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Assignment 4

From the data set `assign4.dta`:

The study on bankruptcy firm employs the following regression model.

$$z_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} \tag{1}$$

The log-likelihood function of this model is as follows:

$$\ln L = \begin{cases} \ln \Phi(z_i) \text{ if } y_i = 1 \\ \ln \Phi(-z_i) \text{ if } y_i = 0 \end{cases} \tag{2}$$

where: y_i = 1 for bankruptcy firm and 0 otherwise.

x_{1i} = Debt coverage ratio of firm i

x_{2i} = Liquidity ratio of firm i

x_{3i} = Profitability index of firm i

x_{4i} = Solidity ratio of firm i

Let $\Phi(.)$ = Logistic probability distribution function. $\Phi(z_i) = \dfrac{1}{1+e^{-z_i}}$

From the given data set (`assig8-2.dta`):

a. Estimate the above models using MLE with Newton-Ralphson algorithm.

b. Perform hypothesis testing whether $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ using LR-test and Wald test.

c. Estimate the above models using MLE with BHHH algorithm, make comparison of the estimated result with the result from (1), and give explanation why are they different?

Let $\Phi(.)$ = Cumulation standard normal probability distribution function and

$$z_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} \tag{3}$$

d. Estimate the models using MLE with Newton-Ralphson algorithm.

Assume that there exists heteroskedasticity in the model as: $\sigma_i^2 = \exp(\gamma x_{4i})^2$, then,

$\Phi(.)$ = Cumulation standard normal probability distribution function $\Phi\ z_i/\exp(\gamma x_{4i})$

e. Estimate the models with heteroskedasticity using MLE with Newton-Ralphson algorithm. Perform LR-test whether there exists significant heteroskedasticity.

Assignment 4

From the data set `assign4.dta`:

The study on bankruptcy firm employs the following regression model.

$$z_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} \quad (1)$$

The log-likelihood function of this model is as follows:

$$\ln L = \begin{cases} \ln \Phi(z_i) \text{ if } y_i = 1 \\ \ln \Phi(-z_i) \text{ if } y_i = 0 \end{cases} \quad (2)$$

where: y_i = 1 for bankruptcy firm and 0 otherwise.
x_{1i} = Debt coverage ratio of firm i
x_{2i} = Liquidity ratio of firm i
x_{3i} = Profitability index of firm i
x_{4i} = Solidity ratio of firm i

Let $\Phi(.)$ = Logistic probability distribution function. $\Phi(z_i) = \frac{1}{1+e^{-z_i}}$

From the given data set (`assig8-2.dta`):

a. Estimate the above models using MLE with Newton-Ralphson algorithm.

The model above is estimated by using "Maximum Likelihood Estimation" technique altogether with Newton-Ralphson algorithm, the results are as follow.

```
2 . 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
```

First create the program for this distribution.

```
3 . ml model lf ml_logit (y=x1 x2 x3 x4)

4 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -86.130008
rescale:       log likelihood = -86.130008
Iteration 0:   log likelihood = -86.130008
Iteration 1:   log likelihood = -66.355929
Iteration 2:   log likelihood = -63.355207
Iteration 3:   log likelihood = -57.727585
Iteration 4:   log likelihood =  -55.02581
Iteration 5:   log likelihood = -54.628361
Iteration 6:   log likelihood = -54.627603
Iteration 7:   log likelihood = -54.627603

                                                Number of obs     =        130
                                                Wald chi2(4)      =      22.79
Log likelihood = -54.627603                     Prob > chi2       =     0.0001
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.4835128	.1686119	2.87	0.004	.1530396	.8139859
x2	1.454009	.5001373	2.91	0.004	.4737577	2.43426
x3	2.173186	.7757021	2.80	0.005	.652838	3.693535
x4	1.855464	.7138855	2.60	0.009	.4562739	3.254653
_cons	-1.400447	.5531237	-2.53	0.011	-2.484549	-.316344

$$\hat{z}_i = \underset{(0.55)}{-1.40} + \underset{(0.17)}{0.48X_{1i}} + \underset{(0.50)}{1.45X_{2i}} + \underset{(0.78)}{2.17X_{3i}} + \underset{(0.71)}{1.86X_{4i}}$$

b. Perform hypothesis testing whether $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ using LR-test and Wald test.

Then, I have performed the overall test, firstly, by using Wald test.

