

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

(Readable handwriting and printed version are acceptable)

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Student Signature Pongpanot

Date 21/3/2021

1a)

```
. reg y1 y2 x3
```

Source	SS	df	MS	Number of obs	=	50
Model	53641.1607	2	26820.5804	F(2, 47)	=	105.60
Residual	11937.3193	47	253.985517	Prob > F	=	0.0000
				R-squared	=	0.8180
				Adj R-squared	=	0.8102
Total	65578.48	49	1338.33633	Root MSE	=	15.937

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
y1					
y2	.0009798	.0002004	4.89	0.000	.0005767 .001383
x3	.0070911	.0011265	6.29	0.000	.0048248 .0093575
_cons	48.16661	16.76879	2.87	0.006	14.43215 81.90106

Estimated model (1)

```
. reg y2 y1 x1 x2
```

Source	SS	df	MS	Number of obs	=	50
Model	8.6346e+09	3	2.8782e+09	F(3, 46)	=	34.20
Residual	3.8711e+09	46	84153502.5	Prob > F	=	0.0000
				R-squared	=	0.6905
				Adj R-squared	=	0.6703
Total	1.2506e+10	49	255217016	Root MSE	=	9173.5

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
y2					
y1	305.4783	45.34514	6.74	0.000	214.2033 396.7533
x1	248.301	129.3171	1.92	0.061	-12.00086 508.6029
x2	-.0004058	.0003213	-1.26	0.213	-.0010525 .000241
_cons	-37418.53	8638.956	-4.33	0.000	-54807.85 -20029.22

Estimated model (2)

By using OLS on each model, they will not show that there is correlation on error term between 2 models and can not find endogeneity bias.

1b) Estimate model (1) and (2) using Two Stage Least Squares (2SLS)

```
. reg3 ( y1 y2 x3 ) ( y2 y1 x1 x2 ) , 2slls nodfk inst( x1 x2 x3 )
```

Two-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	F-Stat	P
y1	50	2	16.26188	0.8105	98.57	0.0000
y2	50	3	9173.526	0.6905	30.52	0.0000

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
y1					
y2	.0012587	.0005236	2.40	0.018	.0002189 .0022985
x3	.005989	.0022161	2.70	0.008	.0015883 .0103897
_cons	56.01137	21.47323	2.61	0.011	13.36979 98.65296
y2					
y1	305.1981	56.32913	5.42	0.000	193.3396 417.0566
x1	248.7832	138.4853	1.80	0.076	-26.22129 523.7876
x2	-.0004062	.0003118	-1.30	0.196	-.0010253 .000213
_cons	-37383.31	9429.053	-3.96	0.000	-56107.54 -18659.08

Endogenous variables: y1 y2
Exogenous variables: x1 x2 x3

1) continued. Reduced form and structural form of these simultaneous equation models.

$$\begin{aligned}
 y_{1t} &= \beta_{10} + \delta_{11}y_{2t} + \beta_{13}x_{3t} + u_{1t} \\
 y_{2t} &= \beta_{20} + \delta_{21}y_{1t} + \beta_{21}x_{1t} + \beta_{22}x_{2t} + u_{2t} \\
 \textcircled{1} \quad y_{2t} &= \beta_{20} + \delta_{21}(\beta_{10} + \delta_{11}y_{2t} + \beta_{13}x_{3t} + u_{1t}) + \beta_{21}x_{1t} + \beta_{22}x_{2t} + u_{2t} \\
 y_{2t} &= \beta_{20} + \delta_{21}\beta_{10} + \delta_{21}\delta_{11}y_{2t} + \delta_{21}\beta_{13}x_{3t} + \delta_{21}u_{1t} + \beta_{21}x_{1t} + \beta_{22}x_{2t} + u_{2t} \\
 y_{2t} &= \frac{\beta_{20} + \delta_{21}\beta_{10}}{(1 - \delta_{21}\delta_{11})} + \frac{\delta_{21}\beta_{13}x_{3t}}{(1 - \delta_{21}\delta_{11})} + \frac{\beta_{21}x_{1t} + \beta_{22}x_{2t} + u_{2t} + \delta_{21}u_{1t}}{(1 - \delta_{21}\delta_{11})} \\
 y_{2t} &= \pi_4 + \pi_5x_{3t} + \pi_6x_{1t} + \pi_7x_{2t} + u_{1t} // \\
 \textcircled{2} \quad y_{1t} &= \beta_{10} + \delta_{12}(\beta_{20} + \delta_{21}y_{1t} + \beta_{21}x_{1t} + u_{2t}) + \beta_{13}x_{3t} + u_{1t} \\
 y_{1t} &= \beta_{10} + \delta_{12}\beta_{20} + \delta_{12}\delta_{21}y_{1t} + \delta_{12}\beta_{21}x_{1t} + \delta_{12}u_{2t} + \beta_{13}x_{3t} + u_{1t} \\
 y_{1t} - \delta_{12}\delta_{21}y_{1t} &= \beta_{10} + \delta_{12}\beta_{20} + \delta_{12}\beta_{21}x_{1t} + \delta_{12}\beta_{22}x_{2t} + \beta_{13}x_{3t} + \delta_{12}u_{2t} + u_{1t} \\
 y_{1t} &= \frac{\beta_{10} + \delta_{12}\beta_{20}}{(1 - \delta_{12}\delta_{21})} + \frac{\delta_{12}\beta_{21}x_{1t}}{(1 - \delta_{12}\delta_{21})} + \frac{\delta_{12}\beta_{22}x_{2t} + \beta_{13}x_{3t}}{(1 - \delta_{12}\delta_{21})} + \frac{\delta_{12}u_{2t} + u_{1t}}{(1 - \delta_{12}\delta_{21})} \\
 y_{1t} &= \pi_0 + \pi_1x_{1t} + \pi_2x_{2t} + \pi_3x_{3t} + u_{1t} //
 \end{aligned}$$

