

Assignment 9

MN Logit & Ordered Logit Models

The model

In the study of problems of the business, the most serious problem was the price-war. The analysis is trying to estimate the model that determines factors that have impact on the degree of seriousness of the problem.

$$Prob(y_i=j|X) = f(x_1, x_2, x_3, x_4)$$

where: y_i is categorical data = 0 for no problem, = 1 for less serious, ..., and = 5 for very serious, and $i=1$ or 2.

x_1 is dummy variable = 0 for nonfamily firm and =1 for family firm.

x_2 is dummy variable = 0 for no brand and =1 for have own-brand name.

x_3 is dummy variable = 0 for low technology and =1 for high technology firm.

x_4 is log of the size of the firm.

Requirements: From data file – Assign09.dta:

- 1 Estimate the model using multinomial logit of y_i . Perform IIA test. Interpret your estimated result (overall test, individual test, pseudo R^2 , counted R^2).

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

Multinomial logistic regression	Number of obs	=	152
	LR chi2(20)	=	50.72
	Prob > chi2	=	0.0002
Log likelihood = -203.28337	Pseudo R2	=	0.1109

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
0		(base outcome)					
1							
	x1	-.1220175	1.086872	-0.11	0.911	-2.252248	2.008213
	x2	-2.016388	1.349482	-1.49	0.135	-4.661323	.6285484
	x3	1.253423	1.23587	1.01	0.310	-1.168837	3.675683
	x4	1.307279	.5491571	2.38	0.017	.2309504	2.383607
	_cons	-18.06503	8.062973	-2.24	0.025	-33.86817	-2.261896
2							
	x1	.9699943	.991428	0.98	0.328	-.9731688	2.913157
	x2	-1.631037	1.27855	-1.28	0.202	-4.136949	.8748753
	x3	-1.034421	.9547311	-1.08	0.279	-2.905659	.836818
	x4	.2042703	.3925818	0.52	0.603	-.5651758	.9737165
	_cons	-.9022321	5.40243	-0.17	0.867	-11.4908	9.686336
3							
	x1	-.4040394	.938099	-0.43	0.667	-2.24268	1.434601
	x2	-.9533924	1.222189	-0.78	0.435	-3.348838	1.442053

	x3		-.1658373	.8733107	-0.19	0.849	-1.877495	1.54582
	x4		.2174653	.3490812	0.62	0.533	-.4667212	.9016518
	_cons		-1.061943	4.802704	-0.22	0.825	-10.47507	8.351185
4								
	x1		1.677905	.9300468	1.80	0.071	-.1449532	3.500763
	x2		-2.104352	1.212395	-1.74	0.083	-4.480602	.2718986
	x3		-1.209535	.8915675	-1.36	0.175	-2.956975	.5379055
	x4		.1831672	.3654684	0.50	0.616	-.5331376	.899472
	_cons		-.0171095	5.005591	-0.00	0.997	-9.827887	9.793669
5								
	x1		1.832363	.8632903	2.12	0.034	.1403452	3.524381
	x2		-2.368735	1.168139	-2.03	0.043	-4.658246	-.079224
	x3		.0976971	.8455682	0.12	0.908	-1.559586	1.75498
	x4		.4905651	.3468626	1.41	0.157	-.189273	1.170403
	_cons		-4.204706	4.763082	-0.88	0.377	-13.54017	5.130762

. est store m1

. est restore m1
(results m1 are active now)

. fitstat

Measures of Fit for mlogit of y

Log-Lik Intercept Only:	-228.644	Log-Lik Full Model:	-203.283
D(122):	406.567	LR(20):	50.721
		Prob > LR:	0.000
McFadden's R2:	0.111	McFadden's Adj R2:	-0.020
Maximum Likelihood R2:	0.284	Cragg & Uhler's R2:	0.298
Count R2:	0.086	Adj Count R2:	0.021
AIC:	3.070	AIC*n:	466.567
BIC:	-206.347	BIC':	49.757

.

From the estimated result, overall test from LR chi-squared test has p-value of 0.002, suggesting that the model is significant. For individual test, only size of firm and base case can significantly explain when the price war is less serious (y = 1). When price war is very serious, being family or non-family brand and having brand name or not can significantly explain such incident.

Pseudo-R-squared and Counted-R-squared are quite low. Hence, this suggests limited explaining power of this model.