```
5 . test x1=x2=x3=x4=0

 ( 1)  [eq1]x1 - [eq1]x2 = 0
 ( 2)  [eq1]x1 - [eq1]x3 = 0
 ( 3)  [eq1]x1 - [eq1]x4 = 0
 ( 4)  [eq1]x1 = 0

           chi2(  4) =   22.79
         Prob > chi2 =    0.0001
```

with the p-value = 0.0001, the null hypothesis is rejected at any reasonable levels. Thus, all explanatory variables are all jointly significant.

Next, by using LR test, the results are provided.

```
3 . ml model lf ml_logit (y=x1 x2 x3 x4)

4 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -86.130008
rescale:       log likelihood = -86.130008
Iteration 0:   log likelihood = -86.130008
Iteration 1:   log likelihood = -66.355929
Iteration 2:   log likelihood = -63.355207
Iteration 3:   log likelihood = -57.727585
Iteration 4:   log likelihood =  -55.02581
Iteration 5:   log likelihood = -54.628361
Iteration 6:   log likelihood = -54.627603
Iteration 7:   log likelihood = -54.627603

                                                Number of obs     =        130
                                                Wald chi2(4)      =      22.79
Log likelihood = -54.627603                     Prob > chi2       =     0.0001
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.4835128	.1686119	2.87	0.004	.1530396	.8139859
x2	1.454009	.5001373	2.91	0.004	.4737577	2.43426
x3	2.173186	.7757021	2.80	0.005	.652838	3.693535
x4	1.855464	.7138855	2.60	0.009	.4562739	3.254653
_cons	-1.400447	.5531237	-2.53	0.011	-2.484549	-.316344

Unrestricted Model

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

8 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -86.130008
rescale:       log likelihood = -86.130008
Iteration 0:   log likelihood = -86.130008
Iteration 1:   log likelihood = -86.129902
Iteration 2:   log likelihood = -86.129902

                                                Number of obs     =        130
                                                Wald chi2(0)      =          .
Log likelihood = -86.129902                     Prob > chi2       =          .
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.5026289	.1809802	2.78	0.005	.1479141	.8573436

```
9 . est store res
```

Restricted Model

```
10 . lrtest unres res

Likelihood-ratio test                                 LR chi2(4)  =     63.00
(Assumption: res nested in unres)                     Prob > chi2 =    0.0000
```

The result reveals p-value = 0.00 meaning that all regressors are jointly significant at any reasonable levels.

c. Estimate the above models using MLE with BHHH algorithm, make comparison of the estimated result with the result from (1), and give explanation why are they different?

So, I run the model with BHHH algorithm instead of Newton-Ralphson algorithm. The results are as follow.

```
11 . ml model lf ml_logit (y=x1 x2 x3 x4), tech(bhhh)

12 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -86.130008
rescale:       log likelihood = -86.130008
Iteration 0:   log likelihood = -86.130008
Iteration 1:   log likelihood = -64.805009
Iteration 2:   log likelihood = -58.076419
Iteration 3:   log likelihood = -55.104476
Iteration 4:   log likelihood = -54.737891
Iteration 5:   log likelihood = -54.673222
Iteration 6:   log likelihood = -54.653417
Iteration 7:   log likelihood = -54.641919
Iteration 8:   log likelihood = -54.636424
Iteration 9:   log likelihood = -54.632812
Iteration 10:  log likelihood = -54.630848
Iteration 11:  log likelihood = -54.629561
Iteration 12:  log likelihood = -54.628821
Iteration 13:  log likelihood = -54.628345
Iteration 14:  log likelihood = -54.628063
Iteration 15:  log likelihood = -54.627885
Iteration 16:  log likelihood = -54.627777
Iteration 17:  log likelihood =  -54.62771
Iteration 18:  log likelihood = -54.627669
Iteration 19:  log likelihood = -54.627644
Iteration 20:  log likelihood = -54.627628
Iteration 21:  log likelihood = -54.627618
Iteration 22:  log likelihood = -54.627612
Iteration 23:  log likelihood = -54.627609
Iteration 24:  log likelihood = -54.627607
Iteration 25:  log likelihood = -54.627605

                                                Number of obs     =        130
                                                Wald chi2(4)      =      16.34
Log likelihood = -54.627605                     Prob > chi2       =     0.0026
```

y	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.4833318	.1542635	3.13	0.002	.180981	.7856827
x2	1.453275	.597925	2.43	0.015	.2813639	2.625187
x3	2.172641	.8589781	2.53	0.011	.489075	3.856207
x4	1.854961	.7142729	2.60	0.009	.4550117	3.25491
_cons	-1.400063	.5625155	-2.49	0.013	-2.502573	-.2975527

