# Interactions in Logistic Regression

### **New Version**

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## 1 Background

The purpose of this tutorial is to illustrate the idea that in *logistic regression*, the  $\beta$  parameter for an interaction term may not accurately characterize the underlying interactive relationships.

This idea may be easier to describe if we recall the formula for a logistic regression:

$$\ln\left(\frac{P(y)}{1-P(y)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 \times x_2$$

### ⚠ Warning

In the above formula, the sign, and statistical significance, of  $\beta_3$  may not accurately characterize the underlying relationship.

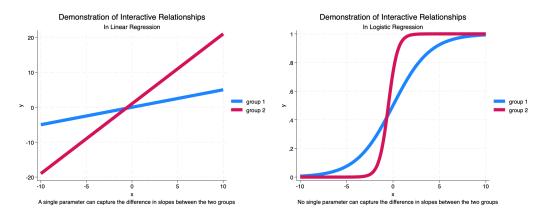


Figure 1: Demonstration of Interactive Relationships

### **?** Key Idea

In a linear model, a single parameter can capture the difference in slopes between the two groups. In a non-linear model, no single parameter can capture the difference in slopes between the two groups.

### Some Calculus (Not Essential To The Discussion)

Imagine a linear model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 \times x_2 + e_i$$

Here (following Ai and Norton (2003)):

$$\frac{\partial y}{\partial x_1 \partial x_2} = \beta_3$$

We use logit to describe:

$$\ln\left(\frac{P(y)}{1 - P(y)}\right)$$

In the logistic model, the quantity:

$$\frac{\partial \mathrm{logit}(y)}{\partial x_1 \partial x_2}$$

does not have such a straightforward solution, and–importantly for this discussion–is not simply equal to  $\beta_3$ .

### 2 Get The Data

We start by obtaining *simulated data* from StataCorp.

```
clear all
graph close _all
use http://www.stata-press.com/data/r15/margex, clear
```

(Artificial data for margins)

### 3 Describe The Data

The variables are as follows:

```
describe
```

> ile.do ...

Running /Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/prof

Contains data from http://www.stata-press.com/data/r15/margex.dta

Observations: 3,000 Artificial data for margins

Variables: 11 27 Nov 2016 14:27

\_\_\_\_\_

Variable Storage Display Value

name type format label Variable label

		,,o.og 	
arm	byte	%8.0g	-
agegroup	byte	%8.0g	agelab
treatment	byte	%2.0f	
ус	float	%6.1f	
ycn	float	%6.1f	
distance	float	%6.2f	
age	float	%3.0f	
group	byte	%2.0f	
sex	byte	%6.0f	sexlbl
outcome	byte	%2.0f	
У	float	%6.1f	

Sorted by: group

## 4 Estimate Logistic Regression

We then run a logistic regression model in which outcome is the dependent variable. age and group are the independent variables. We estimate an interaction of group and age.

We note that the regression coefficient for the interaction terms are not statistically significant.

```
logit outcome c.age##i.group
```

 ${\tt Running /Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/profile} \\$ 

```
> ile.do ...
```

```
Iteration 0: Log likelihood = -1366.0718
Iteration 1: Log likelihood = -1125.2149
Iteration 2: Log likelihood = -1077.539
Iteration 3: Log likelihood = -1074.8422
Iteration 4: Log likelihood = -1074.7864
Iteration 5: Log likelihood = -1074.7863
```

Logistic regression

Number of obs = 3,000 LR chi2(5) = 582.57 Prob > chi2 = 0.0000

outcome	Coefficient	Std. err.	z	P> z	[95% conf.	interval]
age	.091183	.0084697	10.77	0.000	.0745827	.1077834
group						
2	8272665	.6648279	-1.24	0.213	-2.130305	.4757722
3	-1.085445	1.044802	-1.04	0.299	-3.133219	.9623292
I						
group#c.age						
2	.0013522	.0139747	0.10	0.923	0260378	.0287421
3 l	0164596	.0259182	-0.64	0.525	0672584	.0343392
I						
_cons	-5.184398	.4274964	-12.13	0.000	-6.022275	-4.34652

## 5 Margins

We use the margins command to estimate predicted probabilities at different values of group and age.

```
margins group, at(age = (20 30 40 50 60))
```

Running /Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/prof > ile.do ...

Adjusted predictions Model VCE: OIM

Number of obs = 3,000

Expression: Pr(outcome), predict()

1.\_at: age = 20 2.\_at: age = 30 3.\_at: age = 40 4.\_at: age = 50 5.\_at: age = 60

	Delta-method						
		Margin	std. err.	z	P> z	[95% conf.	interval]
_at#group	+ 						
1 1		.0335453	.0084761	3.96	0.000	.0169325	.0501582
1 2		.0153532	.0044572	3.44	0.001	.0066173	.0240891
1 3		.0083644	.0041378	2.02	0.043	.0002545	.0164742
2 1		.0795185	.0132311	6.01	0.000	.0535861	.105451
2 2		.0378475	.0070835	5.34	0.000	.023964	.0517309
2 3		.0174959	.0054051	3.24	0.001	.0069021	.0280896
3 1		.1769607	.0155126	11.41	0.000	.1465565	.2073649
3 2		.0902771	.0095282	9.47	0.000	.0716022	.108952
3 3		.0362321	.0091647	3.95	0.000	.0182697	.0541945
4 1		.3485893	.0149941	23.25	0.000	.3192014	.3779772
4 2		.2002224	.0188064	10.65	0.000	.1633625	.2370823
4 3		.0735312	.0271556	2.71	0.007	.0203072	.1267553
5 1		.5711598	.0265203	21.54	0.000	.5191809	.6231386
5 2		.3870919	.0467552	8.28	0.000	.2954535	.4787304
5 3	I	.1435103	.0746567	1.92	0.055	0028141	. 2898347

## 6 Plotting Margins

margins provides a lot of results, which can be difficult to understand. Therefore, we use marginsplot to plot these margins results.