. mlogit y x1 x2 x3 x4 if y!=3, b(0) nolog

Multinomial logistic regression	Number of obs	=	129
	LR chi2(16)	=	32.43
	Prob > chi2	=	0.0088
Log likelihood = -147.82992	Pseudo R2	=	0.0989

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

0		(base outcome)						

1								
	x1		-.0345956	1.076916	-0.03	0.974	-2.145311	2.07612
	x2		-1.944929	1.348267	-1.44	0.149	-4.587483	.6976246
	x3		1.008411	1.20889	0.83	0.404	-1.360971	3.377792
	x4		1.173903	.5383718	2.18	0.029	.1187139	2.229093
	_cons		-16.06881	7.865552	-2.04	0.041	-31.48501	-.6526125

2								
	x1		.9993361	1.003331	1.00	0.319	-.967156	2.965828
	x2		-1.54066	1.271611	-1.21	0.226	-4.032971	.951652
	x3		-1.07311	.964317	-1.11	0.266	-2.963137	.8169163
	x4		.1708932	.3712134	0.46	0.645	-.5566718	.8984581
	_cons		-.4976237	5.1088	-0.10	0.922	-10.51069	9.51544

4								
	x1		1.712027	.9430093	1.82	0.069	-.1362369	3.560292
	x2		-1.984394	1.206891	-1.64	0.100	-4.349858	.3810699
	x3		-1.268538	.9054895	-1.40	0.161	-3.043265	.5061886
	x4		.1397741	.3466199	0.40	0.687	-.5395885	.8191367
	_cons		.5172055	4.746061	0.11	0.913	-8.784904	9.819315

5								
	x1		1.81674	.8680124	2.09	0.036	.1154673	3.518013
	x2		-2.242124	1.163729	-1.93	0.054	-4.522991	.0387429
	x3		.0269395	.8572861	0.03	0.975	-1.65331	1.707189
	x4		.4149522	.3281144	1.26	0.206	-.2281403	1.058045
	_cons		-3.16993	4.505839	-0.70	0.482	-12.00121	5.661352

. est store m2

. hausman m2 m1, alleq constant

Note: the rank of the differenced variance matrix (19) does not equal the number of coefficients being tested (20); be sure this is

what you expect, or there may be problems computing the test. Examine the output of your estimators for anything unexpected

and possibly consider scaling your variables so that the coefficients are on a similar scale.

		---- Coefficients ----			
		(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
		m2	m1	Difference	S.E.
1					
	x1	-.0345956	-.1220175	.087422	.
	x2	-1.944929	-2.016388	.0714583	.
	x3	1.008411	1.253423	-.2450125	.
	x4	1.173903	1.307279	-.1333753	.
	_cons	-16.06881	-18.06503	1.996222	.
2					
	x1	.9993361	.9699943	.0293418	.1540878
	x2	-1.54066	-1.631037	.0903772	.
	x3	-1.07311	-1.034421	-.0386898	.1356314

	x4		.1708932	.2042703	-.0333771	.
	_cons		-.4976237	-.9022321	.4046085	.

4						
	x1		1.712027	1.677905	.0341224	.155819
	x2		-1.984394	-2.104352	.1199581	.
	x3		-1.268538	-1.209535	-.0590035	.1581729
	x4		.1397741	.1831672	-.0433931	.
	_cons		.5172055	-.0171095	.5343149	.

5						
	x1		1.81674	1.832363	-.0156229	.090417
	x2		-2.242124	-2.368735	.1266108	.
	x3		.0269395	.0976971	-.0707576	.1412581
	x4		.4149522	.4905651	-.075613	.
	_cons		-3.16993	-4.204706	1.034776	.

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

Test: Ho: difference in coefficients not systematic

chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 2.04
Prob>chi2 = 1.0000
(V_b-V_B is not positive definite)

```
. predict zero one two three four five
(option pr assumed; predicted probabilities)
(73 missing values generated)

. g yhat=0 if zero==max(zero,one,two,three,four,five)
(152 missing values generated)

. replace yhat=1 if one==max(zero,one,two,three,four,five)
(73 real changes made)

. replace yhat=2 if two==max(zero,one,two,three,four,five)
(73 real changes made)

. replace yhat=3 if three==max(zero,one,two,three,four,five)
(111 real changes made)

. replace yhat=4 if four==max(zero,one,two,three,four,five)
(79 real changes made)

. replace yhat=5 if five==max(zero,one,two,three,four,five)
(181 real changes made)

. tab y yhat
```

		yhat			
	y	3	4	5	Total

	0	6	0	23	29
	1	3	0	11	14
	2	5	1	21	27
	3	12	1	20	33

4	5	2	28	35
5	7	2	78	87
-----+-----				
Total	38	6	181	225

From the Hausman-test, p-value is 1.000 which suggests that IIA assumption is valid.

