	2038.725	-4.30	0.000	-12774.74	-4761.438

. est store olsy3

. sum y3

Variable	Obs	Mean	Std. Dev.	Min	Max
y3	450	3459.331	14741.52	-466.0042	98951.63

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

```
Tobit regression                               Number of obs   =          450
                                                LR chi2(1)      =          219.81
                                                Prob > chi2     =           0.0000
Log likelihood = -3049.2422                    Pseudo R2      =           0.0348
```

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x	225.3074	13.60203	16.56	0.000	198.5759 252.039
_cons	-272.8349	42.84203	-6.37	0.000	-357.0307 -188.6391
/sigma	293.0897	10.14415			273.1537 313.0256

```
0 left-censored observations
426 uncensored observations
24 right-censored observations at y3 >= 1000
```

```
. est store tby3
```

```
. lrtest olsy3 tby3, force
```

```
Likelihood-ratio test                               LR chi2(1) = 3777.40
(Assumption: olsy3 nested in tby3)                 Prob > chi2 = 0.0000
```

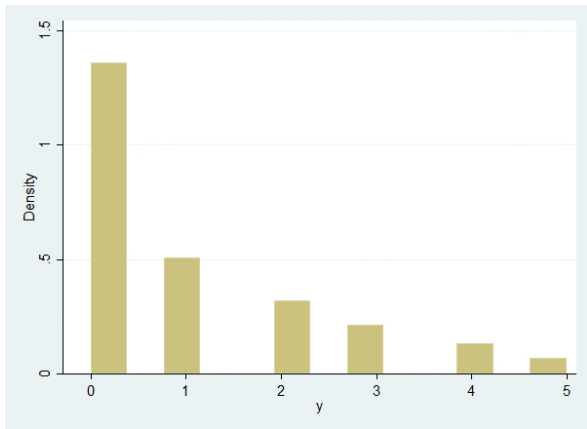
- According to significant LR-test between linear regression model and tobit model, it can be conclude that tobit regression model is more appropriated since null hypothesis of LR test is rejected. The major problem caused by sample is exist an outlier which will make OLS estimator be bias.

```
. log close
  name: <unnamed>
  log: C:\Users\User\Desktop\EE 426 stata\final\q2.log
  log type: text
  closed on: 28 May 2021, 09:42:36
```

Q3)

name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\final\q3.log
log type: text
opened on: 28 May 2021, 09:53:13

a) . use "C:\Users\User\Desktop\EE 426 stata\final\Final_q3_5.dta", clear
. histogram y
(bin=13, start=0, width=.38461538)



According to histogram, it exist that the distribution of dependent variable follows Poission distribution *which* is non-negative and also discrete, thus, Poissin regression model shold be applied.

. reg y x1 x2 x3 x4

Source	SS	df	MS	Number of obs	=	195
Model	38.4431604	4	9.6107901	F(4, 190)	=	5.68
Residual	321.474788	190	1.69197257	Prob > F	=	0.0002
				R-squared	=	0.1068
				Adj R-squared	=	0.0880
Total	359.917949	194	1.85524716	Root MSE	=	1.3008

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x1	.0971247	.0451219	2.15	0.033	.0081205 .186129
x2	.1395925	.0479669	2.91	0.004	.0449765 .2342085
x3	.2021471	.0685933	2.95	0.004	.066845 .3374493
x4	-.0408543	.0488395	-0.84	0.404	-.1371916 .055483
_cons	.9619949	.1101297	8.74	0.000	.7447609 1.179229

```
. est store olsy
. poisson y x1 x2 x3 x4, nolog
```

```
b) Poisson regression
Log likelihood = -276.91085
Number of obs = 195
LR chi2(4) = 38.14
Prob > chi2 = 0.0000
Pseudo R2 = 0.0644
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.0938557	.0338186	2.78	0.006	.0275723	.160139
x2	.1362419	.0360021	3.78	0.000	.0656792	.2068047
x3	.2098668	.0540778	3.88	0.000	.1038763	.3158573
x4	-.040898	.0370102	-1.11	0.269	-.1134367	.0316407
_cons	-.1317629	.0920147	-1.43	0.152	-.3121084	.0485826

```
. estat gof
```

```
Deviance goodness-of-fit = 317.1627
Prob > chi2(190) = 0.0000

Pearson goodness-of-fit = 327.5988
Prob > chi2(190) = 0.0000
```

- According to GOF test, null hypothesis of the test was rejected, thus, Poisson model is inappropriate.

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

```
Poisson regression
Log likelihood = -276.91085
Number of obs = 195
LR chi2(4) = 38.14
Prob > chi2 = 0.0000
Pseudo R2 = 0.0644
```

y	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	1.098401	.0371464	2.78	0.006	1.027956	1.173674
x2	1.145959	.0412569	3.78	0.000	1.067884	1.229742
x3	1.233514	.0667057	3.88	0.000	1.109463	1.371435
x4	.959927	.0355271	-1.11	0.269	.8927607	1.032147
_cons	.8765488	.0806554	-1.43	0.152	.7319022	1.049782