BHHH Algorithm

```
3 . ml model lf ml_logit (y=x1 x2 x3 x4)

4 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -86.130008
rescale:       log likelihood = -86.130008
Iteration 0:   log likelihood = -86.130008
Iteration 1:   log likelihood = -66.355929
Iteration 2:   log likelihood = -63.355207
Iteration 3:   log likelihood = -57.727585
Iteration 4:   log likelihood =  -55.02581
Iteration 5:   log likelihood = -54.628361
Iteration 6:   log likelihood = -54.627603
Iteration 7:   log likelihood = -54.627603

                                                Number of obs     =        130
                                                Wald chi2(4)      =      22.79
Log likelihood = -54.627603                     Prob > chi2       =     0.0001
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.4835128	.1686119	2.87	0.004	.1530396	.8139859
x2	1.454009	.5001373	2.91	0.004	.4737577	2.43426
x3	2.173186	.7757021	2.80	0.005	.652838	3.693535
x4	1.855464	.7138855	2.60	0.009	.4562739	3.254653
_cons	-1.400447	.5531237	-2.53	0.011	-2.484549	-.316344

Newton-Ralphson Algorithm

With different algorithms, it is cleary that the results are not the same. To magnify the cause, firstly, the objective of Maximum Likelihood Estimation (MLE) is to maximize the log-likelihood function. By the first order condition, we have that $\frac{\partial l(\theta)}{\partial \theta} = 0$ where $\frac{\partial l(\theta)}{\partial \theta}$ is called "Gradient Matrix" $(G(\theta))$. However, the gradient matrix is a nonlinear function. Thus, we have to do the "Linear approximation" with the result $G(\theta) \cong G(\theta_0) + \left.\frac{\partial G(\theta)}{\partial \theta}\right|_{\theta=\theta_0}(\theta-\theta_0) = 0$, where $\left.\frac{\partial G(\theta)}{\partial \theta}\right|_{\theta=\theta_0}$ is called "Hessian Matrix" $(H(\theta_0))$. After we have simplified and rearraged the terms, we would get $\boxed{\hat{\theta} = \theta_0 - H(\theta_0)^{-1}G(\theta_0)}$. The thing is MLE is an iterative process. It keeps repeating until the last term is equal to zero; the last term here varies due to the algorithm used. For example, if we use the Newton-Ralphson algorithm, the last term that needs to be zero (or convergence value) is $H(\theta_0)^{-1}G(\theta_0)$ as written above. On the other hand, if the algorithm in question is BHHH, then it will be $(GG')^{-1}G(\theta_0)$. Hence, this is the reason why the result changes when we use different algorithm.

Let $\Phi(.)$ = Cumulation standard normal probability distribution function and

$$z_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} \qquad (3)$$

d. Estimate the models using MLE with Newton-Ralphson algorithm.

Now, the distribution changes. So, we have to create another program.

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

Next, we can run the model using MLE with Newton-Ralphson algorithm. The result is provided below.

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

10 . ml maximize

   initial:       log likelihood = -90.109133
   alternative:   log likelihood = -87.504336
   rescale:       log likelihood = -86.291737
   Iteration 0:   log likelihood = -86.291737
   Iteration 1:   log likelihood = -78.555778
   Iteration 2:   log likelihood = -65.283096
   Iteration 3:   log likelihood = -60.750303
   Iteration 4:   log likelihood = -60.695527
   Iteration 5:   log likelihood = -60.695503
   Iteration 6:   log likelihood = -60.695503

                                                   Number of obs     =        130
                                                   Wald chi2(2)      =      22.61
   Log likelihood = -60.695503                     Prob > chi2       =     0.0000
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.3592444	.0871351	4.12	0.000	.1884627	.5300262
x2	1.139607	.3224845	3.53	0.000	.5075491	1.771665
_cons	-.7729211	.2765064	-2.80	0.005	-1.314864	-.2309785

$$\hat{z}_i = \underset{(0.28)}{-0.77} + \underset{(0.09)}{0.36}X_{1i} + \underset{(0.32)}{1.14}X_{2i}$$

Assume that there exists heteroskedasticity in the model as: $\sigma_i^2 = \exp(\gamma x_{4i})^2$, then,

$\Phi(.)$ = Cumulation standard normal probability distribution function $\Phi\ z_i/\exp(\gamma x_{4i})$

e. Estimate the models with heteroskedasticity using MLE with Newton-Ralphson algorithm. Perform LR-test whether there exists significant heteroskedasticity.

Starting with the new program,

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

8 . quietly replace `lnf'=ln(1-normal(`z')) if $ML_y1==0
  7.
9 . end
```

