

## Multinomial Logit

### Simulated Data

```

set obs 500
set seed 12345
g x1=(runiform())>0.7)
g u=rnormal(0,1)
g i2=-0.7+0.5*x1+u
g i3=-0.5-0.7*x1+u
g e2=exp(i2)
g e3=exp(i3)
g p1=1/(1+e2+e3)
g p2=e2/(1+e2+e3)
g p3=e3/(1+e2+e3)
g y=1 if p1==max(p1,p2,p3)
replace y=2 if p2==max(p1,p2,p3)
replace y=3 if p3==max(p1,p2,p3)

```

```
. mlogit y x1, nolog
```

```

Multinomial logistic regression          Number of obs   =          500
                                          LR chi2(2)      =          45.34
                                          Prob > chi2     =          0.0000
Log likelihood = -501.34448              Pseudo R2       =          0.0433

```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1		(base outcome)					
2	x1	1.050613	.2434391	4.32	0.000	.5734812	1.527745
	_cons	-1.188763	.1568918	-7.58	0.000	-1.496266	-.881261
3	x1	-.8923277	.2813813	-3.17	0.002	-1.443825	-.3408305
	_cons	-.2390744	.1142208	-2.09	0.036	-.4629431	-.0152057

```
. est store m1
```

```
. tab x1
```

x1	Freq.	Percent	Cum.
0	364	72.80	72.80
1	136	27.20	100.00
Total	500	100.00	

From the estimated result:

$$P(y = 2 | x_1 = 0) = \exp(-1.1888) = 0.3046$$

$$P(y = 2 | x_1 = 1) = \exp(-1.1888 + 1.0506) = 0.8710$$

$$rrr = \frac{P(y = 2 | x_1 = 1)}{P(y = 2 | x_1 = 0)} = \frac{0.8710}{0.3046} = 2.8594 = \exp(1.0506)$$

```
. mlogit y x1, rrr nolog
Multinomial logistic regression      Number of obs   =       500
                                     LR chi2(2)       =       45.34
                                     Prob > chi2      =       0.0000
Log likelihood = -501.34448          Pseudo R2       =       0.0433
```

	y	RRR	Std. Err.	z	P> z	[95% Conf. Interval]	
1		(base outcome)					
2							
	x1	2.859404	.6960907	4.32	0.000	1.774433	4.607774
	_cons	.3045977	.0477889	-7.58	0.000	.2239649	.4142602
3							
	x1	.409701	.1152822	-3.17	0.002	.2360233	.7111794
	_cons	.7873563	.0899325	-2.09	0.036	.6294285	.9849093

```
. margins, dydx(*) predict(outcome(1))
Average marginal effects      Number of obs   =       500
Model VCE      : OIM
Expression    : Pr(y==1), predict(outcome(1))
dy/dx w.r.t. : x1
```

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.028185	.0521529	0.54	0.589	-.0740328	.1304029

```
. margins, dydx(*) predict(outcome(2))
Average marginal effects      Number of obs   =       500
Model VCE      : OIM
Expression    : Pr(y==2), predict(outcome(2))
dy/dx w.r.t. : x1
```

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
x1	.2133354	.0317421	6.72	0.000	.1511221	.2755488

```
. margins, dydx(*) predict(outcome(3))
Average marginal effects      Number of obs   =       500
Model VCE      : OIM
Expression    : Pr(y==3), predict(outcome(3))
dy/dx w.r.t. : x1
```

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.2415204	.0502526	-4.81	0.000	-.3400137	-.1430272

```
. mlogit y x1 if y!=3, nolog
Multinomial logistic regression      Number of obs   =       343
                                     LR chi2(1)       =       18.79
                                     Prob > chi2      =       0.0000
Log likelihood = -203.49155          Pseudo R2       =       0.0441
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1		(base outcome)					
2							
	x1	1.050613	.2434391	4.32	0.000	.5734811	1.527745
	_cons	-1.188763	.1568918	-7.58	0.000	-1.496266	-.881261