```
. est store psy
```

```
. mfx
```

Marginal effects after poisson

y = Predicted number of events (predict)
= .9256095

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x1	.0868737	.03082	2.82	0.005	.026468 .147279	-.302817
x2	.1261068	.03236	3.90	0.000	.062684 .189529	.832297
x3	.1942547	.04821	4.03	0.000	.099762 .288747	-.297057
x4	-.0378556	.03416	-1.11	0.268	-.104802 .029091	-.778271

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-squared-test-significant, Pseudo R-squared 0.0644-not quite fit the data, Individual z-test- all significant except x4.

9)

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

Negative binomial regression	Number of obs	=	195
	LR chi2(4)	=	20.99
Dispersion = mean	Prob > chi2	=	0.0003
Log likelihood = -262.50146	Pseudo R2	=	0.0384

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.123127	.0518823	2.37	0.018	.0214396 .2248144
x2	.1561944	.0516737	3.02	0.003	.0549158 .2574731
x3	.202838	.0698301	2.90	0.004	.0659735 .3397026
x4	-.0418786	.0496397	-0.84	0.399	-.1391705 .0554134
_cons	-.1515219	.120795	-1.25	0.210	-.3882757 .0852318
/lnalpha	-.2312574	.2930315			-.8055886 .3430738
alpha	.7935352	.2325308			.4468249 1.409273

Likelihood-ratio test of alpha=0: $\chi^2(01) = 28.82$ Prob>= $\chi^2 = 0.000$

According to LR test of alpha, null hypothesis of the test was rejected indicating

that the distribution of dependent variable follows Negative Binomial 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)                          =       20.99
Dispersion = mean                    Prob > chi2     =       0.0003
Log likelihood = -262.50146          Pseudo R2      =       0.0384
```

y	IRR	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	1.131028	.0586803	2.37	0.018	1.021671	1.25209
x2	1.169054	.0604094	3.02	0.003	1.056452	1.293657
x3	1.224874	.0855331	2.90	0.004	1.068198	1.40453
x4	.9589862	.0476038	-0.84	0.399	.8700796	1.056977
_cons	.859399	.1038111	-1.25	0.210	.6782253	1.088969
/lnalpha	-.2312574	.2930315			-.8055886	.3430738
alpha	.7935352	.2325308			.4468249	1.409273

Likelihood-ratio test of alpha=0: $\chi^2(01) = 28.82$ Prob>= $\chi^2 = 0.000$

```
. est store nby
```

```
. mfx
```

```
Marginal effects after nbreg
y = Predicted number of events (predict)
= .91716472
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		X
x1	.1129277	.0474	2.38	0.017	.020018	.205837	-.302817
x2	.143256	.04717	3.04	0.002	.050805	.235707	.832297
x3	.1860359	.06371	2.92	0.003	.061174	.310898	-.297057
x4	-.0384096	.04552	-0.84	0.399	-.127622	.050803	-.778271

-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-squared-test-significant, Pseudo R-squared 0.0384-not quite fit the data, Individual z-test- all significant except x4.

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

```

Zero-inflated Poisson regression          Number of obs   =      195
                                           Nonzero obs     =       93
                                           Zero obs        =      102

Inflation model = logit                  LR chi2(3)      =      15.87
Log likelihood = -261.385                 Prob > chi2     =      0.0012

```

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

	y						
	x1	.1022734	.0428335	2.39	0.017	.0183214	.1862255
	x2	.1240459	.0402747	3.08	0.002	.045109	.2029829
	x3	.151463	.0553266	2.74	0.006	.0430249	.2599011
	_cons	.3327101	.1144229	2.91	0.004	.1084454	.5569748

	inflate						
	x4	.0468225	.1036519	0.45	0.651	-.1563315	.2499765
	_cons	-.5777237	.2634859	-2.19	0.028	-1.094147	-.0613008

```

Vuong test of zip vs. standard Poisson:          z =      2.52  Pr>z = 0.0058

```

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

```
. mfx
```

```

Marginal effects after zip
y = Predicted number of events (predict)
  = .93006399

```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		X

x1	.0951208	.03949	2.41	0.016	.017732	.17251	-.302817
x2	.1153707	.03673	3.14	0.002	.043389	.187353	.832297
x3	.1408703	.05036	2.80	0.005	.042167	.239573	-.297057
x4	-.0152901	.03403	-0.45	0.653	-.081982	.051402	-.778271

- 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-squared-test-significant, Individual z-test- all significant except x4.

-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 regression

model is more appropriated than Poisson regression model.

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

-Also, histogram illustrate zero inflated distribution of dependent variable, therefore, Zero inflated regression model should be applied in this case

```
. log close
  name: <unnamed>
  log: C:\Users\User\Desktop\EE 426 stata\final\q3.log
  log type: text
  closed on: 28 May 2021, 09:53:48
```


Q.4

```
-----
name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\final\q4.log
log type: text
opened on: 28 May 2021, 12:57:36
```

