

1)

```

name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q1.log
log type: text
opened on: 21 Mar 2021, 09:01:09

```

```

. use "C:\Users\User\Desktop\EE 426 stata\midterm exam\Midterm_q1_5.dta", clear
(1980 Census housing data)

```

Since endogenous variable (y_{1t}, y_{2t}) are effect each of them and if we use OLS to estimate will reflect in endogeneity bias, OLS estimator will be biased, inconsistent, and inefficient.

a)

```

. reg y1 y2 x3

```

Source	SS	df	MS	Number of obs	=	50
Model	54894.8643	2	27447.4321	F(2, 47)	=	125.26
Residual	10299.2157	47	219.132249	Prob > F	=	0.0000
Total	65194.08	49	1330.49143	R-squared	=	0.8420
				Adj R-squared	=	0.8353
				Root MSE	=	14.803

will be biased, inconsistent, and inefficient.

y1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
y2	.0009205	.0001806	5.10	0.000	.0005572 .0012839
x3	.0076616	.0010146	7.55	0.000	.0056206 .0097027
_cons	39.28822	15.54271	2.53	0.015	8.020331 70.55611

```

. reg y2 y1 x1 x2

```

Source	SS	df	MS	Number of obs	=	50
Model	8.4448e+09	3	2.8149e+09	F(3, 46)	=	32.37
Residual	4.0006e+09	46	86968769.4	Prob > F	=	0.0000
Total	1.2445e+10	49	253988016	R-squared	=	0.6786
				Adj R-squared	=	0.6576
				Root MSE	=	9325.7

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
y1	300.6902	46.08303	6.52	0.000	207.9299 393.4506
x1	254.501	130.153	1.96	0.057	-7.483434 516.4853
x2	-.0004191	.000324	-1.29	0.202	-.0010712 .000233
_cons	-36814.58	8831.225	-4.17	0.000	-54590.91 -19038.25

b)

```

. ivregress 2sls y1 x3 (y2= x1 x2 x3)

```

Endogenous variable = y_{1t}, y_{2t}
 Exogenous variable = x_{1t}, x_{2t}, x_{3t}

Instrumental variables (2SLS) regression

Number of obs	=	50
Wald chi2(2)	=	242.66
Prob > chi2	=	0.0000

R-squared = 0.8417
 Root MSE = 14.368

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
y2	.0009794	.0004701	2.08	0.037	.0000579	.0019009
x3	.0074373	.0019323	3.85	0.000	.0036501	.0112245
_cons	40.81419	18.85414	2.16	0.030	3.86076	77.76762

Instrumented: y2
 Instruments: x3 x1 x2

. ivregress 2sls y2 x1 x2 (y1= x1 x2 x3)

Instrumental variables (2SLS) regression Number of obs = 50
 Wald chi2(3) = 82.58
 Prob > chi2 = 0.0000
 R-squared = 0.6759
 Root MSE = 8981.4

y2	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
y1	272.4446	55.85342	4.88	0.000	162.9739	381.9153
x1	302.3284	137.8725	2.19	0.028	32.10325	572.5535
x2	-.0004531	.0003147	-1.44	0.150	-.0010698	.0001636
_cons	-33213.72	9540.729	-3.48	0.000	-51913.2	-14514.23

Instrumented: y1
 Instruments: x1 x2 x3

. reg y1 x1 x2 x3

Source	SS	df	MS	Number of obs	=	50
Model	50098.8491	3	16699.6164	F(3, 46)	=	50.89
Residual	15095.2309	46	328.157192	Prob > F	=	0.0000
Total	65194.08	49	1330.49143	R-squared	=	0.7685
				Adj R-squared	=	0.7534
				Root MSE	=	18.115

y1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	$\pi_{11} = .4005562$.2493027	1.61	0.115	-.101264	.9023764
x2	$\pi_{12} = -6.37e-07$	6.23e-07	-1.02	0.312	-1.89e-06	6.17e-07
x3	$\pi_{13} = .010164$.001145	8.88	0.000	.0078592	.0124688
cons	$\pi{10} = 11.26776$	18.3155	0.62	0.541	-25.59943	48.13495

reduce form: $y_{1t} = \pi_{10} + \pi_{11}x_{1t} + \pi_{12}x_{2t} + \pi_{13}x_{3t} + w_{1t}$
 $y_{2t} = \pi_{20} + \pi_{21}x_{1t} + \pi_{22}x_{2t} + \pi_{23}x_{3t} + w_{2t}$

. predict y1hat, xb

. reg y2 x1 x2 x3

Source	SS	df	MS	Number of obs	=	50
-----				F(3, 46)	=	17.66
Model	6.6614e+09	3	2.2205e+09	Prob > F	=	0.0000
Residual	5.7840e+09	46	125738827	R-squared	=	0.5353
-----				Adj R-squared	=	0.5049
Total	1.2445e+10	49	253988016	Root MSE	=	11213

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	$\pi_{21} = 411.4577$	154.3194	2.67	0.011	100.8288	722.0867
x2	$\pi_{22} = -.0006267$.0003858	-1.62	0.111	-.0014033	.0001499
x3	$\pi_{23} = 2.769135$.7087753	3.91	0.000	1.342444	4.195825
cons	$\pi{20} = -30143.88$	11337.37	-2.66	0.011	-52964.83	-7322.927

. predict y2hat, xb

Structural form $y_{1t} = 40.81 + 0.001 \hat{y}_{2t} + 0.007 x_{3t} + \varepsilon_{1t}$

. reg y1 y2hat x3

$y_{2t} = -33213.72 + 272.445 \hat{y}_{1t} + 302.33 x_{1t} - 0.0005 x_{2t} + \varepsilon_{2t}$

Source	SS	df	MS	Number of obs	=	50
-----				F(2, 47)	=	77.99
Model	50098.1271	2	25049.0636	Prob > F	=	0.0000
Residual	15095.9529	47	321.190487	R-squared	=	0.7684
-----				Adj R-squared	=	0.7586
Total	65194.08	49	1330.49143	Root MSE	=	17.922

y1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
y2hat	.0009794	.0005864	1.67	0.102	-.0002003	.0021591
x3	.0074373	.0024101	3.09	0.003	.0025887	.0122859
_cons	40.81419	23.51693	1.74	0.089	-6.495774	88.12415

. reg y2 y1hat x1 x2

Source	SS	df	MS	Number of obs	=	50
-----				F(3, 46)	=	17.66
Model	6.6614e+09	3	2.2205e+09	Prob > F	=	0.0000
Residual	5.7840e+09	46	125738836	R-squared	=	0.5353
-----				Adj R-squared	=	0.5049
Total	1.2445e+10	49	253988016	Root MSE	=	11213