Endogenous variables: y1t, y2t

Exogenous variables: x1t, x2t, x3t

```
. reg y1 x1 x2 x3
```

Source	SS	df	MS	Number of obs	=	50
Model	49051.6619	3	16350.554	F(3, 46)	=	45.51
Residual	16526.8181	46	359.278655	Prob > F	=	0.0000
				R-squared	=	0.7480
				Adj R-squared	=	0.7315
Total	65578.48	49	1338.33633	Root MSE	=	18.955

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	.5220712	.2579887	2.02	0.049	.002767	1.041376
x2	-5.07e-07	6.60e-07	-0.77	0.446	-1.84e-06	8.21e-07
x3	.0096092	.001166	8.24	0.000	.0072621	.0119562
_cons	14.47665	19.02827	0.76	0.451	-23.82528	52.77857

```
. predict y1hat
(option xb assumed; fitted values)
```

```
. reg y2 x1 x2 x3
```

Source	SS	df	MS	Number of obs	=	50
Model	7.0882e+09	3	2.3627e+09	F(3, 46)	=	20.06
Residual	5.4175e+09	46	117771073	Prob > F	=	0.0000
				R-squared	=	0.5666
				Adj R-squared	=	0.5385
Total	1.2506e+10	49	255217016	Root MSE	=	10852

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x1	408.1183	147.7081	2.76	0.008	110.7973	705.4393
x2	-.0005609	.0003777	-1.49	0.144	-.0013212	.0001993
x3	2.932698	.6675867	4.39	0.000	1.588915	4.276481
_cons	-32965.07	10894.39	-3.03	0.004	-54894.34	-11035.75

```
. predict y2hat
(option xb assumed; fitted values)
```

1b) continued

```
. reg y1 y2hat x3
```

Source	SS	df	MS	Number of obs	=	50
Model	49005.8864	2	24502.9432	F(2, 47)	=	69.49
Residual	16572.5936	47	352.608375	Prob > F	=	0.0000
				R-squared	=	0.7473
				Adj R-squared	=	0.7365
Total	65578.48	49	1338.33633	Root MSE	=	18.778

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
y2hat	.0012587	.0006237	2.02	0.049	4.07e-06 .0025133
x3	.005989	.0026394	2.27	0.028	.0006793 .0112987
_cons	56.01137	25.57462	2.19	0.034	4.561882 107.4609


```
. reg y2 y1hat x1 x2
```

Source	SS	df	MS	Number of obs	=	50
Model	7.0882e+09	3	2.3627e+09	F(3, 46)	=	20.06
Residual	5.4175e+09	46	117771071	Prob > F	=	0.0000
				R-squared	=	0.5668
				Adj R-squared	=	0.5385
Total	1.2506e+10	49	255217016	Root MSE	=	10852

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
y1hat	305.1981	69.47398	4.39	0.000	165.3542 445.042
x1	248.7832	170.802	1.46	0.152	-95.02342 592.5897
x2	-.0004062	.0003846	-1.06	0.296	-.0011802 .0003679
_cons	-37383.31	11629.4	-3.21	0.002	-60792.07 -13974.55

1c)

```
. reg3 (y1 y2 x3 x4) ( y2 y1 x1 x2), 3sls inst( x1 x2 x3)
```

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
y1	50	3	18.07708	0.7508	150.11	0.0000
y2	50	3	8798.937	0.6905	91.55	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
y1					
y2	.0016267	.001152	1.41	0.158	-.0006313 .0038846
x3	.0048354	.0039945	1.21	0.226	-.0029937 .0126645
x4	-7.110954	18.99942	-0.37	0.708	-44.34913 30.12722
_cons	79.97872	68.60696	1.17	0.244	-54.48846 214.4459
y2					
y1	305.1981	56.32913	5.42	0.000	194.795 415.6012
x1	248.7832	138.4853	1.80	0.072	-22.64312 520.2094
x2	-.0004062	.0003118	-1.30	0.193	-.0010173 .000205
_cons	-37383.31	9429.053	-3.96	0.000	-55863.92 -18902.71

Endogenous variables: y1 y2 x4
 Exogenous variables: x1 x2 x3

The difference among 3 estimation method is standard error which shows the significant different from one another.