```
. clear
```

```
. use "C:\Users\User\Desktop\EE 426 stata\final\Final_q4_5.dta", clear
```

```
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	----- 1% Critical Value	----- Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-15.041	-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.	-.9741483	.0647646	-15.04	0.000	-1.101396 - .8469002
LD.	-.0596799	.0449893	-1.33	0.185	-.1480738 .0287141
_trend	.0016069	.0021098	0.76	0.447	-.0025384 .0057521
_cons	.847649	.6115603	1.39	0.166	-.3539311 2.049229

```
. dfuller x, trend lag(1) regress
```

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

	Test Statistic	----- 1% Critical Value	----- Interpolated Dickey-Fuller 5% Critical Value	----- 10% Critical Value
Z(t)	-15.196	-3.980	-3.420	-3.130

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

D.x		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
	x						
	L1.	-.9858092	.0648745	-15.20	0.000	-1.113273	-.8583452
	LD.	-.0507006	.0449955	-1.13	0.260	-.1391069	.0377056
	_trend	.0025677	.0030127	0.85	0.394	-.0033516	.008487
	_cons	.4416065	.8696308	0.51	0.612	-1.267025	2.150238

$X \sim I(0)$ and $Y \sim I(0)$, then both are stationary.

- ✓ The Unit root test is testing of the variable be stationary or nonstationary, which if the data be stationary \rightarrow OLS still be used but if the data be 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 which is high frequency is a nonstationary which will lead to OLS estimator occur to be biased.

b)

```
. qui arima y, arima(1,0,1) nolog
. est store arima101
. qui arima y, arima(1,0,2) nolog
. est store arima102
. qui arima y, arima(1,0,3) nolog
. est store arima103
. qui arima y, arima(1,0,4) nolog
. est store arima104
. qui arima y, arima(2,0,1) nolog
. est store arima201
. qui arima y, arima(2,0,2) nolog
. est store arima202
. qui arima y, arima(2,0,3) nolog
. est store arima203
. qui arima y, arima(2,0,4) nolog
```

```

. est store arima20
. drop _est_arima20
. est store arima204
. qui arima y, arima(3,0,1) nolog
. est store arima301
. qui arima y, arima(3,0,2) nolog
. est store arima302
. 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 arima40
. drop _est_arima40
. 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	1.2874023***	1.2902715***	1.288291***	1.2886347***

ARMA				
ar				
L1.	-.85541374***	.81345909***	-.85721355***	-.81881647***
ma				
L1.	.81268327***	-.85066462***	.82433636***	.78640022***
L2.		.07159677	.02829955	.02739884
L3.			.01974742	.05074721
L4.				.04792866
sigma				
_cons	6.7336***	6.7340175***	6.7316818***	6.7247573***
Statistics				
N	500	500	500	500
ll	-1663.0396	-1663.057	-1662.8937	-1662.3693
chi2	51.568958	21.559155	51.944637	43.761226
aic	3334.0792	3336.1139	3337.7874	3338.7386
bic	3350.9376	3357.187	3363.075	3368.2408

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	arima20
arima204				
y				
_cons	1.2902918***	1.2905493***	1.2903492***	1.2906628***
1.2906628***				

ARMA				
ar				
L1.	.724438***	.0260208	-.01537063	-.02929012
-.02929012				
L2.	.07630296	.72460303***	.72266798***	.68437402**
.68437402**				
ma				
L1.	-.76405932***	-.04781212	-.0199575	-.0051159
-.0051159				
L2.		-.65697586**	-.6564224**	-.63145367*
-.63145367*				
L3.			.02428282	.02361024
.02361024				

```

L4. | .02339928
.02339928
-----+-----
sigma |
_cons | 6.7331327*** 6.7224701*** 6.7209864*** 6.7194516***
6.7194516***
-----+-----

```

```

Statistics |
N | 500 500 500 500
500
ll | -1662.9972 -1662.217 -1662.1009 -1661.9957
-1661.9957
chi2 | 18.56475 20.402998 21.511795 20.357788
20.357788
aic | 3335.9943 3336.434 3338.2018 3339.9915
3339.9915
bic | 3357.0674 3361.7216 3367.704 3373.7083
3373.7083
-----+-----

```

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 | 1.2881807*** 1.2906021*** 1.3062418*** 1.3062245***
-----+-----
ARMA
ar
L1. | -.84882318*** -.04672649 1.068269*** 1.0679434***
L2. | .03145816 .72386838*** .64967944** .6503497*
L3. | .02166601 .02497534 -.83388217*** -.8342446***
ma
L1. | .81759708** .012316 -1.125611 -1.1255938
L2. | -.65836104** -.55267624 -.55315898
L3. | .80446399 .80533897
L4. | -.00044313
-----+-----

```

```

sigma
_cons | 6.7317069*** 6.7209909*** 6.6390975 6.6390876
-----+-----

```

```
Statistics |
```

N	500	500	500	500
ll	-1662.8808	-1662.1086	-1658.0395	-1658.0395
chi2	53.494077	22.105695	51255.011	51321.092
aic	3337.7617	3338.2172	3330.079	3332.0789
bic	3363.0493	3367.7194	3359.5813	3365.7958