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
----	-------	-----------	---	------	----------------------	--

y1hat	272.4446	69.7337	3.91	0.000	132.0779	412.8112
x1	302.3284	172.1355	1.76	0.086	-44.16246	648.8193
x2	-.0004531	.0003929	-1.15	0.255	-.0012439	.0003377
_cons	-33213.72	11911.72	-2.79	0.008	-57190.77	-9236.669

c) . reg3 (y1 y2 x3) (y2 y1 x1 x2), 3sls inst(x1 x2 x3)

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
y1	50	2	14.36836	0.8417	242.66	0.0000
y2	50	3	8980.313	0.6760	82.58	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y1					
y2	.0009794	.0004701	2.08	0.037	.0000579 .0019009
x3	.0074373	.0019323	3.85	0.000	.0036501 .0112245
_cons	40.81419	18.85414	2.16	0.030	3.86076 77.76762
y2					
y1	272.878	55.37052	4.93	0.000	164.3538 381.4023
x1	301.4264	137.0264	2.20	0.028	32.85957 569.9933
x2	-.0004599	.000293	-1.57	0.117	-.0010342 .0001145
_cons	-33225.71	9538.573	-3.48	0.000	-51920.97 -14530.45

Endogenous variables: y1 y2
Exogenous variables: x1 x2 x3

```
. log close
name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q1.log
log type: text
closed on: 21 Mar 2021, 09:23:54
```

c) 3SLS → OLS + IV + FGLS Estimator of (endogeneity biased) exist OLS → biased, inconsistent, inefficient
2SLS → OLS + IV 2SLS → biased, consistent, Asymptotic Advantage efficient
OLS → OLS 3SLS → biased, consistent, a more Asymptotic efficient

disadvantage → 3SLS is a system equation estimation method which is a specification error exist in one equation will spread problem to other equation in system

From result below.
 estimated value of $\lambda = e^{2.08}$

2)

```
name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q2.log
log type: text
opened on: 21 Mar 2021, 09:48:32
```

$\theta = 0.3095$
 $\beta = 0.8205$
 $\alpha = -0.9502$
 $\sigma = 1.448$

```
. log using "C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q2.log"
log file already open
r(604);

. use "C:\Users\User\Desktop\EE 426 stata\midterm exam\Midterm_q2_5.dta", clear
```

a)

```
. nl (lnC =
.nl (lnC={lnlamda}-({beta}/{alpha})*ln({theta}*R^(-{alpha})+(1-{theta})*W^(-{alpha}))), init(lnlamda 1 theta 0.5 beta 0.5 alpha -0.5)
(obs = 250)
```

```
Iteration 0: residual SS = 272.8386
Iteration 1: residual SS = 269.7382
Iteration 2: residual SS = 269.5436
Iteration 3: residual SS = 269.5402
Iteration 4: residual SS = 269.5397
Iteration 5: residual SS = 269.5397
Iteration 6: residual SS = 269.5397
Iteration 7: residual SS = 269.5397
Iteration 8: residual SS = 269.5397
Iteration 9: residual SS = 269.5397
Iteration 10: residual SS = 269.5397
Iteration 11: residual SS = 269.5397
```

Source	SS	df	MS	Number of obs =	250
Model	52.987566	3	17.6625221	R-squared	= 0.1643
Residual	269.53966	246	1.09568968	Adj R-squared	= 0.1541
Total	322.52723	249	1.29529007	Root MSE	= 1.046752
				Res. dev.	= 728.2829

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
/lnlamda	2.082157	.7495103	2.78	0.006	.6058805 3.558433
/beta	.8204874	.1438338	5.70	0.000	.5371846 1.10379
/alpha	-.9501815	.5170818	-1.84	0.067	-1.968654 .0682909
/theta	.3094593	.2021046	1.53	0.127	-.0886169 .7075355

Parameter lnlamda taken as constant term in model & ANOVA table

Model	52.987566	3	17.6625221	R-squared	= 0.1643
Residual	269.53966	246	1.09568968	Adj R-squared	= 0.1541
				Root MSE	= 1.046752
Total	322.52723	249	1.29529007	Res. dev.	= 728.2829

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
/lnlamda	-.2715428	1.705172	-0.16	0.874	-3.630142 3.087057
/beta	.8204874	.1438337	5.70	0.000	.5371847 1.10379
/alpha	-.9501834	.5170783	-1.84	0.067	-1.968649 .068282
/thata	4.724789	4.468535	1.06	0.291	-4.07668 13.52626

/theta | -9.543121

```
test (_b[/theta]=0) (_b[/alpha]=0) (_b[/beta]=0) ANOVA table
```

```
( 1) [theta]_cons = 0
( 2) [alpha]_cons = 0
( 3) [beta]_cons = 0
```

```
F( 3, 246) = 49.35
Prob > F = 0.0000
```

```
sca sigma=1/(1-(_b[/theta]))
```

```
sca list sigma
```

```
sigma = 1.4481406
```

$H_0: \theta = 0, \alpha = 0, \beta = 0$

$H_a: \text{Otherwise}$

$< 0.05 \rightarrow H_0$ is rejected

```
. est store lognls1
```

```
b) . nl (lnC =
{lnlamda}-({beta}/{alpha})*ln({thata}*R^(-{alpha})+(1-{theta})*W^(-{alpha}))),
init(lnlamda 0.5 theta 0.1 beta 0.1 alpha -0.1)
(obs = 250)
```

```
Iteration 0: residual SS = 392.0881
Iteration 1: residual SS = 292.3054
Iteration 2: residual SS = 290.4649
Iteration 3: residual SS = 290.1282
Iteration 4: residual SS = 289.5729
Iteration 5: residual SS = 289.0515
Iteration 6: residual SS = 288.5264
Iteration 7: residual SS = 287.9692
Iteration 8: residual SS = 287.9013
Iteration 9: residual SS = 287.2156
Iteration 10: residual SS = 286.0925
Iteration 11: residual SS = 284.9419
Iteration 12: residual SS = 282.4999
Iteration 13: residual SS = 270.8794
Iteration 14: residual SS = 269.5694
Iteration 15: residual SS = 269.5403
Iteration 16: residual SS = 269.5398
Iteration 17: residual SS = 269.5397
Iteration 18: residual SS = 269.5397
Iteration 19: residual SS = 269.5397
Iteration 20: residual SS = 269.5397
Iteration 21: residual SS = 269.5397
Iteration 22: residual SS = 269.5397
Iteration 23: residual SS = 269.5397
```

\therefore The estimated result will not be the same due to the different set of initial value will give the different in estimate result

Iteration 24: residual SS = 269.5397

Source	SS	df	MS		
Model	52.987566	3	17.6625221	Number of obs =	250
Residual	269.53966	246	1.09568968	R-squared =	0.1643
				Adj R-squared =	0.1541
				Root MSE =	1.046752
Total	322.52723	249	1.29529007	Res. dev. =	728.2829

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
/lnlamda	-1.413019	2.284255	-0.62	0.537	-5.912211	3.086172
/beta	.8204874	.1438337	5.70	0.000	.5371847	1.10379
/alpha	-.9501829	.5170793	-1.84	0.067	-1.96865	.0682845
/thata	17.7207	16.75958	1.06	0.291	-15.28987	50.73127
/theta	-38.54279