The advantage of the single equation is that it provides all SSR, SSE, and SST. On the other hand, it does not show any correlation of the error term, leading to endogeneity bias. For system equations, the advantage is that it can point r-square together and identify endogeneity.

2)a)

```
. nl ( lnC = {lnlambda}-({beta}/{alpha})*ln({theta}*R^{-(alpha)}+(1-{theta})*
> -{alpha})), init(lnlambda 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 =	25
Model	52.987566	3	17.6625221	R-squared =	0.164
Residual	269.53966	246	1.09568968	Adj R-squared =	0.154
Total	322.52723	249	1.29529007	Root MSE =	1.04675
				Res. dev. =	728.282

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval
/lnlambda	2.082157	.7495103	2.78	0.006	.6058805 3.55843
/beta	.8204874	.1438338	5.70	0.000	.5371846 1.1037
/alpha	-.9501815	.5170818	-1.84	0.067	-1.968654 .068290
/theta	.3094593	.2021046	1.53	0.127	-.0886169 .707535

Parameter lnlambda taken as constant term in model & ANOVA table

```
. est store lognl
. sca sigma=1/(1-(_b[/theta]))
```

```
. sca list sigma
sigma = 1.4481406
. test (-b[/theta]=0) (_b[/alpha]=0) (_b[/beta]=0)
b not found
r(111):
. test (_b[/theta]=0) (_b[/alpha]=0) (_b[/beta]=0)
( 1) [theta]_cons = 0
( 2) [alpha]_cons = 0
( 3) [beta]_cons = 0
F( 3, 246) = 49.35
Prob > F = 0.0000
```

According to the above estimated results, estimated value of $\ln(\lambda) = 2.082157$, $\beta = .8204874$, $\alpha = -.9501815$, $\theta = .3094593$. F-test whether $\theta=0$, $\alpha=0$, $\beta=0$ with $p\text{-value} < 0.05$, the null hypothesis is rejected.

2b)

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

```
Iteration 0: residual SS = 4589.928
Iteration 1: residual SS = 3682.143
Iteration 2: residual SS = 285.9504
Iteration 3: residual SS = 275.9036
Iteration 4: residual SS = 271.2478
Iteration 5: residual SS = 269.957
Iteration 6: residual SS = 269.5398
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
Iteration 12: residual SS = 269.5397
Iteration 13: residual SS = 269.5397
Iteration 14: 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]
/lnlambda	2.082157	.7495103	2.78	0.006	.6058805 3.558433
/beta	.8204874	.1438337	5.70	0.000	.5371847 1.10379
/alpha	-.9501827	.5170796	-1.84	0.067	-1.968651 .0682852
/theta	.309459	.2021044	1.53	0.127	-.0886167 .7075347

Parameter lnlambda taken as constant term in model & ANOVA table

It shows that it happens to be the same as (2a)

```
. est store logn12
. est table logn1 logn12, star(.1 .05 .01) stat(N rss r2 r2_a)
```

Variable	logn1	logn12
lnlambda		
_cons	2.0821566***	2.0821566***
beta		
_cons	.82048738***	.82048739***
alpha		
_cons	-.95018154*	-.95018274*
theta		
_cons	.30945931	.30945899
Statistics		
N	250	250
rss	269.53966	269.53966
r2	.16428866	.16428866
r2_a	.15409706	.15409706

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

The difference will be by 0.0000001 decimal are beta, alpha, and theta.

2c) 0.1 or (1e-1)

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

```
Iteration 0: residual SS = 4589.928
Iteration 1: residual SS = 3682.143
Iteration 2: residual SS = 285.9504
Iteration 3: residual SS = 275.9036
Iteration 4: residual SS = 271.2478
Iteration 5: residual SS = 269.957
Iteration 6: residual SS = 269.5398
```

Source	SS	df	MS	Number of obs =	250
Model	52.987417	3	17.6624723	R-squared =	0.1643
Residual	269.53981	246	1.09569029	Adj R-squared =	0.1541
Total	322.52723	249	1.29529007	Root MSE =	1.046752
				Res. dev. =	728.2831