Then estimate the model using MLE with Newton-Ralphson algorithm.

```
10 . ml model lf ml_probit_het (y= x1 x2) (x4, noconstant)

11 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -83.932039
rescale:       log likelihood = -83.932039
rescale eq:    log likelihood =  -70.42663
Iteration 0:   log likelihood =  -70.42663
Iteration 1:   log likelihood = -69.416378
Iteration 2:   log likelihood = -67.899365
Iteration 3:   log likelihood = -64.594892
Iteration 4:   log likelihood =  -62.95563
Iteration 5:   log likelihood = -61.165879
Iteration 6:   log likelihood = -59.528663
Iteration 7:   log likelihood = -59.423117
Iteration 8:   log likelihood = -59.404566
Iteration 9:   log likelihood = -59.404451
Iteration 10:  log likelihood = -59.404451

                                                Number of obs     =        130
                                                Wald chi2(2)      =      16.42
Log likelihood = -59.404451                     Prob > chi2       =     0.0003
```

Variance Regression

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eq1						
x1	.2921402	.0773776	3.78	0.000	.140483	.4437975
x2	.9417318	.2800571	3.36	0.001	.3928301	1.490634
_cons	-.6388431	.2144267	-2.98	0.003	-1.059112	-.2185745
eq2						
x4	1.183929	.5851992	2.02	0.043	.0369597	2.330899

The estimated result is

$$\hat{z}_i = \underset{(0.21)}{-0.64} + \underset{(0.08)}{0.29}\, x_{1i} + \underset{(0.28)}{0.94}\, x_{2i}$$

Then perform the LR test. The result shows p-value = 0 ; thus, the null hypothesis is rejected.

There exists heteroskedasticity.

```
12 . est store unres

13 . ml model lf ml_probit_het (y=) (x4, noconstant)

14 . ml maximize

   initial:       log likelihood = -90.109133
   alternative:   log likelihood = -83.932039
   rescale:       log likelihood = -83.932039
   rescale eq:    log likelihood =  -70.42663
   Iteration 0:   log likelihood =  -70.42663
   Iteration 1:   log likelihood = -69.976275
   Iteration 2:   log likelihood = -69.973883
   Iteration 3:   log likelihood = -69.973882

                                                Number of obs     =        130
                                                Wald chi2(0)      =          .
   Log likelihood = -69.973882                  Prob > chi2       =          .
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eq1						
_cons	.6158099	.2005698	3.07	0.002	.2227003	1.008919
eq2						
x4	-8.17863	3.212406	-2.55	0.011	-14.47483	-1.882429

```
15 . est store res

16 . lrtest unres res

   Likelihood-ratio test                                  LR chi2(2)  =      21.14
   (Assumption: res nested in unres)                      Prob > chi2 =     0.0000
```

```
  ___  ____  ____  ____  ____(R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/
  Statistics/Data Analysis
```

```
                                              Number of obs     =        130
      name:  <unnamed>
       log:  C:\Users\Chaiyapong M\Desktop\BE\EE426\Assignment 4\Assignment 4_1.smcl
  log type:  smcl
 opened on:  16 Feb 2021, 21:44:59

1 . do "C:\Users\Chaiyapong M\Desktop\BE\EE426\Assignment 4\Assignment 4_1.do"
```

(a)

```
2 . 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

3 . ml model lf ml_logit (y=x1 x2 x3 x4)

4 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -86.130008
rescale:       log likelihood = -86.130008
Iteration 0:   log likelihood = -86.130008
Iteration 1:   log likelihood = -66.355929
Iteration 2:   log likelihood = -63.355207
Iteration 3:   log likelihood = -57.727585
Iteration 4:   log likelihood =  -55.02581
Iteration 5:   log likelihood = -54.628361
Iteration 6:   log likelihood = -54.627603
Iteration 7:   log likelihood = -54.627603