2 Estimate the model using order logit of y_i . Interpret your estimated result (overall test, individual test, pseudo R^2 , counted R^2).

```
. ologit y x1 x2 x3 x4
```

```
Iteration 0:  log likelihood = -228.64363
Iteration 1:  log likelihood = -216.35652
Iteration 2:  log likelihood = -216.2376
Iteration 3:  log likelihood = -216.23748
Iteration 4:  log likelihood = -216.23748
```

Ordered logistic regression	Number of obs	=	152
	LR chi2(4)	=	24.81
	Prob > chi2	=	0.0001
Log likelihood = -216.23748	Pseudo R2	=	0.0543

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
x1	1.26067	.3475145	3.63	0.000	.5795538	1.941786
x2	-.8530234	.3508641	-2.43	0.015	-1.540705	-.1653424
x3	.2068371	.3398536	0.61	0.543	-.4592637	.8729379
x4	.1261028	.1511501	0.83	0.404	-.1701459	.4223515
-----+-----						
/cut1	-.8807685	2.139511			-5.074134	3.312597
/cut2	-.0328063	2.126237			-4.200155	4.134542
/cut3	.6557008	2.118367			-3.496223	4.807624
/cut4	1.48964	2.117389			-2.660365	5.639646
/cut5	2.283969	2.124223			-1.879432	6.447371
-----+-----						

```
. fitstat
```

Measures of Fit for ologit of y

```
variable cut1 not found
r(111);
```

```
. est store ologit1
```

```
. drop zero one two three four five yhat
```

```
. predict zero one two three four five
(option pr assumed; predicted probabilities)
(73 missing values generated)
```

```

.
. g yhat=0 if zero==max(zero,one,two,three,four,five)
(152 missing values generated)

.
. replace yhat=1 if one==max(zero,one,two,three,four,five)
(73 real changes made)

.
. replace yhat=2 if two==max(zero,one,two,three,four,five)
(73 real changes made)

.
. replace yhat=3 if three==max(zero,one,two,three,four,five)
(86 real changes made)

.
. replace yhat=4 if four==max(zero,one,two,three,four,five)
(73 real changes made)

.
. replace yhat=5 if five==max(zero,one,two,three,four,five)
(212 real changes made)

.
. tab y yhat

```

	y	yhat		
		3	5	Total
0		2	27	29
1		0	14	14
2		3	24	27
3		4	29	33
4		2	33	35
5		2	85	87
Total		13	212	225

LR-chi-squared test has p-value of 0.0001, suggesting that the model is significant.

Pseudo-R-squared is 0.0543. Counted R-squared is 0.3956. They are both quite low which mean that the model can be better.

Individual test suggests that only being a family brand or not can significantly explain degree of price war.

3 From (a) and (b), compare the two models. Perform order logit test. Which model is more appropriated in this case? Why?

```

. gologit2 y x1 x2 x3 x4, pl sto(oprobit) link(p)

```

Generalized Ordered Probit Estimates	Number of obs	=	152
	LR chi2(4)	=	23.50
	Prob > chi2	=	0.0001
Log likelihood = -216.89508	Pseudo R2	=	0.0514

```

( 1)  [0]x1 - [1]x1 = 0
( 2)  [0]x2 - [1]x2 = 0
( 3)  [0]x3 - [1]x3 = 0
( 4)  [0]x4 - [1]x4 = 0
( 5)  [1]x1 - [2]x1 = 0
( 6)  [1]x2 - [2]x2 = 0
( 7)  [1]x3 - [2]x3 = 0
( 8)  [1]x4 - [2]x4 = 0
( 9)  [2]x1 - [3]x1 = 0
(10)  [2]x2 - [3]x2 = 0
(11)  [2]x3 - [3]x3 = 0
(12)  [2]x4 - [3]x4 = 0
(13)  [3]x1 - [4]x1 = 0
(14)  [3]x2 - [4]x2 = 0
(15)  [3]x3 - [4]x3 = 0
(16)  [3]x4 - [4]x4 = 0