Parameter lnlamda taken as constant term in model & ANOVA table

```
. est store lognls2
```

```
d) . nl (lnC =  
{lnlamda}-({beta}/{alpha})*ln({thata}*R^(-{alpha})+(1-{theta})*W^(-{alpha}))),  
init(lnlamda 0.5 theta 0.1 beta 0.1 alpha -0.1)  
> eps(1e-1)  
(obs = 250)
```

```
Iteration 0: residual SS = 392.0881  
Iteration 1: residual SS = 292.3054  
Iteration 2: residual SS = 290.4649  
Iteration 3: residual SS = 290.1282  
Iteration 4: residual SS = 289.5729  
Iteration 5: residual SS = 289.0515  
Iteration 6: residual SS = 288.5264  
Iteration 7: residual SS = 287.9692  
Iteration 8: residual SS = 287.9013  
Iteration 9: residual SS = 287.2156  
Iteration 10: residual SS = 286.0925  
Iteration 11: residual SS = 284.9419  
Iteration 12: residual SS = 282.4999  
Iteration 13: residual SS = 270.8794  
Iteration 14: residual SS = 269.5694  
Iteration 15: residual SS = 269.5403
```

Source	SS	df	MS		
Model	52.986883	3	17.6622942	Number of obs =	250
				R-squared =	0.1643

Residual		269.54035	246	1.09569246	Adj R-squared =	0.1541
-----					Root MSE	= 1.046753
Total		322.52723	249	1.29529007	Res. dev.	= 728.2836

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
/lnlamda	-1.37827	2.276555	-0.61	0.545	-5.862295	3.105756
/beta	.8210859	.143908	5.71	0.000	.5376369	1.104535
/alpha	-.9595803	.511271	-1.88	0.062	-1.966607	.0474467
/thata	17.44928	16.33312	1.07	0.286	-14.72132	49.61988
/theta	-38.54279

Parameter alpha taken as constant term in model & ANOVA table

```
. nl (lnC =
{lnlamda}-({beta}/{alpha})*ln({thata}*R^(-{alpha})+(1-{theta})*W^(-{alpha}))),
init(lnlamda 0.5 theta 0.1 beta 0.1 alpha -0.1)
> eps(1e-15) iter(40)
(obs = 250)
```

```
Iteration 0: residual SS = 392.0881
Iteration 1: residual SS = 292.3054
Iteration 2: residual SS = 290.4649
Iteration 3: residual SS = 290.1282
Iteration 4: residual SS = 289.5729
Iteration 5: residual SS = 289.0515
Iteration 6: residual SS = 288.5264
Iteration 7: residual SS = 287.9692
Iteration 8: residual SS = 287.9013
Iteration 9: residual SS = 287.2156
Iteration 10: residual SS = 286.0925
Iteration 11: residual SS = 284.9419
Iteration 12: residual SS = 282.4999
Iteration 13: residual SS = 270.8794
Iteration 14: residual SS = 269.5694
Iteration 15: residual SS = 269.5403
Iteration 16: residual SS = 269.5398
Iteration 17: residual SS = 269.5397
Iteration 18: residual SS = 269.5397
Iteration 19: residual SS = 269.5397
Iteration 20: residual SS = 269.5397
Iteration 21: residual SS = 269.5397
Iteration 22: residual SS = 269.5397
Iteration 23: residual SS = 269.5397
Iteration 24: residual SS = 269.5397
Iteration 25: residual SS = 269.5397
Iteration 26: residual SS = 269.5397
Iteration 27: residual SS = 269.5397
Iteration 28: residual SS = 269.5397
```

```

Iteration 29: residual SS = 269.5397
Iteration 30: residual SS = 269.5397
Iteration 31: residual SS = 269.5397
Iteration 32: residual SS = 269.5397
Iteration 33: residual SS = 269.5397
Iteration 34: residual SS = 269.5397
Iteration 35: residual SS = 269.5397
Iteration 36: residual SS = 269.5397
Iteration 37: residual SS = 269.5397
Iteration 38: residual SS = 269.5397
Iteration 39: residual SS = 269.5397

```

Source	SS	df	MS		
Model	52.987566	3	17.6625221	Number of obs =	250
Residual	269.53966	246	1.09568968	R-squared =	0.1643
Total	322.52723	249	1.29529007	Adj R-squared =	0.1541
				Root MSE =	1.046752
				Res. dev. =	728.2829

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
/lnlamda	-1.413017	2.284257	-0.62	0.537	-5.912214	3.08618
/beta	.8204874	.1438337	5.70	0.000	.5371847	1.10379
/alpha	-.9501836	.517078	-1.84	0.067	-1.968648	.0682811
/thata	17.72068	16.75959	1.06	0.291	-15.28991	50.73128
/theta	-38.54279

Parameter lnlamda taken as constant term in model & ANOVA table
convergence not achieved
r(430);

```
. g C = exp(lnC)
```

```
. nl (C =
{lamda}*({theta}*R^(-{alpha})+(1-{theta})*W^(-{alpha}))^(-({beta}/{alpha}))), init(
lamda 1 theta 0.5 beta 0.5 alpha -0.5)
(obs = 250)
```

```

Iteration 0: residual SS = 1.03e+09
Iteration 1: residual SS = 4.42e+08
Iteration 2: residual SS = 4.41e+08
Iteration 3: residual SS = 4.39e+08
Iteration 4: residual SS = 4.36e+08
Iteration 5: residual SS = 4.33e+08
Iteration 6: residual SS = 4.32e+08
Iteration 7: residual SS = 4.27e+08
Iteration 8: residual SS = 4.24e+08

```

```

Iteration 9: residual SS = 4.16e+08
Iteration 10: residual SS = 3.71e+08
Iteration 11: residual SS = 3.66e+08
Iteration 12: residual SS = 3.66e+08
Iteration 13: residual SS = 3.66e+08
Iteration 14: residual SS = 3.66e+08
Iteration 15: residual SS = 3.66e+08

```

Source	SS	df	MS		
Model	6.823e+08	4	170572553	Number of obs =	250
Residual	3.656e+08	246	1486126.57	R-squared =	0.6511
Total	1.048e+09	250	4191509.4	Adj R-squared =	0.6454
				Root MSE =	1219.068
				Res. dev. =	4258.358