                                                Number of obs     =        130
                                                Wald chi2(4)      =      22.79
Log likelihood = -54.627603                     Prob > chi2       =     0.0001
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.4835128	.1686119	2.87	0.004	.1530396	.8139859
x2	1.454009	.5001373	2.91	0.004	.4737577	2.43426
x3	2.173186	.7757021	2.80	0.005	.652838	3.693535
x4	1.855464	.7138855	2.60	0.009	.4562739	3.254653
_cons	-1.400447	.5531237	-2.53	0.011	-2.484549	-.316344

(b)


```
5 . test x1=x2=x3=x4=0

 ( 1)  [eq1]x1 - [eq1]x2 = 0
 ( 2)  [eq1]x1 - [eq1]x3 = 0
 ( 3)  [eq1]x1 - [eq1]x4 = 0
 ( 4)  [eq1]x1 = 0

           chi2(  4) =   22.79
         Prob > chi2 =    0.0001

6 . est store unres

7 . ml model lf ml_logit (y=)

8 . ml maximize

initial:       log likelihood = -90.109133
alternative:   log likelihood = -86.130008
rescale:       log likelihood = -86.130008
Iteration 0:   log likelihood = -86.130008
Iteration 1:   log likelihood = -86.129902
Iteration 2:   log likelihood = -86.129902

                                                Number of obs     =        130
                                                Wald chi2(0)      =          .
Log likelihood = -86.129902                     Prob > chi2       =          .
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.5026289	.1809802	2.78	0.005	.1479141	.8573436

```
9 . est store res
```

```
10 . lrtest unres res

   Likelihood-ratio test                             LR chi2(4)  =     63.00
   (Assumption: res nested in unres)                 Prob > chi2 =    0.0000
```

(c)

```
11 . ml model lf ml_logit (y=x1 x2 x3 x4), tech(bhhh)

12 . ml maximize

   initial:       log likelihood = -90.109133
   alternative:   log likelihood = -86.130008
   rescale:       log likelihood = -86.130008
   Iteration 0:   log likelihood = -86.130008
   Iteration 1:   log likelihood = -64.805009
   Iteration 2:   log likelihood = -58.076419
   Iteration 3:   log likelihood = -55.104476
   Iteration 4:   log likelihood = -54.737891
   Iteration 5:   log likelihood = -54.673222
   Iteration 6:   log likelihood = -54.653417
   Iteration 7:   log likelihood = -54.641919
   Iteration 8:   log likelihood = -54.636424
   Iteration 9:   log likelihood = -54.632812
   Iteration 10:  log likelihood = -54.630848
   Iteration 11:  log likelihood = -54.629561
   Iteration 12:  log likelihood = -54.628821
   Iteration 13:  log likelihood = -54.628345
   Iteration 14:  log likelihood = -54.628063
   Iteration 15:  log likelihood = -54.627885
   Iteration 16:  log likelihood = -54.627777
   Iteration 17:  log likelihood =  -54.62771
   Iteration 18:  log likelihood = -54.627669
   Iteration 19:  log likelihood = -54.627644
   Iteration 20:  log likelihood = -54.627628
   Iteration 21:  log likelihood = -54.627618
   Iteration 22:  log likelihood = -54.627612
   Iteration 23:  log likelihood = -54.627609
   Iteration 24:  log likelihood = -54.627607
   Iteration 25:  log likelihood = -54.627605

                                                Number of obs     =        130
                                                Wald chi2(4)      =      16.34
   Log likelihood = -54.627605                  Prob > chi2       =     0.0026
```

y	Coef.	OPG Std. Err.	z	P>|z|	[95% Conf.	Interval]
x1	.4833318	.1542635	3.13	0.002	.180981	.7856827
x2	1.453275	.597925	2.43	0.015	.2813639	2.625187
x3	2.172641	.8589781	2.53	0.011	.489075	3.856207
x4	1.854961	.7142729	2.60	0.009	.4550117	3.25491
_cons	-1.400063	.5625155	-2.49	0.013	-2.502573	-.2975527

```
13 .
   end of do-file

14 . log close
        name:  <unnamed>
         log:  C:\Users\Chaiyapong M\Desktop\BE\EE426\Assignment 4\Assignment 4_1.smcl
    log type:  smcl
   closed on:  16 Feb 2021, 21:46:23
```

```
                                                   ___  ____  ____  ____  ____(R)
                                                  /__    /   ____/   /   ____/
                                                 ___/   /   /___/   /   /___/
                                                   Statistics/Data Analysis

  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
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Notes:
      1.  Unicode is supported; see help unicode_advice.
      2.  More than 2 billion observations are allowed; see help obs_advice.
      3.  Maximum number of variables is set to 5000; see help set_maxvar.
      4.  New update available; type -update all-