```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
0							
	x1	.7194818	.2020884	3.56	0.000	.3233959	1.115568
	x2	-.5041496	.2049628	-2.46	0.014	-.9058693	-.1024299
	x3	.1109476	.2041695	0.54	0.587	-.2892173	.5111125
	x4	.0732426	.0867141	0.84	0.398	-.0967139	.2431991
	_cons	.4623429	1.229346	0.38	0.707	-1.947131	2.871817
1							
	x1	.7194818	.2020884	3.56	0.000	.3233959	1.115568
	x2	-.5041496	.2049628	-2.46	0.014	-.9058693	-.1024299
	x3	.1109476	.2041695	0.54	0.587	-.2892173	.5111125
	x4	.0732426	.0867141	0.84	0.398	-.0967139	.2431991
	_cons	.0266402	1.224714	0.02	0.983	-2.373756	2.427036
2							
	x1	.7194818	.2020884	3.56	0.000	.3233959	1.115568
	x2	-.5041496	.2049628	-2.46	0.014	-.9058693	-.1024299
	x3	.1109476	.2041695	0.54	0.587	-.2892173	.5111125
	x4	.0732426	.0867141	0.84	0.398	-.0967139	.2431991
	_cons	-.3534276	1.220028	-0.29	0.772	-2.744639	2.037784
3							
	x1	.7194818	.2020884	3.56	0.000	.3233959	1.115568
	x2	-.5041496	.2049628	-2.46	0.014	-.9058693	-.1024299
	x3	.1109476	.2041695	0.54	0.587	-.2892173	.5111125
	x4	.0732426	.0867141	0.84	0.398	-.0967139	.2431991
	_cons	-.8395408	1.218495	-0.69	0.491	-3.227746	1.548665
4							
	x1	.7194818	.2020884	3.56	0.000	.3233959	1.115568
	x2	-.5041496	.2049628	-2.46	0.014	-.9058693	-.1024299
	x3	.1109476	.2041695	0.54	0.587	-.2892173	.5111125
	x4	.0732426	.0867141	0.84	0.398	-.0967139	.2431991
	_cons	-1.315206	1.220947	-1.08	0.281	-3.708217	1.077805

```
. help gologit2
```

```
. gologit2 y x1 x2 x3 x4, npl sto(goprobit) link(p)
```

```

Generalized Ordered Probit Estimates      Number of obs   =      152
                                          LR chi2(20)      =      62.94
                                          Prob > chi2      =      0.0000
Log likelihood = -197.17374              Pseudo R2       =      0.1376

```

	y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
0							
	x1	.3572168	.4029218	0.89	0.375	-.4324953	1.146929
	x2	-.8430554	.5215851	-1.62	0.106	-1.865344	.1792327
	x3	.2174726	.4699002	0.46	0.644	-.7035149	1.13846
	x4	.6301649	.2667108	2.36	0.018	.1074213	1.152909
	_cons	-7.270173	3.882206	-1.87	0.061	-14.87916	.3388114
1							
	x1	.3815073	.3018235	1.26	0.206	-.210056	.9730705
	x2	-.0159532	.3528003	-0.05	0.964	-.7074291	.6755227
	x3	-.4463186	.318717	-1.40	0.161	-1.070992	.1783554
	x4	-.3245584	.1577207	-2.06	0.040	-.6336852	-.0154316
	_cons	5.945013	2.271297	2.62	0.009	1.493353	10.39667
2							
	x1	.3404404	.2758876	1.23	0.217	-.2002895	.8811702
	x2	.0353617	.3074022	0.12	0.908	-.5671356	.637859
	x3	-.0702493	.2585965	-0.27	0.786	-.577089	.4365905
	x4	-.1951006	.1263031	-1.54	0.122	-.4426502	.0524489
	_cons	3.376936	1.791931	1.88	0.059	-.1351848	6.889057
3							
	x1	1.140714	.2586096	4.41	0.000	.6338481	1.647579
	x2	-.6973459	.2627334	-2.65	0.008	-1.212294	-.1823979
	x3	-.0515296	.2426607	-0.21	0.832	-.5271359	.4240766
	x4	-.0319761	.1198625	-0.27	0.790	-.2669022	.20295
	_cons	.6640111	1.677911	0.40	0.692	-2.624635	3.952657
4							
	x1	.7732183	.2551915	3.03	0.002	.2730522	1.273384
	x2	-.6291826	.243014	-2.59	0.010	-1.105481	-.1528838
	x3	.4068852	.2489172	1.63	0.102	-.0809836	.8947539
	x4	.1212267	.1142629	1.06	0.289	-.1027244	.3451778
	_cons	-2.159693	1.595193	-1.35	0.176	-5.286213	.9668279