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
/lnlambda	2.080346	.7498896	2.77	0.006	.6033229 3.557369
/beta	.8210009	.1442144	5.69	0.000	.5369485 1.105053
/alpha	-.947774	.5355935	-1.77	0.078	-2.002708 .10716
/theta	.3092967	.2038804	1.52	0.131	-.0922772 .7108706

Parameter beta taken as constant term in model & ANOVA table

(1e-15)

```
. nl ( lnC = {lnlambda}-((beta)/(alpha))*ln((theta)*R^(-(alpha))+(1-(theta))*W^
> -(alpha))), init(lnlambda 0.5 theta 0.1 beta 0.1 alpha -0.1) iter(40) eps(1e-1
> 5)
(obs = 250)
```

```
Iteration 0: residual SS = 482.5041
Iteration 1: residual SS = 378.0788
Iteration 2: residual SS = 375.5952
Iteration 3: residual SS = 375.5391
Iteration 4: residual SS = 375.5335
Iteration 5: residual SS = 321.1261
Iteration 6: residual SS = 321.1261
Iteration 7: residual SS = 321.1261
Iteration 8: residual SS = 321.1261
Iteration 9: residual SS = 321.1261
Iteration 10: residual SS = 321.1261
Iteration 11: residual SS = 321.1261
Iteration 12: residual SS = 321.1261
Iteration 13: residual SS = 321.1261
Iteration 14: residual SS = 321.1261
Iteration 15: residual SS = 321.1261
Iteration 16: residual SS = 321.1261
Iteration 17: residual SS = 321.1261
Iteration 18: residual SS = 321.1261
Iteration 19: residual SS = 321.1261
Iteration 20: residual SS = 321.1261
Iteration 21: residual SS = 321.1261
Iteration 22: residual SS = 321.1261
Iteration 23: residual SS = 321.1261
Iteration 24: residual SS = 321.1261
Iteration 25: residual SS = 321.1261
Iteration 26: residual SS = 321.1261
Iteration 27: residual SS = 321.1261
Iteration 28: residual SS = 321.1261
Iteration 29: residual SS = 321.1261
Iteration 30: residual SS = 321.1261
Iteration 31: residual SS = 321.1261
Iteration 32: residual SS = 321.1261
Iteration 33: residual SS = 321.1261
Iteration 34: residual SS = 321.1261
Iteration 35: residual SS = 321.1261
Iteration 36: residual SS = 321.1261
Iteration 37: residual SS = 321.1261
```

2c) continued

```
Iteration 37: residual SS = 321.1261
Iteration 38: residual SS = 321.1261
Iteration 39: residual SS = 321.1261
```

Source	SS	df	MS			
Model	11869.411	2	5934.7055	Number of obs =	250	
Residual	321.12615	248	1.2948635	R-squared =	0.9737	
				Adj R-squared =	0.9734	
				Root MSE =	1.137921	
Total	12190.537	250	48.7621486	Res. dev. =	772.0625	

lnC	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
/lnlambda	6.47352	.4067951	15.91	0.000	5.672306	7.274733
/beta	-.07207	.0692844	-1.04	0.299	-.2085308	.0643908
/alpha	1.763183
/theta	-10.62973

```
convergence not achieved
r(430);
```

```
. est table lognl nls3 nls4, star(.1 .05 .01) stat(N rss r2 r2_a)
```

Variable	lognl	nls3	nls4
lnlambda			
_cons	2.0821566***	2.0803462***	6.4735197***
beta			
_cons	.82048738***	.82100088***	-.07207002
alpha			
_cons	-.95018154*	-.94777396*	1.7631829
theta			
_cons	.30945931	.30929669	-10.62973
Statistics			
N	250	250	250
rss	269.53966	269.53981	321.12615
r2	.16428866	.1642882	.97365775
r2_a	.15409706	.15409659	.97344531

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

According to the above estimated results, it indicated that using different convergence values can give the different estimated results.

2d) the reason is that when range of observation to large will need to long time to get, with log, it will shorten iteration ex: 1 to 1000, with log, it become 0 to3.

3a)i)

```
. program ml_logit
1. args lnf theta
2. quietly replace `lnf'=ln(1/(1+exp(-`theta')))) if $ML_y1==1
3. quietly replace `lnf'=ln(1-(1/(1+exp(-`theta')))) if $ML_y1==0
4. end
.
end of do-file

. ml model lf ml_logit (y=x1 x2 x3)

. ml max

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 = -228.34261
Iteration 2:  log likelihood = -227.83354
Iteration 3:  log likelihood = -227.83324
Iteration 4:  log likelihood = -227.83324

                                Number of obs   =       400
                                Wald chi2(3)      =       68.02
Log likelihood = -227.8324      Prob > chi2   =       0.0000
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.4921629	.1199063	4.10	0.000	.2571508	.727175
x2	-.595503	.0739328	-8.05	0.000	-.7404086	-.4505974
x3	.0537453	.1145407	0.47	0.639	-.1707504	.2782411
_cons	.4002173	.1838358	2.18	0.029	.0399057	.7605289