```
. est store m2
```

```
. hausman m1 m2, alleqs constant
```

	---- Coefficients ----		(b-B)	sqrt(diag(V_b-V_B))
	(b)	(B)	Difference	S.E.
	m1	m2		
x1	1.050613	1.050613	1.91e-08	.000016
_cons	-1.188763	-1.188763	-1.94e-08	.000016

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

Test: Ho: difference in coefficients not systematic

$$\begin{aligned} \text{chi2(2)} &= (b-B)' [(V_b-V_B)^{-1}] (b-B) \\ &= 0.00 \\ \text{Prob>chi2} &= 1.0000 \end{aligned}$$

## Multinomial Logit & Ordered Probit Models

### Pecking Order Model

#### Objectives

To test whether pecking order holds for Thai firms after financial crisis.

The study applied:

- Multinomial Logit to measure determinants of financing choices.
- Ordered Probit Regressions to determine which financing hierarchy fits the data best.

#### Multinomial Logit Model

Dependent variable has more than two choices.

$$p_{ij} = \frac{e^{x_i' \beta_j}}{\sum_{h=1}^3 e^{x_i' \beta_h}} = \frac{e^{x_i' \beta_j}}{1 + \sum_{h=2}^3 e^{x_i' \beta_h}}$$

#### Ordered Probit Model

In case that choices are ordered, ordered probit model can be applied.

$$y_i^* = x_i' \beta + \varepsilon_i, \quad E(\varepsilon_i) = 0$$

$$y_i = 1 \quad \text{if } -\infty < y_i^* \leq c_1,$$

$$y_i = 2 \quad \text{if } c_1 < y_i^* \leq c_2,$$

$$y_i = 3 \quad \text{if } c_2 < y_i^* \leq \infty$$

where:  $c_i$  = Threshold value and  $i=1,2$

#### Data

Dependent Variables--Financing Choices (y)

1 = Internal Finance

2 = Long- term debt and bond

3 = Share issues

Independent Variables ( $x_k$ ):

$x_1$  = Liquidity

$x_2$  = Profitability

$x_3$  = Interest Payments

$x_4$  = Log of firm size

**Multinomial Logit Model**

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

```
Multinomial logistic regression      Number of obs      =      344
                                      LR chi2(8)          =     118.14
                                      Prob > chi2         =      0.0000
Log likelihood = -169.69647          Pseudo R2          =      0.2582
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1		(base outcome)					
2							
	x1	-11.38892	1.553865	-7.33	0.000	-14.43444	-8.3434
	x2	2.034482	1.693449	1.20	0.230	-1.284617	5.353581
	x3	-.4413597	.2234444	-1.98	0.048	-.8793026	-.0034168
	x4	21.82959	9.663678	2.26	0.024	2.889132	40.77005
	_cons	.9764104	.3125365	3.12	0.002	.3638501	1.588971
3							
	x1	-5.395832	2.537593	-2.13	0.033	-10.36942	-.4222399
	x2	12.5627	4.1843	3.00	0.003	4.361623	20.76378
	x3	-1.36024	.7521521	-1.81	0.071	-2.834431	.1139514
	x4	19.36181	34.27936	0.56	0.572	-47.82451	86.54814
	_cons	-2.120951	.7741203	-2.74	0.006	-3.638199	-.6037027

```
. est store m1
```

```
. fitstat
```

```
Measures of Fit for mlogit of y
```

Log-Lik Intercept Only:	-228.765	Log-Lik Full Model:	-169.696
D(329):	339.393	LR(8):	118.138
		Prob > LR:	0.000
McFadden's R2:	0.258	McFadden's Adj R2:	0.193
ML (Cox-Snell) R2:	0.291	Cragg-Uhler(Nagelkerke) R2:	0.395
Count R2:	0.826	Adj Count R2:	0.318
AIC:	1.074	AIC*n:	369.393
BIC:	-1582.178	BIC':	-71.413
BIC used by Stata:	397.799	AIC used by Stata:	359.393

```
. mlogit y x1 x2 x3 x4, rrr nolog
```

```
Multinomial logistic regression      Number of obs      =      344
                                      LR chi2(8)          =     118.14
                                      Prob > chi2         =      0.0000
Log likelihood = -169.69647          Pseudo R2          =      0.2582
```