 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	arima40	arima402	arima403

arima404				

y				
_cons	1.2890523***	1.290403***	1.290403***	1.3062081***
1.2914098***				

ARMA				
ar				
L1.	-.77921781**	-.06563608	-.06563608	1.0673878***
.07395155				
L2.	.03192593	.65062881*	.65062881*	.65094806
-.23344034				
L3.	.05331952	.02604046	.02604046	-.83389345***
-.05226883				
L4.	.04926943	.0253664	.0253664	-.00045793
.70203058***				
ma				
L1.	.74692793**	.03081332	.03081332	-1.1250374
-.11013446				
L2.		-.59829892	-.59829892	-.5537899
.31694994				
L3.				.80504019
.0524378				
L4.				
-.65198176**				

sigma				
_cons	6.724336***	6.7195655***	6.7195655***	6.6390935
6.6793316***				

Statistics				

	N	500	500	500	500
500					
	ll	-1662.3498	-1661.9971	-1661.9971	-1658.0395
-1659.2626					
	chi2	37.266974	19.775625	19.775625	35562.274
1365.0745					
	aic	3338.6996	3339.9943	3339.9943	3332.0789
3338.5252					
	bic	3368.2018	3373.7112	3373.7112	3365.7958
3380.6713					

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

*** p<.01

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

. est store arima101

. qui arima x, arima(1,0,2) nolog

. est store arima102

. qui arima x, arima(1,0,3) nolog

. est store arima103

. qui arima x, arima(1,0,4) nolog

. est store arima104

. qui arima x, arima(2,0,1) nolog

. est store arima201

. qui arima x, arima(2,0,2) nolog

. est store arima202

. qui arima x, arima(2,0,3) nolog

. est store arima203

. qui arima x, arima(2,0,4) nolog

. est store arima204

. qui arima x, arima(3,0,1) nolog

. est store arima301

```

. qui arima x, arima(3,0,2) nolog
. est store arima302
. qui arima x, arima(3,0,3) nolog
. est store arima303
. qui arima x, arima(3,0,4) nolog
. est store arima304
. qui arima x, arima(4,0,1) nolog
. est store arima401
. qui arima x, arima(4,0,2) nolog
. est store arima402
. qui arima x, arima(4,0,3) nolog
. est store arima403
. qui arima x, 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
x	_cons	1.1040613***	1.1092974**	1.1049174**	1.1060064**
ARMA	ar				
	L1.	-.87005301***	.82679948***	-.86901952***	-.8258264***
	ma				
	L1.	.82836446***	-.86699209***	.83493892***	.79155671***
	L2.		.07227494	.0178063	.01585736
	L3.			.0101572	.05004247
	L4.				.05978747
sigma	_cons	9.6082122***	9.6106134***	9.6071806***	9.5916364***

Statistics		500	500	500	500
N		500	500	500	500
ll		-1840.7903	-1840.908	-1840.7368	-1839.933
chi2		64.285058	24.42206	63.883066	51.37323
aic		3689.5807	3691.816	3693.4737	3693.8659
bic		3706.4391	3712.8891	3718.7613	3723.3682

 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	arima20

x				
_cons	1.1092009**	1.1095437**	1.1086369**	
1.109393**				

ARMA				
ar				
L1.	.74379709***	.02146868	-.0182115	-.02929012
-.05040519				
L2.	.07536362	.75489719***	.74841679***	.68437402**
.6873056**				
ma				
L1.	-.78544691***	-.043393	-.0193752	-.0051159
.01484827				
L2.		-.69079951***	-.68527197***	-.63145367*
-.64404225**				
L3.			.0262218	.02361024
.02566103				
L4.				.02339928
.03406793				

sigma				
_cons	9.6097788***	9.5933785***	9.5911829***	6.7194516***
9.5868767***				

y				
_cons				1.2906628***

Statistics				
	N	500	500	500
500	ll	-1840.8739	-1840.0384	-1839.9037
-1839.6834	chi2	21.660621	24.747731	25.820006
23.486668	aic	3691.7478	3692.0768	3693.8074
3695.3669	bic	3712.8209	3717.3644	3723.3097
3729.0837				

 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
x	_cons	1.1049615**	1.1086172**	1.1358592**	1.1103101**
ARMA	ar				
	L1.	-1.0289664***	-.04878782	1.0489249***	-1.0742471***
	L2.	.01500504	.75016102***	.68178142**	.65221954
	L3.	.04738783	.02609321	-.84769673***	.80012959***
	ma				
	L1.	.99318116***	.01254514	-1.1067196	1.0432097***
	L2.		-.68774664***	-.58781396	-.64252531
	L3.			.82287465	-.71653656***
	L4.				.05861813
sigma	_cons	9.6156135***	9.591522***	9.4729783	9.560988***
Statistics					
	N	500	500	500	500
	ll	-1841.2093	-1839.9157	-1835.8015	-1838.4431
	chi2	5013.9263	26.636776	50650.503	6513.9672
	aic	3694.4185	3693.8314	3687.603	3694.8862
	bic	3719.7062	3723.3337	3721.3199	3732.8177

 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	arima40	arima402	arima403

arima404				

x				
_cons	1.1064112**		1.1090475**	1.1103938**
1.1106289**				

ARMA				
ar				
L1.	-.78220586***	-.06563608	-.09411863	-1.140674***
.06492152				
L2.	.02151636	.65062881*	.63427661*	.58724403
-.21230686				
L3.	.05157706	.02604046	.02931802	.85591686***
-.05105028				
L4.	.06001502	.0253664	.03802218	.05913088
.72759243***				
ma				
L1.	.74835919***	.03081332	.05738537	1.1102674***
-.1029541				
L2.		-.59829892	-.59230655*	-.576632
.28993601				
L3.				-.77067192***
.05257197				
L4.				
-.6763714***				

sigma				
_cons	9.5918253***	6.7195655***	9.5866556***	9.561108***
9.5314973***				

y				
_cons		1.290403***		

Statistics				
N	500	500	500	500
500				
ll	-1839.9462	-1661.9971	-1839.673	-1838.4544
-1837.0396				

chi2		41.898238	19.775625	22.40566	7594.7861
1205.5824					
aic		3693.8924	3339.9943	3695.3459	3694.9087
3694.0792					
bic		3723.3946	3373.7112	3729.0628	3732.8402
3736.2253					

 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)	=	51.57
Log likelihood = -1663.04	Prob > chi2	=	0.0000

	y	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
y	_cons	1.287402	.2962245	4.35	0.000	.706813	1.867992
ARMA	ar						
	L1.	-.8554137	.1656713	-5.16	0.000	-1.180124	-.530704
	ma						
	L1.	.8126833	.1871691	4.34	0.000	.4458385	1.179528
	/sigma	6.7336	.2153008	31.28	0.000	6.311618	7.155582

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

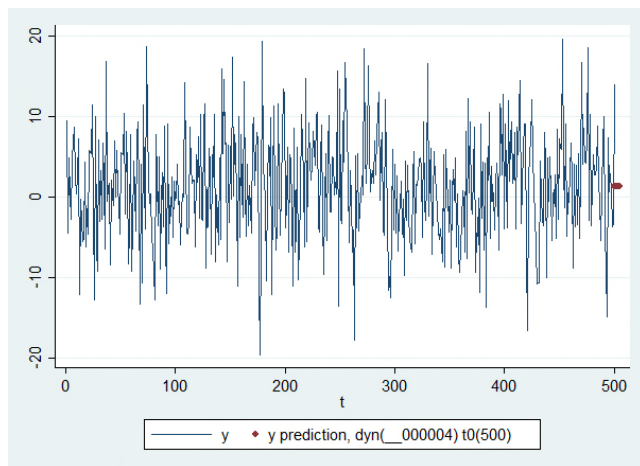
. set obs 505
 number of observations (_N) was 500, now 505

. 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(2,0,1) nolog
```