C	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
/lamda	10.92389	8.914749	1.23	0.222	-6.635086 28.48286
/theta	.2579155	.2150237	1.20	0.231	-.1656068 .6814378
/alpha	-.8748373	.4752491	-1.84	0.067	-1.810914 .0612391
/beta	.8567903	.1478706	5.79	0.000	.5655364 1.148044

```
. est store nls1
```

```
. nl (C =
{lamda}*({theta}*R^(-{alpha})+(1-{theta})*W^(-{alpha}))^(-({beta}/{alpha}))), init(
lamda 0.5 theta 0.1 beta 0.1 alpha -0.1)
(obs = 250)
```

```

Iteration 0: residual SS = 1.05e+09
Iteration 1: residual SS = 1.05e+09
Iteration 2: residual SS = 1.05e+09
Iteration 3: residual SS = 1.05e+09
Iteration 4: residual SS = 1.05e+09
Iteration 5: residual SS = 6.27e+08
Iteration 6: residual SS = 6.24e+08
Iteration 7: residual SS = 6.21e+08
Iteration 8: residual SS = 6.20e+08
Iteration 9: residual SS = 6.18e+08
Iteration 10: residual SS = 6.14e+08
Iteration 11: residual SS = 6.08e+08
Iteration 12: residual SS = 6.02e+08
Iteration 13: residual SS = 5.99e+08
Iteration 14: residual SS = 5.90e+08
Iteration 15: residual SS = 5.85e+08
Iteration 16: residual SS = 5.80e+08
Iteration 17: residual SS = 5.37e+08

```

```

Iteration 18: residual SS = 4.41e+08
Iteration 19: residual SS = 3.66e+08
Iteration 20: residual SS = 3.66e+08
Iteration 21: residual SS = 3.66e+08
Iteration 22: residual SS = 3.66e+08
Iteration 23: residual SS = 3.66e+08

```

Source	SS	df	MS		
Model	6.823e+08	4	170572553	Number of obs =	250
Residual	3.656e+08	246	1486126.57	R-squared =	0.6511
Total	1.048e+09	250	4191509.4	Adj R-squared =	0.6454
				Root MSE =	1219.068
				Res. dev. =	4258.358

C	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
/lamda	10.92388	8.914772	1.23	0.222	-6.635133	28.4829
/theta	.2579155	.2150241	1.20	0.231	-.1656077	.6814386
/alpha	-.8748375	.4752489	-1.84	0.067	-1.810913	.0612386
/beta	.8567904	.1478706	5.79	0.000	.5655365	1.148044

```

. est store nls2
. est table nls1 nls2 lognls1 lognls2, star(.1 .05 .01) stat(N rss r2 r2_a)

```

Variable	nls1	nls2	lognls1	lognls2
lamda				
_cons	10.923886	10.923885		
theta				
_cons	.25791551	.25791546	-9.5431207	-38.542788
alpha				
_cons	-.87483734*	-.87483745*	-.95018345*	-.95018292*
beta				
_cons	.85679034***	.85679037***	.82048739***	.82048739***
lnlamda				
_cons			-.27154276	-1.4130195
thata				
_cons			4.7247891	17.720698
Statistics				

N	250	250	250	250
rss	3.656e+08	3.656e+08	269.53966	269.53966
r2	.65111648	.65111648	.16428866	.16428866
r2_a	.64544358	.64544358	.15409706	.15409706

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

```
. log close
  name: <unnamed>
  log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q2.log
  log type: text
  closed on: 21 Mar 2021, 09:59:19
  -----
```

b) From the above table

∴ The estimated result will not be the same due to the different set of initial value will give the different in estimate result between $\ln(1)$ & $\ln(2)$

c) From the above table

(i) the different in convergence value will lead to the different estimated result
 (ii) the different in Iterative time can lead to unsuccessful estimation (convergence not achieved)

d) From the above table, log form can lead to estimated result that more robust

3)

```

name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q3.log
log type: text
opened on: 21 Mar 2021, 10:27:38

```

```

. clear

. use "C:\Users\User\Desktop\EE 426 stata\midterm exam\Midterm_q3_5.dta", clear

. do "C:\Users\User\AppData\Local\Temp\STD00000000.tmp"

. program ml_probit
program ml_probit already defined
r(110);

end of do-file

r(110);

```

2) . ml model lf ml_logit (y=x1 x2)

```
. ml maximize
```

```

initial:      log likelihood = -277.25887
alternative:  log likelihood = -278.63079
rescale:      log likelihood = -274.87577
Iteration 0:  log likelihood = -274.87577
Iteration 1:  log likelihood = -228.45409
Iteration 2:  log likelihood = -227.9439
Iteration 3:  log likelihood = -227.94274
Iteration 4:  log likelihood = -227.94274

```

∴ The different algorithm will lead to an estimate result due to the different computation function

```
Log likelihood = -227.94274
```

```

Number of obs      =      400
Wald chi2(2)       =      67.86
Prob > chi2        =      0.0000

```

Wald test

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.4934629	.1200559	4.11	0.000	.2581577 .7287682
x2	-.5955166	.0739186	-8.06	0.000	-.7403944 -.4506387
_cons	.3960511	.1836189	2.16	0.031	.0361646 .7559376

```
. est store nr
```

```
. ml model lf ml_logit (y=x1 x2), tech(bhhh)
```

```
. ml maximize
```

```
initial:      log likelihood = -277.25887
alternative:  log likelihood = -278.63079
rescale:     log likelihood = -274.87577
Iteration 0:  log likelihood = -274.87577
Iteration 1:  log likelihood = -228.37778
Iteration 2:  log likelihood = -227.94436
Iteration 3:  log likelihood = -227.94275
Iteration 4:  log likelihood = -227.94274
```

```
Log likelihood = -227.94274
```

Number of obs	=	400
Wald chi2(2)	=	67.46
Prob > chi2	=	0.0000

y	Coef.	OPG Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.4934547	.1270829	3.88	0.000	.2443768	.7425325
x2	-.5955136	.0728042	-8.18	0.000	-.7382072	-.45282
_cons	.3960458	.1762121	2.25	0.025	.0506765	.7414152

```
. est store bhhh
```

```
. ml model lf ml_logit (y=x1 x2), tech(bfgs)
```

```
. ml maximize
```

```
initial:      log likelihood = -277.25887
alternative:  log likelihood = -278.63079
rescale:     log likelihood = -274.87577
Iteration 0:  log likelihood = -274.87577
Iteration 1:  log likelihood = -270.06677 (backed up)
Iteration 2:  log likelihood = -255.6183 (backed up)
Iteration 3:  log likelihood = -253.92226
Iteration 4:  log likelihood = -228.8319
Iteration 5:  log likelihood = -227.98715
Iteration 6:  log likelihood = -227.94638
Iteration 7:  log likelihood = -227.94277
Iteration 8:  log likelihood = -227.94275
Iteration 9:  log likelihood = -227.94274
```

```
Log likelihood = -227.94274
```

Number of obs	=	400
Wald chi2(2)	=	67.86
Prob > chi2	=	0.0000

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

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.4934632	.1200559	4.11	0.000	.2581579 .7287684
x2	-.5955167	.0739186	-8.06	0.000	-.7403946 -.4506388
_cons	.3960516	.183619	2.16	0.031	.036165 .7559381

. est store bfgs

b) . ml model lf ml_logit (y=)

. ml maximize

initial: log likelihood = -277.25887
 alternative: log likelihood = -278.63079
 rescale: log likelihood = -274.87577
 Iteration 0: log likelihood = -274.87577
 Iteration 1: log likelihood = -274.83397
 Iteration 2: log likelihood = -274.83397

From a) Wald test p-value = 0.000
 which less than 0.05, $H_0: \beta_1 = \beta_2 = 0$,
 H_0 is rejected

Log likelihood = -274.83397
 Number of obs = 400
 Wald chi2(0) = .
 Prob > chi2 = .