	y	RRR	Std. Err.	z	P> z	[95% Conf. Interval]	
1		(base outcome)					
2							
	x1	.0000113	.0000176	-7.33	0.000	5.39e-07	.000238
	x2	7.648287	12.95198	1.20	0.230	.2767565	211.3638
	x3	.6431613	.1437108	-1.98	0.048	.4150723	.996589
	x4	3.02e+09	2.92e+10	2.26	0.024	17.9777	5.08e+17
	_cons	2.654909	.8297561	3.12	0.002	1.438859	4.898704
3							
	x1	.0045354	.0115091	-2.13	0.033	.0000314	.6555767
	x2	285701	1195459	3.00	0.003	78.38427	1.04e+09
	x3	.2565993	.1930017	-1.81	0.071	.058752	1.120698
	x4	2.56e+08	8.79e+09	0.56	0.572	1.70e-21	3.87e+37
	_cons	.1199176	.0928306	-2.74	0.006	.0262997	.5467833

```
. margins, dydx(*) predict(outcome(1))
```

```
Average marginal effects      Number of obs      =      344
Model VCE      : OIM
```

```
Expression      : Pr(y==1), predict(outcome(1))
dy/dx w.r.t.   : x1 x2 x3 x4
```

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
x1	1.421686	.1254557	11.33	0.000	1.175797	1.667574
x2	-.4689856	.2205597	-2.13	0.033	-.9012747	-.0366966
x3	.076435	.0300025	2.55	0.011	.0176312	.1352389
x4	-2.892204	1.321013	-2.19	0.029	-5.481341	-.3030667

```
. margins, dydx(*) predict(outcome(2))
```

```
Average marginal effects      Number of obs      =      344
Model VCE      : OIM
```

```
Expression      : Pr(y==2), predict(outcome(2))
dy/dx w.r.t.   : x1 x2 x3 x4
```

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-1.381231	.1317163	-10.49	0.000	-1.63939	-1.123072
x2	.1314409	.2051985	0.64	0.522	-.2707407	.5336224
x3	-.0420846	.0276118	-1.52	0.127	-.0962028	.0120336
x4	2.557803	1.192438	2.15	0.032	.220668	4.894938

```
. margins, dydx(*) predict(outcome(3))
```

```
Average marginal effects      Number of obs      =      344
Model VCE      : OIM
```

```
Expression      : Pr(y==3), predict(outcome(3))
dy/dx w.r.t.   : x1 x2 x3 x4
```

	dy/dx	Delta-method Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.0404542	.0544461	-0.74	0.457	-.1471667	.0662582
x2	.3375448	.1340434	2.52	0.012	.0748246	.6002649
x3	-.0343504	.0224275	-1.53	0.126	-.0783076	.0096067
x4	.3344007	.9642417	0.35	0.729	-1.555478	2.22428

## IIA Test

```
. mlogit y x1 x2 x3 x4 if y!=3, nolog
```

```
Multinomial logistic regression      Number of obs      =      333
LR chi2(4)                          =      104.30
Prob > chi2                          =      0.0000
Log likelihood = -127.92191          Pseudo R2          =      0.2896
```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1		(base outcome)					
2	x1	-11.4855	1.565894	-7.33	0.000	-14.5546	-8.416402
	x2	2.782226	1.772243	1.57	0.116	-.6913068	6.255759
	x3	-.4379965	.224883	-1.95	0.051	-.878759	.0027661
	x4	25.09059	9.9404	2.52	0.012	5.607759	44.57341
	_cons	.9849019	.3154837	3.12	0.002	.3665653	1.603239

```
. est store m2
```

```
. hausman m2 m1, alleqs constant
```

---- Coefficients ----				
	(b) m2	(B) m1	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
x1	-11.4855	-11.38892	-.096579	.1937236
x2	2.782226	2.034482	.7477443	.5225672
x3	-.4379965	-.4413597	.0033633	.0253964
x4	25.09059	21.82959	3.260992	2.329136
_cons	.9849019	.9764104	.0084915	.0430218

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

Test: Ho: difference in coefficients not systematic

$$\begin{aligned} \text{chi2}(5) &= (b-B)'[(V_b-V_B)^{-1}](b-B) \\ &= 1.18 \\ \text{Prob}>\text{chi2} &= 0.9464 \\ &(\text{V}_b-\text{V}_B \text{ is not positive definite}) \end{aligned}$$

```
. est restore m1
(results m1 are active now)
```

```
. mlogtest, iia
```

\*\*\*\* Hausman tests of IIA assumption (N=344)

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted	chi2	df	P>chi2	evidence
2	-0.416	5	---	---
3	1.185	5	0.946	for Ho

Note: If chi2<0, the estimated model does not meet asymptotic assumptions of the test.