ARIMA regression

Sample: 1 - 500

Log likelihood = -1840.874

Number of obs = 500
Wald chi2(3) = 21.66
Prob > chi2 = 0.0001

		Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
x							
	_cons	1.109201	.5194125	2.14	0.033	.0911711	2.127231
ARMA							
	ar						
	L1.	.7437971	.2391062	3.11	0.002	.2751575	1.212437
	L2.	.0753636	.0483268	1.56	0.119	-.0193552	.1700824
	ma						
	L1.	-.7854469	.2322608	-3.38	0.001	-1.24067	-.3302241
/sigma		9.609779	.3114793	30.85	0.000	8.999291	10.22027

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

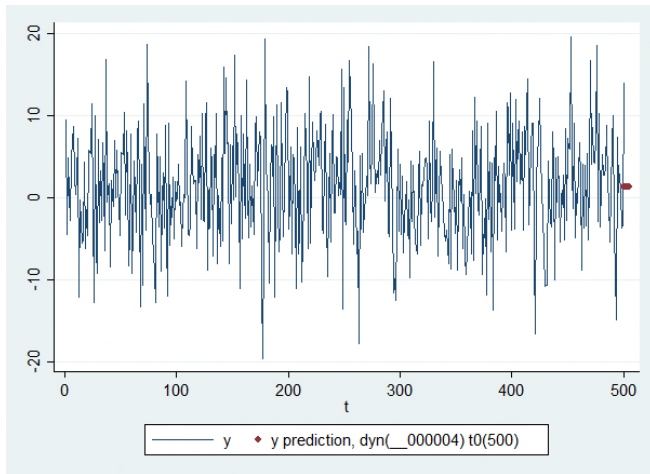
```
. predict yhat2, y dynamic(.) t0(500)
```

Note: beginning dynamic predictions in period

(499 missing values generated)

4.