WARNING! 86 in-sample cases have an outcome with a predicted probability that is less than 0. See the gologit2 help section on Warning Messages for more information.

```
. lrtest goprobit oprobit, stats
```

```

Likelihood-ratio test      LR chi2(16) =      39.44
(Assumption: oprobit nested in goprobit)  Prob > chi2 =      0.0009

```

Akaike's information criterion and Bayesian information criterion

Model	N	ll(null)	ll(model)	df	AIC	BIC
-------	---	----------	-----------	----	-----	-----

oprobit	152	-228.6436	-216.8951	9	451.7902	479.0051
goprobit	152	-228.6436	-197.1737	25	444.3475	519.9445

Note: BIC uses N = number of observations. See [R] BIC note.

From LR-test, p-value is 0.0009. H0 is rejected. It suggests that multinomial logit model is more appropriate.

4 Compute marginal effect at mean and median of both models.

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

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

```
Average marginal effects      Number of obs      =      152
Model VCE      : OIM
```

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

		Delta-method				
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
x1		-.0770801	.0429311	-1.80	0.073	-.1612236 .0070633
x2		-.0090692	.0417711	-0.22	0.828	-.0909391 .0728007
x3		.0862353	.0585697	1.47	0.141	-.0285593 .2010298
x4		.0558661	.02814	1.99	0.047	.0007127 .1110196

```
. margins, dydx(*) predict(outcome(0))
```

```
Average marginal effects      Number of obs      =      152
Model VCE      : OIM
```

```
Expression      : Pr(y==0), predict(outcome(0))
dy/dx w.r.t.    : x1 x2 x3 x4
```

		Delta-method				
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
x1		-.049448	.0394996	-1.25	0.211	-.1268658 .0279698
x2		.0953594	.0625156	1.53	0.127	-.027169 .2178878
x3		.0128947	.0388471	0.33	0.740	-.0632443 .0890336
x4		-.0202353	.0163353	-1.24	0.215	-.0522519 .0117814

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

```
Average marginal effects      Number of obs      =      152
Model VCE      : OIM
```

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



```
. est restore ologit1
(results ologit1 are active now)

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

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

	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.0599322	.0226362	-2.65	0.008	-.1042983	-.015566
x2	.0405527	.0197166	2.06	0.040	.0019088	.0791965
x3	-.009833	.0162697	-0.60	0.546	-.041721	.022055
x4	-.0059949	.0073186	-0.82	0.413	-.0203391	.0083493

```
Expression      : Pr(y==0), predict(outcome(0))
dy/dx w.r.t.   : x1 x2 x3 x4
```

	Delta-method					
	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
x1	-.0681609	.0273944	-2.49	0.013	-.121853	-.0144688
x2	.0461206	.0233188	1.98	0.048	.0004166	.0918247
x3	-.0111831	.0186422	-0.60	0.549	-.0477211	.0253549
x4	-.006818	.0084411	-0.81	0.419	-.0233623	.0097263

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

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
x1		-.0614076	.0202331	-3.04	0.002	-.1010639	-.0217514
x2		.0415511	.0188187	2.21	0.027	.004667	.0784351
x3		-.0100751	.0166518	-0.61	0.545	-.0427121	.0225619

```

x4 | -.0061425 .007391 -0.83 0.406 -.0206285 .0083435
-----

```

```

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

```

```

Average marginal effects          Number of obs    =          152
Model VCE      : OIM

```

```

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

```

```

-----
          |          Delta-method
          |          dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
x1 | -.0649197   .0193261   -3.36   0.001   -.1027982   -.0270412
x2 |  .0439275   .0192343    2.28   0.022    .006229    .081626
x3 | -.0106513   .017627   -0.60   0.546   -.0451996   .0238969
x4 | -.0064938   .0078483   -0.83   0.408   -.0218763   .0088886
-----

```

```

.
. margins, dydx(*) predict(outcome(4))

```

```

Average marginal effects          Number of obs    =          152
Model VCE      : OIM

```