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y					
_cons	-.2208938	.1006105	-2.20	0.028	-.4180869 -.0237008

. est store nocon

. est restore nr
 (results nr are active now)

. lrtest nr nocon

LR test $H_0: \beta_1 = \beta_2 = 0$
 $H_a: \text{Otherwise}$

Likelihood-ratio test
 (Assumption: nocon nested in nr)
 LR chi2(2) = 93.78
 Prob > chi2 = 0.0000 < 0.05

$\therefore H_0$ is rejected

. do "C:\Users\User\AppData\Local\Temp\STD00000000.tmp"

. program ml_probit
 program ml_probit already defined
 r(110);

\therefore LR-test is preferable due to
 more optimal power because
 use of 2 model for testing.

end of do-file

r(110);

d) . ml model lf ml_probit_het (y= x1 x2) (x3, noconstant)

```
. ml maximize
```

```
initial:      log likelihood = -277.25887
alternative:  log likelihood = -291.22568
rescale:      log likelihood = -274.84577
rescale eq:   log likelihood = -274.65472
Iteration 0:  log likelihood = -274.65472
Iteration 1:  log likelihood = -263.63393 (not concave)
Iteration 2:  log likelihood = -236.23643 (not concave)
Iteration 3:  log likelihood = -228.63176
Iteration 4:  log likelihood = -226.44344
Iteration 5:  log likelihood = -223.21726
Iteration 6:  log likelihood = -223.05974
Iteration 7:  log likelihood = -223.05935
Iteration 8:  log likelihood = -223.05935
```

```
Log likelihood = -223.05935      Number of obs      =      400
                                Wald chi2(2)              =      72.97
                                Prob > chi2                =      0.0000
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
eq1	x1	.310077	.0686179	4.52	0.000	.1755882	.4445657
	x2	-.3712427	.0440772	-8.42	0.000	-.4576324	-.284853
	_cons	.2591291	.1020126	2.54	0.011	.059188	.4590702
eq2	x3	-.4096773	.1390194	-2.95	0.003	-.6821503	-.1372044

```
. est store hetprob
```

```
. do "C:\Users\User\AppData\Local\Temp\STD00000000.tmp"
```

```
. program ml_probit
program ml_probit already defined
r(110);
```

```
end of do-file
```

```
r(110);
```

```
. ml model lf ml_probit (y=x1 x2)
```

```
. ml maximize
```

```
initial:      log likelihood = -277.25887
```

```

alternative: log likelihood = -291.2184
rescale: log likelihood = -274.85635
Iteration 0: log likelihood = -274.85635
Iteration 1: log likelihood = -228.21969
Iteration 2: log likelihood = -227.94988
Iteration 3: log likelihood = -227.94971
Iteration 4: log likelihood = -227.94971

```

```

Log likelihood = -227.94971
Number of obs = 400
Wald chi2(2) = 77.68
Prob > chi2 = 0.0000

```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.3012137	.0712688	4.23	0.000	.1615294 .440898
x2	-.3561502	.0413949	-8.60	0.000	-.4372826 -.2750177
_cons	.2318415	.1092333	2.12	0.034	.0177483 .4459348

```
. est store probit
```

$$H_0: \delta_1 = \delta_2 = \dots = \delta_n = \delta$$

```
. lrtest hetprob probit
```

```

Likelihood-ratio test
(Assumption: probit nested in hetprob)

```

```

LR chi2(1) = 9.78
Prob > chi2 = 0.0018 < 0.05

```

```
. log close
```

```

name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q3.log
log type: text
closed on: 21 Mar 2021, 10:29:42

```

c) MLE is χ^2 test because LR \xrightarrow{d} χ^2 , therefore we can't use F test because the different of the distribution.

d) Since P-value of LR-test is less than 0.05, H_0 is reject, heteroskedasticity is significant.

e) MLE assume asymptotic normality ($n \rightarrow \infty$) then MLE is z-test instead.

MLE use log likelihood for make comparison, the higher the better

MLE don't have R^2 due to a linear approximation

4

```
-----  
-----  
name: <unnamed>  
log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q4.log  
log type: text  
opened on: 21 Mar 2021, 10:54:50
```

```
. use "C:\Users\User\Desktop\EE 426 stata\midterm exam\Midterm_q4-1_5.dta", clear
```

```
. tsset time  
time variable: time, 1 to 1326  
delta: 1 unit
```

```
. g dr=f.r-r  
(1 missing value generated)
```

```
a) . gmm (dr-{alpha}-{beta}*r) ((dr-{alpha}-{beta}*r)*r)  
((dr-{alpha}-{beta}*r)^2-{sigma2}*r^(2*{gamma})) (((dr-{alpha}-{beta}*r)^2-{sigma2}*  
> r^(2*{gamma}))*r) winitial(identity)  
note: 1 missing value returned for equation 1 at initial values  
note: 1 missing value returned for equation 2 at initial values  
note: 1 missing value returned for equation 3 at initial values  
note: 1 missing value returned for equation 4 at initial values
```

Step 1

numerical derivatives are approximate
flat or discontinuous region encountered

```
Iteration 0: GMM criterion Q(b) = .00001194  
Iteration 1: GMM criterion Q(b) = 8.809e-06 (backed up)  
Iteration 2: GMM criterion Q(b) = 6.154e-06 (not concave)  
Iteration 3: GMM criterion Q(b) = 4.182e-06 (backed up)  
Iteration 4: GMM criterion Q(b) = 3.231e-06  
Iteration 5: GMM criterion Q(b) = 7.789e-08  
Iteration 6: GMM criterion Q(b) = 3.974e-08
```

Step 2

```
Iteration 0: GMM criterion Q(b) = .00006118  
Iteration 1: GMM criterion Q(b) = 1.335e-09  
Iteration 2: GMM criterion Q(b) = 7.626e-17
```

note: model is exactly identified

GMM estimation

```
Number of parameters = 4 } mom  
Number of moments = 4  
Initial weight matrix: Identity  
GMM weight matrix: Robust  
Number of obs = 1,325
```