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



c) . reg y x

Source	SS	df	MS	Number of obs	=	500
Model	22628.5048	1	22628.5048	F(1, 498)	=	57437.76
Residual	196.194895	498	.393965654	Prob > F	=	0.0000
Total	22824.6997	499	45.7408811	R-squared	=	0.9914
				Adj R-squared	=	0.9914
				Root MSE	=	.62767

	y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
	x	.6976878	.0029111	239.66	0.000	.6919682 .7034074
	_cons	.5171209	.0282542	18.30	0.000	.4616089 .572633

- There exist significant ARCH effect 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.

```
. estat archlm
```

LM test for autoregressive conditional heteroskedasticity (ARCH)

lags(p)	chi2	df	Prob > chi2
1	38.396	1	0.0000

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

D) . qui arch y, arch(1) garch(1) nolog
flat log likelihood encountered, cannot find uphill direction
r(430);
. est store garch11

. qui arch y, arch(1) garch(2) nolog

. est store garch12

. qui arch y, arch(2) garch(1) nolog

. est store garch21

. qui arch y, arch(2) garch(2) nolog

. est store garch22

. est table garch1*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)

Variable	garch11	garch12
—		
__000003 L1.	-.05379312	
__000004 L1.	.05193467	
_cons	48.435566***	
y		
_cons		1.4270204***
ARCH		
arch L1.		.07423885
garch L2.		-.74120852***
_cons		76.766592***
Statistics		
N	468	500
ll	-2614.3017	-1663.7738
chi2		.

```

aic | 5234.6033      3335.5475
bic | 5247.0487      3352.406

```

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

```
. est table garch2*, star(0.1 0.05 0.01) stat(N ll chi2 aic bic)
```

```

-----
Variable |      garch21      garch22
-----+-----
y
  _cons | 1.3292787***    1.319949***
-----+-----
ARCH
  arch
  L2.   | .05985661       .02556616
-----+-----
  garch
  L1.   | -.70844353***
  L2.   |                -.78691701
-----+-----
  _cons | 75.55465***    80.543337***
-----+-----
Statistics
  N     |      500        500
  ll    | -1663.5768     -1664.3588
  chi2  |      .          .
  aic   | 3335.1537      3336.7176
  bic   | 3352.0121      3353.576
-----+-----

```

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

```
. arch y x, garch(1/2) arch(1/1) nolog
```

ARCH family regression

```

Sample: 1 - 500                Number of obs =      500
Distribution: Gaussian          Wald chi2(1) =    72465.95
Log likelihood = -444.17       Prob > chi2 =      0.0000

```

```

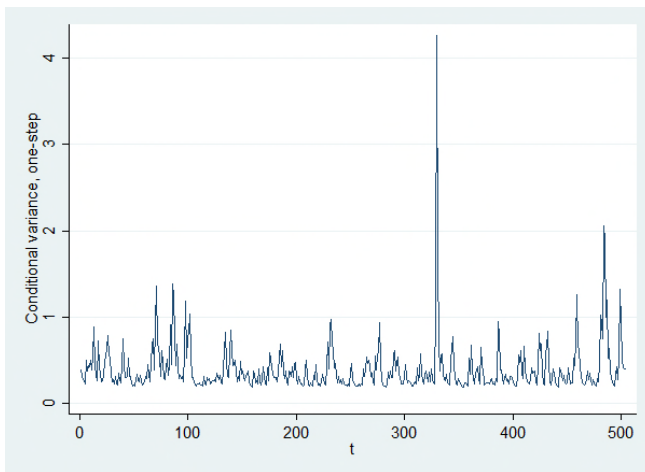
-----
          y |      Coef.      OPG      z      P>|z|      [95% Conf. Interval]
          |      Std. Err.
-----+-----
y
  x       | .6978291   .0025923   269.20   0.000   .6927483   .7029099
  _cons   | .5176582   .0240609   21.51   0.000   .4704996   .5648168
-----+-----
ARCH
  arch    |

```

L1.		.3559144	.073965	4.81	0.000	.2109457	.5008832
garch							
L1.		.3338345	.1730189	1.93	0.054	-.0052763	.6729453
L2.		-.0130087	.1374166	-0.09	0.925	-.2823403	.2563229
_cons		.1290925	.0382959	3.37	0.001	.0540339	.2041511

-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. GARCH is extended from ARCH and GARCH is an asymmetric GARCH model, we react to shock asymmetrically

```
. log close
   name: <unnamed>
   log:  C:\Users\User\Desktop\EE 426 stata\final\q4.log
   log type: text
   closed on: 28 May 2021, 13:01:40
```

Q5

```
-----  
-----  
name: <unnamed>  
log: C:\Users\User\Desktop\EE 426 stata\final\q5.log  
log type: text  
opened on: 28 May 2021, 12:18:52
```

a) . use "C:\Users\User\Desktop\EE 426 stata\final\Final_q5_5.dta", clear

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

```
. varsoc y x, maxlag(5)
```

```
Selection-order criteria  
Sample: 6 - 500  
Number of obs = 495
```