There certainly seems to be some kind of interaction of group and age.

```
marginsplot
graph export mymarginsplot.png, width(1000) replace
```

Running /Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/prof
> ile.do ...

Variables that uniquely identify margins: age group

file

/Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/mymarg > insplot.png saved as PNG format

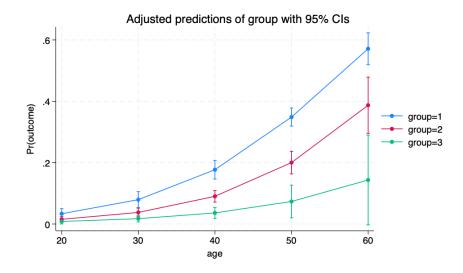


Figure 2: Margins Plot

## 7 Rerun margins, Posting Results

We again employ the margins command, this time using the post option so that the results of the margins command are *posted* as an estimation result. This will allow us to employ the test command to statistically test different margins against each other.

```
margins group, at(age = (20 30 40 50 60)) post
```

Running /Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/prof > ile.do ...

Adjusted predictions Model VCE: OIM

Number of obs = 3,000

```
Expression: Pr(outcome), predict()
1._at: age = 20
2._at: age = 30
3._at: age = 40
4._at: age = 50
5._at: age = 60
```

	I	]	Delta-method				
		Margin	std. err.	z	P> z	[95% conf.	interval]
_at#group	+ 						
1 1		.0335453	.0084761	3.96	0.000	.0169325	.0501582
1 2		.0153532	.0044572	3.44	0.001	.0066173	.0240891
1 3		.0083644	.0041378	2.02	0.043	.0002545	.0164742
2 1		.0795185	.0132311	6.01	0.000	.0535861	.105451
2 2		.0378475	.0070835	5.34	0.000	.023964	.0517309
2 3		.0174959	.0054051	3.24	0.001	.0069021	.0280896
3 1		.1769607	.0155126	11.41	0.000	.1465565	.2073649
3 2		.0902771	.0095282	9.47	0.000	.0716022	.108952
3 3		.0362321	.0091647	3.95	0.000	.0182697	.0541945
4 1		.3485893	.0149941	23.25	0.000	.3192014	.3779772
4 2		.2002224	.0188064	10.65	0.000	.1633625	.2370823
4 3		.0735312	.0271556	2.71	0.007	.0203072	.1267553
5 1		.5711598	.0265203	21.54	0.000	.5191809	.6231386
5 2		.3870919	.0467552	8.28	0.000	.2954535	.4787304
5 3		.1435103	.0746567	1.92	0.055	0028141	.2898347

## 8 margins with coeflegend

We follow up by using the margins command with the coeflegend option to see the way in which Stata has labeled the different margins.

```
margins, coeflegend
```

Running /Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/prof
> ile.do ...

```
Adjusted predictions
                                                    Number of obs = 3,000
Model VCE: OIM
Expression: Pr(outcome), predict()
1._at: age = 20
2. at: age = 30
3._at: age = 40
4._at: age = 50
5._at: age = 60
______
                 Margin Legend
  _at#group |
       1 1 |
               .0335453 _b[1bn._at#1bn.group]
       12 |
               .0153532 _b[1bn._at#2.group]
               .0083644 _b[1bn._at#3.group]
       1 3
       2 1
               .0795185 _b[2._at#1bn.group]
       2 2
                        _b[2._at#2.group]
               .0378475
       2 3
               .0174959 _b[2._at#3.group]
       3 1
               .1769607
                        _b[3._at#1bn.group]
       3 2
               .0902771 _b[3._at#2.group]
       3 3
               .0362321 _b[3._at#3.group]
               .3485893 _b[4._at#1bn.group]
       4 1
               .2002224 _b[4._at#2.group]
       4 2
               .0735312 _b[4._at#3.group]
       4 3
       5 1
               .5711598 _b[5._at#1bn.group]
       5 2
               .3870919
                        _b[5._at#2.group]
       5 3 |
               .1435103 _b[5._at#3.group]
```

## 9 Testing Margins Against Each Other

Lastly, we test the margins at age 20 across some of the groups, and again at ages 50 and 60 for some of the groups.

We note that the original regression parameter for the interaction term was not statistically significant. Indeed, the margins at age 20 are not statistically significantly different by group (1 vs. 2), though they are close to being significantly

different. However, at ages 50 & 60, there is a statistically significant difference by group (1 vs. 2).

```
test _b[1bn._at#1bn.group] = _b[1bn._at#2.group] // groups 1 & 2 at age 20

test _b[4._at#1bn.group] = _b[4._at#2.group] // groups 1 & 2 at age 50

test _b[5._at#1bn.group] = _b[5._at#2.group] // groups 1 & 2 at age 60
```

Running /Users/agrogan/Desktop/GitHub/newstuff/categorical/logistic-interactions-3/prof > ile.do ...

Ai, Chunrong, and Edward C. Norton. 2003. "Interaction Terms in Logit and Probit Models." Economics Letters. https://doi.org/10.1016/S0165-1765(03)00032-6.

Karaca-Mandic, Pinar, Edward C. Norton, and Bryan Dowd. 2012. "Interaction Terms in Nonlinear Models." *Health Services Research*. https://doi.org/10.1111/j.1475-6773.2011. 01314.x.