```
-----  
-----
```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
/alpha	-.0023874	.0011648	-2.05	0.040	-.0046703	-.0001046
/beta	.000431	.0002874	1.50	0.134	-.0001322	.0009942
/sigma2	.0005156	.000328	1.57	0.116	-.0001272	.0011585
/gamma	.0933678	.1802519	0.52	0.604	-.2599195	.4466551

Instruments for equation 1: _cons
 Instruments for equation 2: _cons
 Instruments for equation 3: _cons
 Instruments for equation 4: _cons

. estat overid

Test of overidentifying restriction:

Hansen's J $\chi^2(0) = 1.0e-13$ (p = .)

Note: test cannot be performed because there are no overidentifying restrictions.

. est store unrestricted

. gmm (dr-{alpha}) ((dr-{alpha})*r) ((dr-{alpha})^2-{sigma2})
 (((dr-{alpha})^2-{sigma2})*r) winitial(identity)
 note: 1 missing value returned for equation 1 at initial values
 note: 1 missing value returned for equation 2 at initial values
 note: 1 missing value returned for equation 3 at initial values
 note: 1 missing value returned for equation 4 at initial values

Step 1

Iteration 0: GMM criterion Q(b) = .00001194
 Iteration 1: GMM criterion Q(b) = 4.130e-08
 Iteration 2: GMM criterion Q(b) = 4.129e-08

Step 2

Iteration 0: GMM criterion Q(b) = .00777293
 Iteration 1: GMM criterion Q(b) = .00548447
 Iteration 2: GMM criterion Q(b) = .00548447

GMM estimation

Number of parameters = 2
 Number of moments = 4
 Initial weight matrix: Identity
 GMM weight matrix: Robust
 Number of obs = 1,325

 | Robust

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
/alpha	-.0008163	.0006884	-1.19	0.236	-.0021655	.0005329
/sigma2	.0004387	.0002931	1.50	0.134	-.0001357	.0010131

Instruments for equation 1: _cons
 Instruments for equation 2: _cons
 Instruments for equation 3: _cons
 Instruments for equation 4: _cons

```
estat overid ✓
Test of overidentifying restriction:
Hansen's J chi2(2) = 7.26693 (p = 0.0264)
```

. est store merton

```
. gmm (dr-{alpha}-{beta}*r) ((dr-{alpha}-{beta}*r)*r)
((dr-{alpha}-{beta}*r)^2-{sigma2}) (((dr-{alpha}-{beta}*r)^2-{sigma2})*r) winitial(i
> dentity)
```

note: 1 missing value returned for equation 1 at initial values
 note: 1 missing value returned for equation 2 at initial values
 note: 1 missing value returned for equation 3 at initial values
 note: 1 missing value returned for equation 4 at initial values

Step 1

```
Iteration 0: GMM criterion Q(b) = .00001194
Iteration 1: GMM criterion Q(b) = 3.110e-10
Iteration 2: GMM criterion Q(b) = 3.045e-10
```

Step 2

```
Iteration 0: GMM criterion Q(b) = .00057424
Iteration 1: GMM criterion Q(b) = .00019027
Iteration 2: GMM criterion Q(b) = .00019027
```

GMM estimation

```
Number of parameters = 3
Number of moments = 4
Initial weight matrix: Identity Number of obs = 1,325
GMM weight matrix: Robust
```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
/alpha	-.0027025	.0009807	-2.76	0.006	-.0046247	-.0007803
/beta	.0005344	.0002001	2.67	0.008	.0001422	.0009266
/sigma2	.0005976	.0003004	1.99	0.047	8.90e-06	.0011863

Instruments for equation 1: _cons
 Instruments for equation 2: _cons
 Instruments for equation 3: _cons
 Instruments for equation 4: _cons

. estat overid

Test of overidentifying restriction:

Hansen's J chi2(1) = .252107 (p = 0.6156)

H₀ is not rejected, all moment condition already satisfy.

. est store vasicek

b) . est restore unrestricted
(results unrestricted are active now)

Test coefficient of Unrestricted model that whole model is suitable, using Wald - χ^2 -test.

. test (_b[/beta]=0) (_b[/gamma]=0)

(1) [beta]_cons = 0
(2) [gamma]_cons = 0

∴ H₀ is rejected, Merton is not appropriated

chi2(2) = 7.80
Prob > chi2 = 0.0203 < 0.05

. test (_b[/gamma]=0)

(1) [gamma]_cons = 0

∴ H₀ is not rejected, Vasicek is appropriated

chi2(1) = 0.27
Prob > chi2 = 0.6045 > 0.05

∴ Vasicek is the most appropriated.

. use "C:\Users\User\Desktop\EE 426 stata\midterm exam\Midterm_q4-2_5.dta", clear

c) . ivregress gmm y x3 x4 (x1 x2= z1 z2 z3)

Instrumental variables (GMM) regression

Number of obs = 500
Wald chi2(4) = 153.30
Prob > chi2 = 0.0000
R-squared = 0.5994
Root MSE = 20.244

GMM weight matrix: Robust

y	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
x1	3.276862	.9836373	3.33	0.001	1.348968	5.204756
x2	1.971358	.5390094	3.66	0.000	.9149195	3.027797
x3	1.026236	.309814	3.31	0.001	.4190122	1.633461
x4	1.324641	.175497	7.55	0.000	.9806737	1.668609
_cons	3.356269	7.714633	0.44	0.664	-11.76413	18.47667

Instrumented: x1 x2

Instruments: x3 x4 z1 z2 z3

. estat overid

Test of overidentifying restriction:

$\therefore H_0$ is not rejected, all moment conditions are satisfied

Hansen's J $\chi^2(1) = .005821$ ($p = 0.9392$) > 0.05

. ivregress 2sls y x3 x4 (x1 x2= z1 z2 z3)

Instrumental variables (2SLS) regression	Number of obs	=	500
	Wald $\chi^2(4)$	=	142.97
	Prob > χ^2	=	0.0000
	R-squared	=	0.5995
	Root MSE	=	20.243

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	3.275548	.9668494	3.39	0.001	1.380559 5.170538
x2	1.972494	.5392279	3.66	0.000	.9156265 3.029361
x3	1.027236	.311211	3.30	0.001	.417274 1.637199
x4	1.324484	.1798322	7.37	0.000	.972019 1.676948
_cons	3.340382	8.336292	0.40	0.689	-12.99845 19.67921

Instrumented: x1 x2
 Instruments: x3 x4 z1 z2 z3

. estat overid

Tests of overidentifying restrictions:

Sargan (score) $\chi^2(1) = .005008$ ($p = 0.9436$)
 Basman $\chi^2(1) = .004948$ ($p = 0.9439$)

. log close
 name: <unnamed>
 log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q4.log
 log type: text
 closed on: 21 Mar 2021, 10:56:32

a) From using OLS with endogeneity bias will give estimator that biased, inconsistent and inefficient.

e) GMM have more moment condition than 2SLS

GMM (moment condition)

- $E(u_i) = 0$
- $E(x_3 u_i) = 0$
- $E(x_4 u_i) = 0$
- $E(z_1 u_i) = 0$
- $E(z_2 u_i) = 0$
- $E(z_3 u_i) = 0$

2SLS (moment condition)

- $E(u_i) = 0$
- $E(\hat{x}_1 u_i) = 0$
- $E(\hat{x}_2 u_i) = 0$
- $E(x_3 u_i) = 0$
- $E(x_4 u_i) = 0$

. logit y x1 x2 x3

Iteration 0: log likelihood = -117.78597
 Iteration 1: log likelihood = -110.32738
 Iteration 2: log likelihood = -109.9522
 Iteration 3: log likelihood = -109.95099
 Iteration 4: log likelihood = -109.95099

.. From logit distribution, overall test is significant, for counted R^2 is 0.763 means that predictable that $y=1$ is 8.9%.

Logistic regression

Number of obs = 215
 LR chi2(3) = 15.67
 Prob > chi2 = 0.0013
 Pseudo R2 = 0.0665

Log likelihood = -109.95099

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.0065416	.0026044	2.51	0.012	.0014369 .0116462
x2	.0196932	.0155051	1.27	0.204	-.0106962 .0500826
x3	.1801955	.0802331	2.25	0.025	.0229415 .3374495
_cons	.6570795	.1995791	3.29	0.001	.2659116 1.048247

. fitstat

Measures of Fit for logit of y

Log-Lik Intercept Only:	-117.786	Log-Lik Full Model:	-109.951
D(211):	219.902	LR(3):	15.670
McFadden's R2:	0.067	Prob > LR:	0.001
Maximum Likelihood R2:	0.070	McFadden's Adj R2:	0.033
McKelvey and Zavoina's R2:	0.151	Cragg & Uhler's R2:	0.106
Variance of y*:	3.876	Efron's R2:	0.064
Count R2:	0.763	Variance of error:	3.290
AIC:	1.060	Adj Count R2:	0.000
BIC:	-913.303	AIC*n:	227.902
		BIC':	0.442

. est store logit

b) . mfx, at(mean)

Interpretation of marginal effects at mean of x_{1i} is if we change x_{1t} from 60.852 to 61.852, the probability of y_{1i} will increase by 0.11%, holden x_{2t}, x_{3t} at their mean.

Marginal effects after logit

y = Pr(y) (predict)
 \hat{p} = .78847535

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x1	.001091	.00041	2.63	0.008	.000279 .001903	60.852
x2	.0032845	.00253	1.30	0.195	-.00168 .008249	-1.59106
x3	.0300534	.01277	2.35	0.019	.005023 .055084	1.62016

. mfx, at(median)

Marginal effects after logit

y = Pr(y) (predict)
= .66823646

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x1	.0014502	.00062	2.32	0.020	.000226 .002674	.770154
x2	.0043659	.00346	1.26	0.207	-.002419 .011151	.549624
x3	.0399487	.01853	2.16	0.031	.003631 .076267	.151382

c) . test x1 x2 x3

- (1) [y]x1 = 0
- (2) [y]x2 = 0
- (3) [y]x3 = 0

chi2(3) = 12.12
Prob > chi2 = 0.0070 < 0.05

For Logit
 $H_0: \beta_1 = \beta_2 = \beta_3 = 0$
Wald test for logit distribution
is rejected H_0 .

LR-test

LR-test = 15.67
P-value = 0.01 < 0.05
 $\therefore H_0$ is rejected

. est restore probit
(results probit are active now)

. test x1 x2 x3

- (1) [y]x1 = 0
- (2) [y]x2 = 0
- (3) [y]x3 = 0

chi2(3) = 13.59
Prob > chi2 = 0.0035 < 0.05

For probit:
 $H_0: \beta_1 = \beta_2 = \beta_3 = 0$
Wald test for probit distribution
is rejected H_0

LR-test

LR-test = 15.761
P-value = 0.01 < 0.05
 $\therefore H_0$ is rejected

. test (x1=x2)

- (1) [y]x1 - [y]x2 = 0

chi2(1) = 0.66
Prob > chi2 = 0.4180 > 0.05 $\rightarrow H_0$ is not rejected, $\beta_1 = \beta_2$ (for probit distribution)

$H_0: \beta_1 = \beta_2$

. est restore logit
(results logit are active now)

. test (x1=x2)

- (1) [y]x1 - [y]x2 = 0

chi2(1) = 0.77
Prob > chi2 = 0.3790 > 0.05 → $H_0: \beta_1 = \beta_2$ (For logit distribution)