```
. est store unr
```

ii)

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

. mal max
command mal is unrecognized
r(199);

. ml max

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

                                Number of obs   =       400
                                Wald chi2(2)      =       67.46
Log likelihood = -227.94274    Prob > chi2   =       0.0000
```

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

3a)iii)

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

```
. ml max
```

```
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
```

```
Number of obs   =      400
Wald chi2(2)    =      67.86
Prob > chi2     =      0.0000
Log likelihood = -227.94274
```

y	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
```

```
. est table unr bhhh bfgs, star(.1 .05 .01) stat(N ll chi2 p)
```

Variable	unr	bhhh	bfgs
x1	.49346292***	.49345467***	.49346316***
x2	-.59551656***	-.59551359***	-.59551671***
_cons	.39605112**	.39604584**	.39605159**
N	400	400	400
ll	-227.94274	-227.94274	-227.94274
chi2	67.855358	67.464817	67.855377
p	1.842e-15	2.240e-15	1.842e-15

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

The estimated results using different algorithm can be different because of the different computation function.

3b) Wald test

```
. test x1 x2
```

```
( 1) [eq1]x1 = 0
( 2) [eq1]x2 = 0
```

```
chi2( 2) = 67.86
Prob > chi2 = 0.0000
```

3b) continued

LR-test

```
. ml model lf ml_logit (y=)
. ml max
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

                                Number of obs   =       400
                                Wald chi2(0)      =       .
                                Prob > chi2       =       .

Log likelihood = -274.83397

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

. est store res
. lrtest unr res

Likelihood-ratio test                                LR chi2(2) =    93.78
(Assumption: res nested in unr)                    Prob > chi2 =    0.0000
```

LR-test is more preferable because it will not overstate or understate the value while Wald test use only unrestricted model which leads to overstate the value.

3c) the reason is that MLE is in asymptotic property so it cannot use F-test as F-test involved in degree of freedom where observation is not infinite. Hence, F-test is impossible to be employed as degree of freedom in the F-test is finite

3d)

```
. program ml_probit
1.  args lnf theta
2.  tempvar z
3.  quietly g double `z'=`theta'
4.  quietly replace `lnf'`=ln(normal(`z')) if $ML_y1==1
5.  quietly replace `lnf'`=ln(1-normal(`z')) if $ML_y1==0
6.  end

.
end of do-file

. use "C:\Users\Kang\Desktop\Midterm_q3_11.dta", clear

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

                                Number of obs   =       400
                                Wald chi2(2)      =       77.68
                                Prob > chi2       =       0.0000

Log likelihood = -227.94971

+-----+-----+-----+-----+-----+-----+
|      y      |   Coef.   | Std. Err. |    z    | P>|z|    | [95% Conf. Interval] |
+-----+-----+-----+-----+-----+-----+
|      x1     |  3012137  |  712688   |   4.23  |  0.000   |  1615294   440898 |
|      x2     | -3561502  |  413949   |  -8.60  |  0.000   | -4372826  -2750177 |
|      _cons  |  2318415  | 1092333   |   2.12  |  0.034   |  177483   4459348 |
+-----+-----+-----+-----+-----+

. est store probit
```

```

. program ml_probit_het
1.  args lnf theta sigma
2.  tempvar z s
3.  quietly g double `s'=exp(`sigma')
4.  quietly g double `z'=theta/`s'
5.  quietly replace `lnf'=ln(normal(`z')) if $ML_y1==1
6.  quietly replace `lnf'=ln(1-normal(`z')) if $ML_y1==0
7.  end

.
end of do-file

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

. ml max

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

                                Number of obs   =       400
                                Wald chi2(2)      =       72.97
                                Prob > chi2       =       0.0000

Log likelihood = -223.05935

```

	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

LR-test

```

. est store hetprob

. lrtest hetprob probit

Likelihood-ratio test          LR chi2(1) =       9.78
(Assumption: probit nested in hetprob) Prob > chi2 =       0.0018
]

```

Since P-value of LR-test is less than 0.05, the null hypothesis of no heteroskedasticity is rejected. Thus, there is significant heteroskedasticity.

Wald test and LM test cannot perform because it need restricted and unrestricted model to perform and can lead to overstate or understate the value leading to false information.

e) Since MLE is in asymptotic property, T-test cannot be performed in asymptotic property. However, Z_ test is also individual test that is in asymptotic property. R-square cannot be explained. Logit should be employed as there is no heteroskedasticity.

4a)Unrestricted