\*\*\*\* suest-based Hausman tests of IIA assumption (N=344)

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted	chi2	df	P>chi2	evidence
2	3.918	5	0.561	for Ho
3	5.985	5	0.308	for Ho

\*\*\*\* Small-Hsiao tests of IIA assumption (N=344)

Ho: Odds(Outcome-J vs Outcome-K) are independent of other alternatives.

Omitted	lnL(full)	lnL(omit)	chi2	df	P>chi2	evidence
2	-23.257	-20.835	4.842	5	0.435	for Ho
3	-71.684	-66.675	10.019	5	0.075	for Ho

## Ordered Probit

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

```
Ordered probit regression          Number of obs   =       344
                                   LR chi2(4)         =       83.78
                                   Prob > chi2        =       0.0000
Log likelihood = -186.8747         Pseudo R2       =       0.1831
```

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



---

x2		.1007904	.0559651	1.80	0.072	-.0088991	.2104798
x3		-.0188348	.0081533	-2.31	0.021	-.034815	-.0028546
x4		.6079268	.3066529	1.98	0.047	.0068981	1.208956

---

```
. predict one two three
(option pr assumed; predicted probabilities)
```

```
. g yhat=1 if one==max(one,two,three)
(37 missing values generated)
```

```
. replace yhat=2 if two==max(one,two,three)
(37 real changes made)
```

```
. replace yhat=3 if three==max(one,two,three)
(0 real changes made)
```

```
. tab y yhat
```

y	yhat		Total
	1	2	
1	251	5	256
2	49	28	77
3	7	4	11
Total	307	37	344

**Test Ordered Probit**

```
. oprobit y x1 x2, nolog
```

```
Ordered probit regression          Number of obs   =       500
                                   LR chi2(2)          =       507.50
                                   Prob > chi2         =       0.0000
Log likelihood = -107.13797        Pseudo R2       =       0.7031
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	7.080822	.7097408	9.98	0.000	5.689755	8.471888
x2	3.042603	.2735847	11.12	0.000	2.506387	3.578819
/cut1	-2.195277	.2792163			-2.742531	-1.648024
/cut2	1.112197	.2129245			.6948726	1.529521

Note: 139 observations completely determined. Standard errors questionable.

```
. tab y
```

y	Freq.	Percent	Cum.
1	35	7.00	7.00
2	94	18.80	25.80
3	371	74.20	100.00
Total	500	100.00	

```
. g y12=y>1
```

```
. g y23=y>2
```

```
. tab y y12
```

y	y12		Total
	0	1	
1	35	0	35
2	0	94	94
3	0	371	371
Total	35	465	500

```
. tab y y23
```

y	y23		Total
	0	1	
1	35	0	35
2	94	0	94
3	0	371	371
Total	129	371	500

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

```
Probit regression          Number of obs   =       500
                                   LR chi2(2)          =       186.37
                                   Prob > chi2         =       0.0000
Log likelihood = -33.635442        Pseudo R2       =       0.7348
```

y12	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	7.739885	1.357405	5.70	0.000	5.079421	10.40035
x2	2.807821	.4628369	6.07	0.000	1.900677	3.714964
_cons	1.692526	.3759373	4.50	0.000	.9557026	2.42935

Note: 0 failures and 220 successes completely determined.

```
. est store probit12
```

```
. probit y23 x1 x2, nolog
```

```

Probit regression                               Number of obs   =       500
                                                LR chi2(2)      =       428.07
Log likelihood = -71.442965                    Prob > chi2     =       0.0000
                                                Pseudo R2      =       0.7497

```

y23	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	6.94818	.8545812	8.13	0.000	5.273232	8.623129
x2	3.254541	.3574509	9.10	0.000	2.55395	3.955132
_cons	-.9891503	.2443752	-4.05	0.000	-1.468117	-.5101836

Note: 5 failures and 95 successes completely determined.