```
. log close
  name: <unnamed>
  log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q5.log
  log type: text
  closed on: 21 Mar 2021, 11:25:58
```

d) Counted R^2 is important because it tells how precise of prediction is.
If the threshold is change which will lead to the condition of prediction to be predict that \hat{y}_{21} is harder or easier, then the precise of prediction will change accordingly or counted R^2 change

6)

```

name: <unnamed>
log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q6.log
log type: text
opened on: 21 Mar 2021, 12:06:32

```

```

. use "C:\Users\User\Desktop\EE 426 stata\midterm exam\Midterm_q6_5.dta", clear

. xtset id t
panel variable: id (strongly balanced)
time variable: t, 1 to 12
delta: 1 unit

```

a)

```

. xtgls y x1 x2 x3, igls panels(heteroskedastic)
Iteration 1: tolerance = .00590371
Iteration 2: tolerance = .00177471
Iteration 3: tolerance = .00055434
Iteration 4: tolerance = .000177
Iteration 5: tolerance = .00005721
Iteration 6: tolerance = .00001862
Iteration 7: tolerance = 6.085e-06
Iteration 8: tolerance = 1.993e-06
Iteration 9: tolerance = 6.534e-07
Iteration 10: tolerance = 2.144e-07
Iteration 11: tolerance = 7.040e-08

```

If heteroskedasticity occur, the estimator will not be BLUE but only LUE because it is not minimum variance, t-test & f-test is invalid or not precise.

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares
Panels: heteroskedastic
Correlation: no autocorrelation

Estimated covariances	=	100	Number of obs	=	1,200
Estimated autocorrelations	=	0	Number of groups	=	100
Estimated coefficients	=	4	Time periods	=	12
Log likelihood	=	-6165.009	Wald chi2(3)	=	33298.40
			Prob > chi2	=	0.0000

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.3168738	.0100633	31.49	0.000	.2971501 .3365975
x2	1.311977	.0139878	93.79	0.000	1.284562 1.339393
x3	-.4630102	.011065	-41.84	0.000	-.4846972 -.4413232
_cons	-132.2058	6.140582	-21.53	0.000	-144.2411 -120.1705

```

. est store pannelhet

```

```
. xtgls y x1 x2 x3
```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares
Panels: homoskedastic
Correlation: no autocorrelation

```
Estimated covariances = 1          Number of obs = 1,200
Estimated autocorrelations = 0      Number of groups = 100
Estimated coefficients = 4          Time periods = 12
Log likelihood = -6211.29          Wald chi2(3) = 29882.41
                                   Prob > chi2 = 0.0000
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.3183087	.0109146	29.16	0.000	.2969164 .3397011
x2	1.320714	.0149495	88.34	0.000	1.291413 1.350014
x3	-.4642183	.011884	-39.06	0.000	-.4875104 -.4409262
_cons	-136.2145	6.645908	-20.50	0.000	-149.2402 -123.1887

```
. est store panel
```

```
. local df=e(N_g)-1
```

```
. lrtest pannelhet, df(`df')
```