```
. gmm (dr-{alpha}) ((dr-{alpha})*r) ((dr-{alpha})^2-{sigma2}) (((dr-{alpha})^2-{s
> igma2})*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) = .00001195
 Iteration 1: GMM criterion Q(b) = 4.124e-08
 Iteration 2: GMM criterion Q(b) = 4.124e-08

Step 2
 Iteration 0: GMM criterion Q(b) = .00772783
 Iteration 1: GMM criterion Q(b) = .00546904
 Iteration 2: GMM criterion Q(b) = .00546904

GMM estimation

Number of parameters = 2
 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	-.0008144	.0006886	-1.18	0.237	-.0021641	.0005353
/sigma2	.0004396	.000293	1.50	0.134	-.0001347	.0010139

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

Merton

```
. gmm (dr-{alpha}) ((dr-{alpha})*r) ((dr-{alpha})^2-{sigma2}) (((dr-{alpha})^2-{
> igma2})*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) = .00001195
 Iteration 1: GMM criterion Q(b) = 4.124e-08
 Iteration 2: GMM criterion Q(b) = 4.124e-08

Step 2
 Iteration 0: GMM criterion Q(b) = .00772783
 Iteration 1: GMM criterion Q(b) = .00546904
 Iteration 2: GMM criterion Q(b) = .00546904

GMM estimation

Number of parameters = 2
 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	-.0008144	.0006886	-1.18	0.237	-.0021641	.0005353
/sigma2	.0004396	.000293	1.50	0.134	-.0001347	.0010139

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

4a) continued

```
. gmm (dr-(alpha)-(beta)*r) ((dr-(alpha)-(beta)*r)*r) ((dr-(alpha)-(beta)*r)^2-(s
> igma2)) (((dr-(alpha)-(beta)*r)^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) = .00001195
Iteration 1: GMM criterion Q(b) = 3.109e-10
Iteration 2: GMM criterion Q(b) = 3.044e-10
```

Step 2

```
Iteration 0: GMM criterion Q(b) = .00057191
Iteration 1: GMM criterion Q(b) = .00019007
Iteration 2: GMM criterion Q(b) = .00019007
```

GMM estimation

```
Number of parameters = 3
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	-.0027001	.0009815	-2.75	0.006	-.0046239	-.0007763
/beta	.0005339	.0002002	2.67	0.008	.0001415	.0009263
/sigma2	.0005981	.0003003	1.99	0.046	9.57e-06	.0011867

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

```
. est table Unrestricted Merton Vasicek, star(0.1 0.05 0.01) stat(N J)
```

Variable	Unrestricted	Merton	Vasicek
alpha			
_cons	-.00238571**	-.00270009***	-.00270009***
beta			
_cons	.00043061	.00053387***	.00053387***
sigma2			
_cons	.00051631	.00059814**	.00059814**
gamma			
_cons	.09323815		
Statistics			
N	1325	1325	1325
J	4.211e-13	.25183811	.25183811

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

4b) It shows that Vasicek is the most appropriated model

```
. est restore Unrestricted
(results Unrestricted are active now)

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

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

      chi2( 2) =    7.78
      Prob > chi2 =   0.0205

. test (_b[/gamma]=0)

( 1) [gamma]_cons = 0

      chi2( 1) =    0.27
      Prob > chi2 =   0.6046
```

4c)

```
. use "C:\Users\Kang\Desktop\Midterm_q4-2_11.dta", clear

. reg y x1 x2 x3 x4
```

Source	SS	df	MS	Number of obs	=	500
Model	416867.998	4	104217	F(4, 495)	=	582.05
Residual	88629.8984	495	179.0503	Prob > F	=	0.0000
				R-squared	=	0.8247
				Adj R-squared	=	0.8233
Total	505497.897	499	1013.02184	Root MSE	=	13.381

y	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
x1	6.212286	.2015534	30.82	0.000	5.816281 6.608292
x2	4.914554	.1521558	32.30	0.000	4.615603 5.213505
x3	.9684556	.2069925	4.68	0.000	.5617633 1.375148
x4	1.429656	.1195946	11.95	0.000	1.19468 1.664631
_cons	-84.91347	3.676847	-23.09	0.000	-92.13762 -77.68932