```
. est store probit23
```

```
. suest probit12 probit23
```

Simultaneous results for probit12, probit23

```
Number of obs   =       500
```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
probit12_y12						
x1	7.739885	1.259756	6.14	0.000	5.270809	10.20896
x2	2.807821	.4436205	6.33	0.000	1.93834	3.677301
_cons	1.692526	.3674281	4.61	0.000	.9723804	2.412672
probit23_y23						
x1	6.94818	.8496727	8.18	0.000	5.282853	8.613508
x2	3.254541	.3662897	8.89	0.000	2.536627	3.972456
_cons	-.9891503	.244865	-4.04	0.000	-1.469077	-.5092238

```
. test [probit12_y12]x1=[probit23_y23]x1
```

```
( 1) [probit12_y12]x1 - [probit23_y23]x1 = 0
```

```
      chi2( 1) =    0.26
      Prob > chi2 =    0.6078
```

```
. test [probit12_y12]x2=[probit23_y23]x2
```

```
( 1) [probit12_y12]x2 - [probit23_y23]x2 = 0
```

```
      chi2( 1) =    0.58
      Prob > chi2 =    0.4462
```

### Alternative Test

```
. oprobit y x1 x2, nolog
```

```

Ordered probit regression                               Number of obs   =       500
                                                LR chi2(2)      =       507.50
Log likelihood = -107.13797                    Prob > chi2     =       0.0000
                                                Pseudo R2      =       0.7031

```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	7.080822	.7097408	9.98	0.000	5.689755	8.471888
x2	3.042603	.2735847	11.12	0.000	2.506387	3.578819
/cut1	-2.195277	.2792163			-2.742531	-1.648024
/cut2	1.112197	.2129245			.6948726	1.529521

Note: 139 observations completely determined. Standard errors questionable.

```
. gologit2 y x1 x2, p1 sto(oprobit) link(p)
```

```
Generalized Ordered Probit Estimates                Number of obs   =       500
```

Log likelihood = -107.13797

wald chi2(2)	=	125.88
Prob > chi2	=	0.0000
Pseudo R2	=	0.7031

( 1) [1]x1 - [2]x1 = 0  
( 2) [1]x2 - [2]x2 = 0

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1	x1	7.080822	.7097408	9.98	0.000	5.689755	8.471888
	x2	3.042603	.2735847	11.12	0.000	2.506387	3.578819
	_cons	2.195277	.2792163	7.86	0.000	1.648024	2.742531
2	x1	7.080822	.7097408	9.98	0.000	5.689755	8.471888
	x2	3.042603	.2735847	11.12	0.000	2.506387	3.578819
	_cons	-1.112197	.2129245	-5.22	0.000	-1.529521	-.6948726

. gologit2 y x1 x2, npl sto(goprobit) link(p)

Generalized Ordered Probit Estimates

Number of obs	=	500
LR chi2(4)	=	512.10
Prob > chi2	=	0.0000
Pseudo R2	=	0.7095

Log likelihood = -104.83593

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1	x1	7.737641	1.353034	5.72	0.000	5.085742	10.38954
	x2	2.802474	.4618616	6.07	0.000	1.897242	3.707706
	_cons	1.684816	.3762328	4.48	0.000	.9474136	2.422219
2	x1	6.944568	.8518606	8.15	0.000	5.274952	8.614184
	x2	3.248837	.3571053	9.10	0.000	2.548924	3.948751
	_cons	-.9892647	.2433861	-4.06	0.000	-1.466293	-.5122368

. lrtest oprobit goprobit, stats

Likelihood-ratio test  
(Assumption: oprobit nested in goprobit)

LR chi2(2)	=	4.60
Prob > chi2	=	0.1001

Akaike's information criterion and Bayesian information criterion

Model	obs	ll(null)	ll(model)	df	AIC	BIC
oprobit	500	-360.8862	-107.138	4	222.2759	239.1344
goprobit	500	-360.8862	-104.8359	6	221.6719	246.9595

Note: N=Obs used in calculating BIC; see [R] BIC note.