Likelihood-ratio test
(Assumption: panel nested in pannelhet)

```
LR chi2(99) = 92.56
Prob > chi2 = 0.6629 > 0.05
```

H₀: no heteroskedasticity

b)

```
. xtgls y x1 x2 x3
```

Cross-sectional time-series FGLS regression

Coefficients: generalized least squares
Panels: homoskedastic
Correlation: no autocorrelation

```
Estimated covariances = 1          Number of obs = 1,200
Estimated autocorrelations = 0      Number of groups = 100
Estimated coefficients = 4          Time periods = 12
Log likelihood = -6211.29          Wald chi2(3) = 29882.41
                                   Prob > chi2 = 0.0000
```

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

*H₀ is not rejected,
heteroskedasticity is insignificant*

x1		.3183087	.0109146	29.16	0.000	.2969164	.3397011
x2		1.320714	.0149495	88.34	0.000	1.291413	1.350014
x3		-.4642183	.011884	-39.06	0.000	-.4875104	-.4409262
_cons		-136.2145	6.645908	-20.50	0.000	-149.2402	-123.1887

. xtreg y x1 x2 x3, fe

Fixed-effects (within) regression
Group variable: id

Number of obs = 1,200
Number of groups = 100

R-sq:

within = 0.9502
between = 0.9848
overall = 0.8846

Obs per group:

min = 12
avg = 12.0
max = 12

corr(u_i, Xb) = 0.8057

F(3,1097) = 6980.72
Prob > F = 0.0000

y		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x1		.1014426	.0044866	22.61	0.000	.0926393 .1102459
x2		.6951028	.0085422	81.37	0.000	.678342 .7118637
x3		-.4953168	.0041895	-118.23	0.000	-.5035372 -.4870965
_cons		208.659	4.373144	47.71	0.000	200.0784 217.2397
sigma_u		123.46108				
sigma_e		14.376737				
rho		.98662139	(fraction of variance due to u_i)			

F test that all u_i=0: F(99, 1097) = 96.47 $H_0: \alpha_1 = \alpha_2 = \dots = \alpha_n = 0$ Prob > F = 0.0000 < 0.05

H₀ is rejected, fixed effect is exist.

. est store fixeffect

. xtreg y x1 x2 x3, re

Random-effects GLS regression
Group variable: id

Number of obs = 1,200
Number of groups = 100

R-sq:

within = 0.8956
between = 0.9953
overall = 0.9543

Obs per group:

min = 12
avg = 12.0
max = 12

corr(u_i, X) = 0 (assumed)

Wald chi2(3) = 8707.50
Prob > chi2 = 0.0000

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

x1	.2162513	.0090869	23.80	0.000	.1984414	.2340613
x2	1.028607	.0152844	67.30	0.000	.9986503	1.058564
x3	-.4779339	.0091412	-52.28	0.000	-.4958503	-.4600176
_cons	25.24251	8.000206	3.16	0.002	9.562392	40.92262
sigma_u	12.351151					
sigma_e	14.376737					
rho	.42464732	(fraction of variance due to u_i)				

. est store random

. hausman fixeffect random

---- Coefficients ----				
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	fixeffect	random	Difference	S.E.
x1	.1014426	.2162513	-.1148087	.
x2	.6951028	1.028607	-.3335042	.
x3	-.4953168	-.4779339	-.0173829	.

b = consistent under Ho and Ha; obtained from xtreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
 = -1451.21 chi2<0 ==> model fitted on these
 data fails to meet the asymptotic
 assumptions of the Hausman test;
 see suest for a generalized test

. log close

name: <unnamed>

log: C:\Users\User\Desktop\EE 426 stata\midterm exam\midterm q6.log

log type: text

closed on: 21 Mar 2021, 12:07:47

```
. hausman random fixeffect

----- Coefficients -----
      (b)      (B)      (b-B)      sqrt(diag(V_b-V_B))
      random  fixeffect  Difference      S.E.
-----+-----
x1      .2162513  .1014426  .1148087  .007902
x2      1.028607  .6951028  .3335042  .0126745
x3     -.4779339 -.4953168  .0173829  .0081246

      b = consistent under Ho and Ha; obtained from xtreg
      B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

      chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
              = 1451.21
      Prob>chi2 = 0.0000
```

b) First, test whether fixed effect is exist or not, then test that the effect is significant or not which result in fixed effect is exist and significant.

Random-effect test $H_0: E(\alpha_i x_i) = 0$

$$\chi^2_3 = 1451.21$$

$$P\text{-value} = 0.000 < 0.05$$

H_0 is rejected, fixed effect is more appropriate than random effect

c) Fixed effect estimation: $y_{it} - \bar{y}_i = \cancel{(\beta_1 - \bar{\beta}_1)} \beta_2 (x_{2it} - \bar{x}_{2i}) + \dots + \beta_k (x_{kit} - \bar{x}_{ki}) + \cancel{(\alpha_i - \bar{\alpha})} + (\varepsilon_{it} - \bar{\varepsilon}_i)$
 (computed by using mean)

First difference estimation method: $\cancel{(\beta_1 - \bar{\beta}_1)}$
 $y_{it} - y_{it-1} = \beta_2 (x_{2it} - x_{2it-1}) + \dots + \beta_k (x_{kit} - x_{kit-1}) + \cancel{(\alpha_i - \alpha_i)} + (\varepsilon_{it} - \varepsilon_{it-1})$

Random effect model: $y_{it} - \lambda \bar{y}_i = \beta_1 (1 - \lambda) + \beta_2 (x_{2it} - \lambda \bar{x}_{2i}) + \dots + \beta_k (x_{kit} - \lambda \bar{x}_{ki}) + (u_{it} - \lambda \bar{u}_i)$

where λ is $0 < \lambda < 1$

$\lambda = 1 \rightarrow$ Fixed effect

$\lambda = 0 \rightarrow$ POLS

d) The difference is the computation of each R^2

$$\text{Within } R^2 = \frac{\sum (\hat{y}_{it}^* - \bar{y}^*)^2}{\sum (\hat{y}_{it}^* - \bar{y}^*)^2} = \frac{\sum ((y_{it} - \bar{y}_i) - \overline{(y_{it} - \bar{y}_i)})^2}{\sum ((y_{it} - \bar{y}_i) - \overline{(y_{it} - \bar{y}_i)})^2}$$

$$\text{Overall } R^2 = \frac{\sum (\hat{y}_{it} - \bar{y})^2}{\sum (\hat{y}_{it} - \bar{y})^2}$$

$$\text{Between } R^2 = \frac{\sum (\hat{y}_i - \bar{y})^2}{\sum (\hat{y}_i - \bar{y})^2}$$