4d)

```
. ivregress gmm y ( x1 x2= z1 z2 z3)

Instrumental variables (GMM) regression      Number of obs =    500
                                             Wald chi2(2)    =    69.80
                                             Prob > chi2     =    0.0000
                                             R-squared      =    0.5304
GMM weight matrix: Robust                  Root MSE       =    21.789
```


y	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
x1	3.521234	1.028146	3.42	0.001	1.506105 5.536363
x2	1.707304	.5593749	3.05	0.002	.6109494 2.803659
_cons	12.41304	8.388241	1.48	0.139	-4.027613 28.85369


```
Instrumented:  x1 x2
Instruments:  z1 z2 z3

. estat overid

Test of overidentifying restriction:

Hansen's J chi2(1) = .042568 (p = 0.8365)
```

```
. estat endogenous x1 x2
Test of endogeneity (orthogonality conditions)
Ho: variables are exogenous

GMM C statistic chi2(2) = 151.695 (p = 0.0000)
. ivregress 2sls y ( x1 x2= z1 z2 z3)
Instrumental variables (2SLS) regression
Number of obs = 500
Wald chi2(2) = 62.10
Prob > chi2 = 0.0000
R-squared = 0.5305
Root MSE = 21.786
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	3.523496	1.034645	3.41	0.001	1.495629 5.551363
x2	1.70739	.5619438	3.04	0.002	.6060009 2.80878
_cons	12.37913	8.954064	1.38	0.167	-5.170516 29.92877

```
Instrumented: x1 x2
Instruments: z1 z2 z3
```

By performing estat endogeneous x1 x2, it show that GMM is appropriated.

```
. estat overid
Tests of overidentifying restrictions:

Sargan (score) chi2(1) = .035736 (p = 0.8501)
Basman chi2(1) = .035452 (p = 0.8507)
. estat endogenous x1 x2
Tests of endogeneity
Ho: variables are exogenous

Durbin (score) chi2(2) = 347.458 (p = 0.0000)
Wu-Hausman F(2,495) = 563.753 (p = 0.0000)
```

4e) The difference are caused by different in algorithm

5a)

```
. probit y x1 x2 x3

Iteration 0: log likelihood = -124.34324
Iteration 1: log likelihood = -113.5821
Iteration 2: log likelihood = -113.41374
Iteration 3: log likelihood = -113.41352
Iteration 4: log likelihood = -113.41352

Probit regression                               Number of obs   =       215
                                                LR chi2(3)      =       21.86
                                                Prob > chi2     =       0.0001
Log likelihood = -113.41352                    Pseudo R2      =       0.0879
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.0045138	.001445	3.12	0.002	.0016816	.0073459
x2	.0101606	.0082363	1.23	0.217	-.0059823	.0263035
x3	.1122651	.0428473	2.62	0.009	.028286	.1962442
_cons	.271165	.11951	2.27	0.023	.0369297	.5054003

```
. fitstat

Measures of Fit for probit of y

Log-Lik Intercept Only:   -124.343   Log-Lik Full Model:   -113.414
D(211):                   226.827   LR(3):                21.859
                                                Prob > LR:            0.000
McFadden's R2:           0.088   McFadden's Adj R2:   0.056
Maximum Likelihood R2:   0.097   Cragg & Uhler's R2:  0.141
McKelvey and Zavoina's R2: 0.201   Efron's R2:          0.089
Variance of y*:         1.251   Variance of error:   1.000
Count R2:                0.735   Adj Count R2:        0.000
AIC:                     1.092   AIC*n:               234.827
BIC:                     -906.378  BIC':                -5.748
```

```
. logit y x1 x2 x3

Iteration 0: log likelihood = -124.34324
Iteration 1: log likelihood = -114.03003
Iteration 2: log likelihood = -113.47048
Iteration 3: log likelihood = -113.46844
Iteration 4: log likelihood = -113.46844

Logistic regression                               Number of obs   =       215
                                                LR chi2(3)      =       21.75
                                                Prob > chi2     =       0.0001
Log likelihood = -113.46844                    Pseudo R2      =       0.0875
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.007771	.0026	2.99	0.003	.002675	.012867
x2	.0193635	.0155287	1.25	0.212	-.0110723	.0497992
x3	.2015612	.080263	2.51	0.012	.0442487	.3588738
_cons	.4289595	.1939562	2.21	0.027	.0488124	.8091067

```
. fitstat

Measures of Fit for logit of y

Log-Lik Intercept Only:   -124.343   Log-Lik Full Model:   -113.468
D(211):                   226.937   LR(3):                21.750
                                                Prob > LR:            0.000
McFadden's R2:           0.087   McFadden's Adj R2:   0.055
Maximum Likelihood R2:   0.096   Cragg & Uhler's R2:  0.140
McKelvey and Zavoina's R2: 0.191   Efron's R2:          0.089
Variance of y*:         4.065   Variance of error:   3.290
Count R2:                0.735   Adj Count R2:        0.000
AIC:                     1.093   AIC*n:               234.937
BIC:                     -906.268  BIC':                -5.638
```

```
. est store logit
```


5c) continued

. logit y, nolog

```

Logistic regression                Number of obs   =      215
                                   LR chi2(0)         =      0.00
                                   Prob > chi2         =      .
Log likelihood = -124.34324        Pseudo R2      =      0.0000
    