```

Expression   : Pr(y==4), predict(outcome(4))
dy/dx w.r.t. : x1 x2 x3 x4

```

```

-----
          |          Delta-method
          |          dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
x1 | -.0206373   .0127601   -1.62   0.106   -.0456467    .004372
x2 |  .0139641   .0092144    1.52   0.130   -.0040958    .032024
x3 | -.003386    .0059659   -0.57   0.570   -.0150789    .008307
x4 | -.0020643   .0027613   -0.75   0.455   -.0074764    .0033478
-----

```

```

.
. margins, dydx(*) predict(outcome(5))

```

```

Average marginal effects          Number of obs    =          152
Model VCE      : OIM

```

```

Expression   : Pr(y==5), predict(outcome(5))
dy/dx w.r.t. : x1 x2 x3 x4

```

```

-----
          |          Delta-method
          |          dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
x1 |  .2750578   .0661191    4.16   0.000    .1454667    .4046489
x2 | -.1861159   .0724194   -2.57   0.010   -.3280553   -.0441766
x3 |  .0451285   .073977    0.61   0.542   -.0998638    .1901208
x4 |  .0275136   .032782    0.84   0.401   -.0367379    .0917651
-----

```

```
. margins, dydx(*) predict(outcome(0)) at((median))
```

Model VCE : OIM

$$dy/dx \text{ w.r.t. } : x_1 \quad x_2 \quad x_3 \quad x_4$$

		Delta-method				
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]
x1		-.0681609	.0273944	-2.49	0.013	-.121853 -.0144688
x2		.0461206	.0233188	1.98	0.048	.0004166 .0918247
x3		-.0111831	.0186422	-0.60	0.549	-.0477211 .0253549
x4		-.006818	.0084411	-0.81	0.419	-.0233623 .0097263

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

Model VCE : OIM

$$dy/dx \text{ w.r.t. } : x_1 \quad x_2 \quad x_3 \quad x_4$$

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
x1		-.0599322	.0226362	-2.65	0.008	-.1042983	-.015566
x2		.0405527	.0197166	2.06	0.040	.0019088	.0791965
x3		-.009833	.0162697	-0.60	0.546	-.041721	.022055
x4		-.0059949	.0073186	-0.82	0.413	-.0203391	.0083493

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

Model VCE : OIM

$$dy/dx \text{ w.r.t. } : x_1 \quad x_2 \quad x_3 \quad x_4$$

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
x1		-.0614076	.0202331	-3.04	0.002	-.1010639	-.0217514
x2		.0415511	.0188187	2.21	0.027	.004667	.0784351
x3		-.0100751	.0166518	-0.61	0.545	-.0427121	.0225619
x4		-.0061425	.007391	-0.83	0.406	-.0206285	.0083435

```

.
. margins, dydx(*) predict(outcome(3)) at((median))

```

```

Average marginal effects          Number of obs      =          152
Model VCE      : OIM

```

```

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

```

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		
x1		-.0649197	.0193261	-3.36	0.001	-.1027982	-.0270412
x2		.0439275	.0192343	2.28	0.022	.006229	.081626
x3		-.0106513	.017627	-0.60	0.546	-.0451996	.0238969
x4		-.0064938	.0078483	-0.83	0.408	-.0218763	.0088886

```

.
. margins, dydx(*) predict(outcome(4)) at((median))

```

```

Average marginal effects          Number of obs      =          152
Model VCE      : OIM

```

```

Expression      : Pr(y==4), predict(outcome(4))
dy/dx w.r.t.    : x1 x2 x3 x4

```

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		
x1		-.0206373	.0127601	-1.62	0.106	-.0456467	.004372
x2		.0139641	.0092144	1.52	0.130	-.0040958	.032024
x3		-.003386	.0059659	-0.57	0.570	-.0150789	.008307
x4		-.0020643	.0027613	-0.75	0.455	-.0074764	.0033478

```

.
. margins, dydx(*) predict(outcome(5)) at((median))

```

```

Average marginal effects          Number of obs      =          152
Model VCE      : OIM

```

```

Expression      : Pr(y==5), predict(outcome(5))
dy/dx w.r.t.    : x1 x2 x3 x4

```

		Delta-method				[95% Conf. Interval]	
		dy/dx	Std. Err.	z	P> z		
x1		.2750578	.0661191	4.16	0.000	.1454667	.4046489
x2		-.1861159	.0724194	-2.57	0.010	-.3280553	-.0441766
x3		.0451285	.073977	0.61	0.542	-.0998638	.1901208
x4		.0275136	.032782	0.84	0.401	-.0367379	.0917651