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	-1315.99	1.5951	4	0.810	.727436	5.35752	5.39087	5.44246
3	-1314.88	2.2106	4	0.697	.735996	5.36922	5.4159	5.48814
4	-1312.72	4.3202	4	0.364	.741491	5.37665	5.43667	5.52955
5	-1311.04	3.3601	4	0.499	.748479	5.38603	5.45939	5.5729

```
-----  
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  
Log likelihood = -1329.027  
FPE = .7225668  
Det(Sigma_ml) = .7053975  
Number of obs = 499  
AIC = 5.350808  
HQIC = 5.370686  
SBIC = 5.401461
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
y	3	.994264	0.0150	7.596793	0.0224
x	3	.997069	0.0903	49.51793	0.0000

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

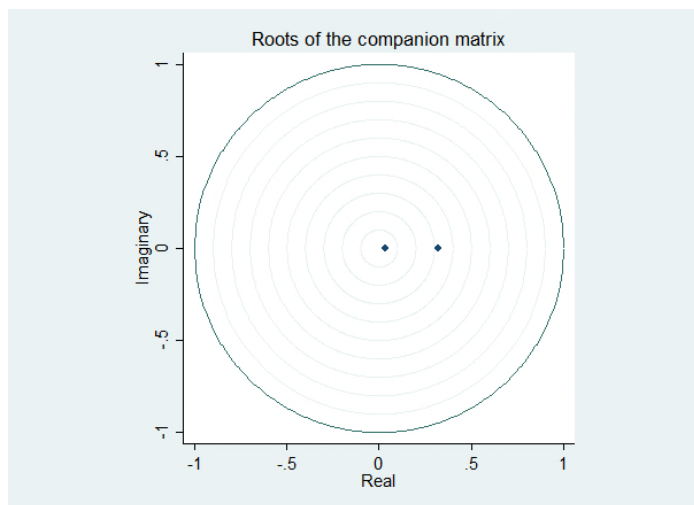
y							
L1.	y	.1378007	.0500738	2.75	0.006	.0396579	.2359436
L1.	x	.0541608	.047949	1.13	0.259	-.0398175	.148139
	_cons	.3370899	.0544641	6.19	0.000	.2303423	.4438375
x							
L1.	y	.3456722	.0502151	6.88	0.000	.2472524	.4440919
L1.	x	.2145758	.0480842	4.46	0.000	.1203324	.3088191
	_cons	.121222	.0546177	2.22	0.026	.0141732	.2282708

. varstable, graph

Eigenvalue stability condition

Eigenvalue	Modulus
.3182991	.318299
.03407743	.034077

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	1.2759	1	0.259
y	ALL	1.2759	1	0.259
x	y	47.387	1	0.000
x	ALL	47.387	1	0.000

- According to stability test, the system is stable since all the eigenvalue lie inside the inside the unit circle.
- According to Granger exogeneity, x is endogenous since the test is significant, while y is not endonous.
- If the stability assumption is unsatisfied, the IRF won't get back to the equilibrium.

```

c) . irf create order1, order(y x) step(5) set(irf0001)
(file irf0001.irf now active)