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_cons	1.019544	.1545088	6.60	0.000	.7167121 1.322375

LR-test = 2(lur - lr) = 2(-113.46844 - (-124.34324)) = 21.7496

Wald test

. test x1 x2 x3

```

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

```

      chi2( 3) =    16.36
      Prob > chi2 =    0.0010
    
```

. logit y x1 x2 x3

```

Iteration 0:  log likelihood = -124.34324
Iteration 1:  log likelihood = -114.03003
Iteration 2:  log likelihood = -113.47048
Iteration 3:  log likelihood = -113.46844
Iteration 4:  log likelihood = -113.46844
    
```

```

Logistic regression                Number of obs   =      215
                                   LR chi2(3)         =      21.75
                                   Prob > chi2         =      0.0001
Log likelihood = -113.46844        Pseudo R2      =      0.0875
    
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x1	.007771	.0026	2.99	0.003	.002675 .012867
x2	.0193635	.0155287	1.25	0.212	-.0110723 .0497992
x3	.2015612	.080263	2.51	0.012	.0442487 .3588738
_cons	.4289595	.1939562	2.21	0.027	.0488124 .8091067

. logit y x3

```

Iteration 0:  log likelihood = -124.34324
Iteration 1:  log likelihood = -119.41824
Iteration 2:  log likelihood = -119.26489
Iteration 3:  log likelihood = -119.26485
Iteration 4:  log likelihood = -119.26485
    
```

```

Logistic regression                Number of obs   =      215
                                   LR chi2(1)         =     10.16
                                   Prob > chi2         =      0.0014
Log likelihood = -119.26485        Pseudo R2      =      0.0408
    
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
x3	.2119727	.0753373	2.81	0.005	.0643142 .3596311
_cons	.7572483	.1716128	4.41	0.000	.4208933 1.093603

5c) continued

$$LR\text{-test} = 2(\ln L - \ln R) = 2(-113.46844 - (-119.26485)) = 23.18564$$

5d) Counted R-square is to determine the chance of the getting actual and predicted are the same and it helps to clarified how much it is explained via the chance of getting both correct. When the probability change, counted r-square will also change because the sensitivity and specificity.

6)

```
. 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

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 het

. 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 pgl

. local df=e(N_g)-1

. lrtest het, df(`df')

Likelihood-ratio test          LR chi2(99) = 92.56
(Assumption: pgl nested in het) Prob > chi2 = 0.6629
```

6a) continued

With LR-chi2 test = 92.56 with p-value of 0.6629>0.05, the null hypothesis of no heteroscedasticity is failed to reject, thus, there is no significant heteroscedasticity problem.

6b)PGLS

. 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

FE

. xtreg y x1 x2 x3, fe

Fixed-effects (within) regression	Number of obs	=	1,200
Group variable: id	Number of groups	=	100
R-sq:	Obs per group:		
within = 0.9502	min =		12
between = 0.9848	avg =		12.0
overall = 0.8846	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 Prob > F = 0.0000

. est store fixed

6b) continued

RE

. xtreg y x1 x2 x3, re

```

Random-effects GLS regression           Number of obs   =    1,200
Group variable: id                     Number of groups =     100

R-sq:                                   Obs per group:
    within = 0.8956                      min           =     12
    between = 0.9953                      avg           =    12.0
    overall = 0.9543                      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 random fixed

	Coefficients		(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
	(b) random	(B) fixed		
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
    
```

According to the fixed effects test, there is the significant fixed effects. According to the significant Hausman test (chi2=1451.21 with p-value of 0.0000<0.05), the null hypothesis of the test is rejected, thus, the fixed effects model is more appropriated than random effects model.

6c) The different between FE estimation method and first difference estimation method is that first difference uses first order conditions to difference-out the unobserved fixed effects while FE use different method ang that lead to different value when $t > 2$ Moreover, FE can do both balanced and unbalanced panels while first different can only find balanced panels. The different between FE estimation method and RE estimation method is that FE has latent variables while RE has error component in model. Hence, RE does not have difference-out everything due to partially correlated of 2 variables while FE has to difference all out to get the latent correlated variables.

6d)

Overall R-square is to weighted- average r-square of both r-square(within and between)

6d) continued

Within r-square is the amount variation of the dependent variable

Between r-square is the amount of variation between variables

$$R^2 = \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2} \quad \text{within-} R^2 = \left(\frac{\sum (Y_{it} - \bar{Y}_i) - (\bar{Y}_{it} - \bar{Y}_i)^2}{\sum ((Y_{it} - \bar{Y}) - (\bar{Y}_{it} - \bar{Y}_i))^2} \right)$$
$$\text{Between } R^2 = \frac{\sum (\hat{Y}_i - \bar{Y})^2}{\sum (Y_i - \bar{Y})^2}$$