1 . use "C:\Users\Chaiyapong M\Desktop\BE\EE426\Assignment 4\assign4.dta"
```

(d)

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

```
  8 . end

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

 10 . ml maximize

    initial:       log likelihood = -90.109133
    alternative:   log likelihood = -87.504336
    rescale:       log likelihood = -86.291737
    Iteration 0:   log likelihood = -86.291737
    Iteration 1:   log likelihood = -78.555778
    Iteration 2:   log likelihood = -65.283096
    Iteration 3:   log likelihood = -60.750303
    Iteration 4:   log likelihood = -60.695527
    Iteration 5:   log likelihood = -60.695503
    Iteration 6:   log likelihood = -60.695503

                                                    Number of obs     =        130
                                                    Wald chi2(2)      =      22.61
    Log likelihood = -60.695503                     Prob > chi2       =     0.0000

    ------------------------------------------------------------------------------
               y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
    -------------+----------------------------------------------------------------
              x1 |   .3592444   .0871351     4.12   0.000     .1884627    .5300262
              x2 |   1.139607   .3224845     3.53   0.000     .5075491    1.771665
           _cons |  -.7729211   .2765064    -2.80   0.005    -1.314864   -.2309785
    ------------------------------------------------------------------------------

 11 .
```

```
                                                     ___  ____  ____  ____  ____(R)
                                                    /__    /   ____/   /   ____/
                                                   ___/   /   /___/   /   /___/
                                                     Statistics/Data Analysis
```

```
  ___  ____  ____  ____  ____ (R)
 /__    /   ____/   /   ____/
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Notes:
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      4.  New update available; type -update all-

  1 . use "C:\Users\Chaiyapong M\Desktop\BE\EE426\Assignment 4\assign4.dta"
```

(e)

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

```
 8 . quietly replace `lnf'=ln(1-normal(`z')) if $ML_y1==0
   7.
 9 . end

10 . ml model lf ml_probit_het (y= x1 x2) (x4, noconstant)

11 . ml maximize

  initial:       log likelihood = -90.109133
  alternative:   log likelihood = -83.932039
  rescale:       log likelihood = -83.932039
  rescale eq:    log likelihood =  -70.42663
  Iteration 0:   log likelihood =  -70.42663
  Iteration 1:   log likelihood = -69.416378
  Iteration 2:   log likelihood = -67.899365
  Iteration 3:   log likelihood = -64.594892
  Iteration 4:   log likelihood =  -62.95563
  Iteration 5:   log likelihood = -61.165879
  Iteration 6:   log likelihood = -59.528663
  Iteration 7:   log likelihood = -59.423117
  Iteration 8:   log likelihood = -59.404566
  Iteration 9:   log likelihood = -59.404451
  Iteration 10:  log likelihood = -59.404451

                                                Number of obs     =        130
                                                Wald chi2(2)      =      16.42
  Log likelihood = -59.404451                   Prob > chi2       =     0.0003
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eq1						
x1	.2921402	.0773776	3.78	0.000	.140483	.4437975
x2	.9417318	.2800571	3.36	0.001	.3928301	1.490634
_cons	-.6388431	.2144267	-2.98	0.003	-1.059112	-.2185745
eq2						
x4	1.183929	.5851992	2.02	0.043	.0369597	2.330899

```
12 . est store unres

13 . ml model lf ml_probit_het (y=) (x4, noconstant)

14 . ml maximize

   initial:       log likelihood = -90.109133
   alternative:   log likelihood = -83.932039
   rescale:       log likelihood = -83.932039
   rescale eq:    log likelihood =  -70.42663
   Iteration 0:   log likelihood =  -70.42663
   Iteration 1:   log likelihood = -69.976275
   Iteration 2:   log likelihood = -69.973883
   Iteration 3:   log likelihood = -69.973882

                                                   Number of obs     =        130
                                                   Wald chi2(0)      =          .
   Log likelihood = -69.973882                     Prob > chi2       =          .
```

y	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
eq1						
_cons	.6158099	.2005698	3.07	0.002	.2227003	1.008919
eq2						
x4	-8.17863	3.212406	-2.55	0.011	-14.47483	-1.882429

```
15 . est store res

16 . lrtest unres res

   Likelihood-ratio test                                LR chi2(2)  =     21.14
   (Assumption: res nested in unres)                    Prob > chi2 =    0.0000

17 .
```