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

```

Results from order1

step	(1)			(2)			(2)		
	irf	Lower	Upper	irf	Lower	Upper	irf	Lower	Upper
0	1	1	1	0	0	0	0	0	0
1	.137801	.039658	.235944	.345672	.247252	.444092			
.054161	-.039817	.148139							
2	.037711	-.011172	.086594	.121807	.069923	.17369			
.019085	-.014427	.052597							
3	.011794	-.008374	.031961	.039172	.01379	.064555			
.006138	-.006354	.01863							
4	.003747	-.003966	.01146	.012482	.000721	.024244			
.001956	-.002677	.006588							
5	.001192	-.001672	.004056	.003974	-.001075	.009022			
.000623	-.001067	.002312							

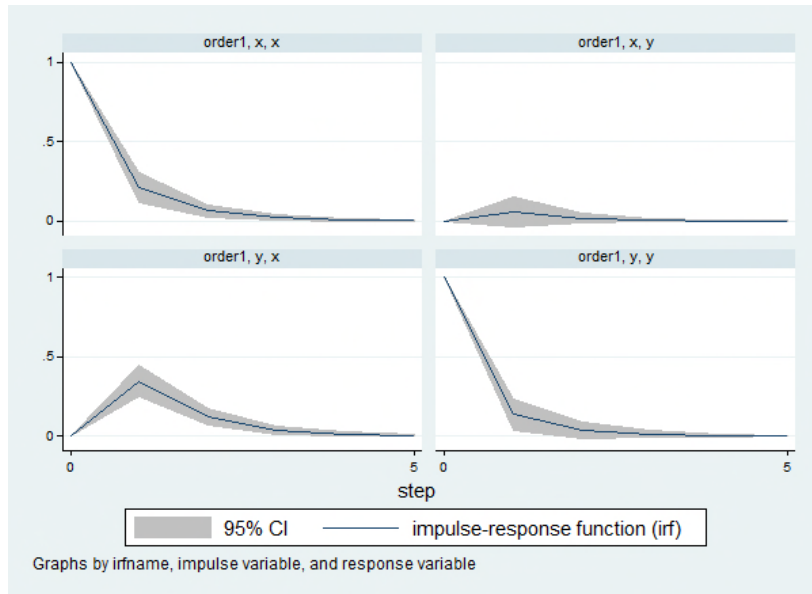
+-----+
+-----+

step	(4) irf	(4) Lower	(4) Upper
0	1	1	1
1	.214576	.120332	.308819
2	.064765	.026552	.102977
3	.020494	.002146	.038842
4	.006519	-.001494	.014533
5	.002075	-.001191	.005341

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) (3)	(1) (3)	(1) (3)	(1) (3)	(2) (2)	(2) (2)	(2) (2)
oirf	Lower	Upper	Lower	Upper	oirf	Lower	Upper
step							

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

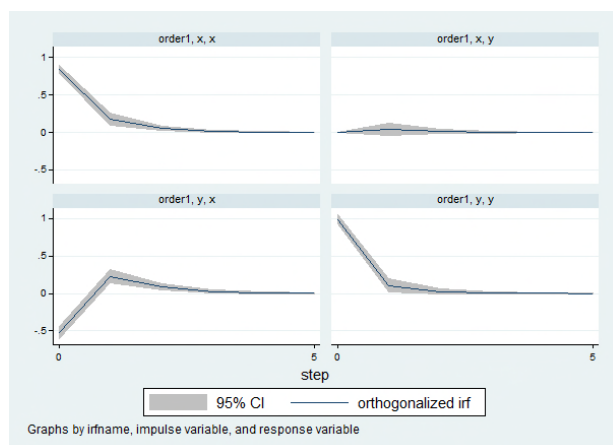
0	.991271	.929771	1.05277	-.519899	-.600935	-.438863	0
	0	0					
1	.10844	.021604	.195276	.231097	.141759	.320435	
.045889	- .033787	.125565					
2	.027459	-.005139	.060058	.087072	.047559	.126585	
.01617	- .012241	.044582					
3	.0085	-.005228	.022228	.028176	.010461	.04589	
.0052	- .005389	.015789					
4	.002697	-.002595	.007989	.008984	.001055	.016913	
.001657	- .002269	.005584					
5	.000858	-.001116	.002833	.00286	-.000543	.006263	
.000528	- .000905	.00196					

step	(4) oirf	(4) Lower	(4) Upper
0	.847275	.794709	.899842
1	.181805	.101162	.262448
2	.054873	.022318	.087429
3	.017364	.001781	.032947
4	.005524	-.001275	.012322
5	.001758	-.001011	.004527

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

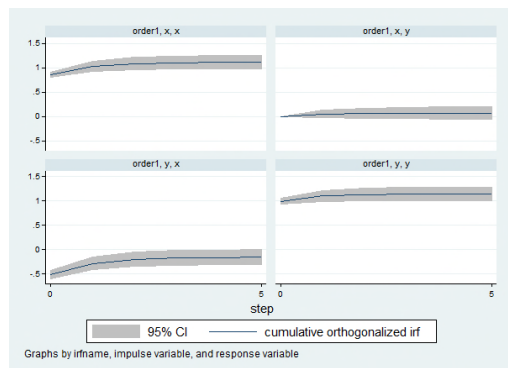
	(3) coirf Lower	(1) coirf Lower Upper	(1) Upper	(2) coirf	(2) Lower	(2) Upper	
0	.991271 0	.929771 0	1.05277	-.519899	-.600935	-.438863	0
1	1.09971 .045889	.989482 .125565	1.20994	-.288801	-.415272	-.162331	
2	1.12717 .062059	.99869 .169759	1.25565	-.201729	-.343749	-.059709	
3	1.13567 .06726	.999461 .185306	1.27188	-.173553	-.323005	-.024102	
4	1.13837 .068917	.999125 .190769	1.27761	-.164569	-.317153	-.011986	
5	1.13923 .069444	.998861 .192674	1.27959	-.161709	-.315521	-.007898	

step	(4) coirf	(4) Lower	(4) Upper
0	.847275	.794709	.899842
1	1.02908	.926844	1.13132
2	1.08395	.959646	1.20826
3	1.10132	.967671	1.23496
4	1.10684	.969381	1.2443
5	1.1086	.96967	1.24753

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 Lower	(1) Lower Upper	(1) Upper	(2) fevd	(2) Lower	(2) Upper
0	0	0	0	0	0	0
1	1	1	1	.27353	.206858	.340203
2	.997887	.990557	1.00522	.301221	.236432	.366009
.002113	-.005216	.009443				
3	.997627	.989406	1.00585	.305267	.24105	.369483
.002373	-.005847	.010594				
4	.9976	.989274	1.00593	.30569	.24154	.369839
.0024	-.005926	.010726				
5	.997597	.989259	1.00594	.305733	.24159	.369875
.002403	-.005935	.010741				

step	(4) fevd	(4) Lower	(4) Upper
0	0	0	0
1	.72647	.659797	.793142
2	.698779	.633991	.763568
3	.694733	.630517	.75895
4	.69431	.630161	.75846
5	.694267	.630125	.75841

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

```
. log close
  name: <unnamed>
  log: C:\Users\User\Desktop\EE 426 stata\final\q5.log
  log type: text
  closed on: 28 May 2021, 12:19:49
```


e) Yes, because the change in order will reflect in the change in matrix.