

Biostatistics 200

Review & Short Topics



Interaction terms

- Always include each main effect as well as the interaction term
- Center your continuous variables
- Is one continuous and the other categorical?
 - This will divide the data into (2 or more) strata and then regress Y on the continuous variable
- Are they both categorical?
 - This just divides the data into strata for a regression of Y on any other variables (=ANOVA)
- Are both the variables continuous?
 - Statistically an interaction is just multiplying them together but how to interpret this?

Using the Class dataset

Gender almost predicts the amount of cash you are carrying

Height predicts the amount of cash you are carrying

```
. reg cash sex
```

Source	SS	df	MS	Number of obs	=	104
Model	7088.56199	1	7088.56199	F(1, 102)	=	3.59
Residual	201316.202	102	1973.68825	Prob > F	=	0.0609
				R-squared	=	0.0340
				Adj R-squared	=	0.0245
Total	208404.764	103	2023.34722	Root MSE	=	44.426

cash	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
sex	16.76473	8.846201	1.90	0.061	-.7816665	34.31113
_cons	14.84379	13.24092	1.12	0.265	-11.4195	41.10709

```
. reg cash height
```

Source	SS	df	MS	Number of obs	=	103
Model	9622.91663	1	9622.91663	F(1, 101)	=	4.90
Residual	198222.331	101	1962.59734	Prob > F	=	0.0291
				R-squared	=	0.0463
				Adj R-squared	=	0.0369
Total	207845.248	102	2037.69851	Root MSE	=	44.301

cash	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
height	2.304966	1.040942	2.21	0.029	.2400159	4.369915
_cons	-115.5096	69.81001	-1.65	0.101	-253.9939	22.97464

Create new variable = Height*Sex

```
. reg cash height sex htsex
```

Source	SS	df	MS	Number of obs	=	103
Model	15184.9449	3	5061.64829	F(3, 99)	=	2.60
Residual	192660.303	99	1946.06367	Prob > F	=	0.0563
Total	207845.248	102	2037.69851	R-squared	=	0.0731
				Adj R-squared	=	0.0450
				Root MSE	=	44.114

cash	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
height	3.885287	1.873133	2.07	0.041	.1685854	7.601989
sex	250.2801	170.7333	1.47	0.146	-88.49177	589.052
htsex	-3.821873	2.521609	-1.52	0.133	-8.825293	1.181547
_cons	-222.5126	130.7697	-1.70	0.092	-481.9881	36.9629

In a t-test comparing cash by sex we see that on average Males = \$48.37 and Females = \$31.61)p = 0.061 and for height Males = 69.7 in, Females = 64.94 (p<0.001)

In my model, Males=0 and Females=1

Equation says $3.89 \cdot Ht + 250 \cdot \text{sex} - 3.82 \cdot Ht\text{sex} - 222.5 = \text{Cash}$

Multinomial Logit (sometimes ordered)

- Multinomial Logit strategy - Contrast outcomes with a common reference point
 - Similar to conducting a series of 2-outcome logit models comparing pairs of categories
 - The “reference category” is like the reference group when using dummy variables in regression
- It serves as the contrast point for all analyses (use mlogit in Stata)
- Example: Multinomial Logit strategy for types of graduate schools
 - Analysis of 5 categories yields 4 tables of results:
 - No grad school vs. MA
 - No grad school vs. MBA
 - No grad school vs. Prof'l school
 - No grad school vs. PhD.

Multinomial Logit Example: Family Vacation

- Mode of Travel. Reference category = Train

```
. mlogit mode income familysize
```

Large families less likely to take bus (vs. train)

Multinomial logistic regression

Number of obs = 152

LR chi2(4) = 42.63

Prob > chi2 = 0.0000

Pseudo R2 = 0.1332

Log likelihood = -138.68742

mode	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
Bus						
income	.0311874	.0141811	2.20	0.028	.0033929	.0589818
family size	-.6731862	.3312153	-2.03	0.042	-1.322356	-.0240161
_cons	-.5659882	.580605	-0.97	0.330	-1.703953	.5719767
-----+-----						
Car						
income	.057199	.0125151	4.57	0.000	.0326698	.0817282
family size	.1978772	.1989113	0.99	0.320	-.1919817	.5877361
_cons	-2.272809	.5201972	-4.37	0.000	-3.292377	-1.253241

(mode==Train is the base outcome)

Note: It is hard to directly compare Car vs. Bus in this table

Multinomial Logit Example: Family Vacation

- Mode of Travel. Reference category = Car

```
. mlogit mode income familysize, base(3)
```

Multinomial logistic regression

Number of obs = 152

LR chi2(4) = 42.63

Prob > chi2 = 0.0000

Pseudo R2 = 0.1332

Log likelihood = -138.68742

	mode	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
Train							
	income	-.057199	.0125151	-4.57	0.000	-.0817282	-.0326698
	family size	-.1978772	.1989113	-0.99	0.320	-.5877361	.1919817
	_cons	2.272809	.5201972	4.37	0.000	1.253241	3.292377
-----+-----							
Bus							
	income	-.0260117	.0139822	-1.86	0.063	-.0534164	.001393
	family size	-.8710634	.3275472	-2.66	0.008	-1.513044	-.2290827
	_cons	1.706821	.6464476	2.64	0.008	.439807	2.973835

(mode==Car is the base outcome)

Here, the pattern is clearer: Wealthy & large families use cars

Multinomial Logit - Stata Notes: mlogit

- Dependent variable: any categorical variable
 - Don't need to be positive or sequential
 - Ex: Bus = 1, Train = 2, Car = 3
 - Or: Bus = 0, Train = 10, Car = 35
- Base category can be set with option:
 - `mlogit mode income familysize, baseoutcome(3)`
- Exponentiated coefficients called “relative risk ratios”, rather than odds ratios
 - `mlogit mode income familysize, rrr`

MLogit Example: Car vs. Bus vs. Train

- Exponentiated coefficients: relative risk ratios

Multinomial logistic regression

Number of obs = 152

LR chi2(4) = 42.63

Prob > chi2 = 0.0000

Log likelihood = -138.68742

Pseudo R2 = 0.1332

mode	RRR	Std. Err.	z	P> z	[95% Conf. Interval]	
Train						
income	.9444061	.0118194	-4.57	0.000	.9215224	.9678581
familysize	.8204706	.1632009	-0.99	0.320	.5555836	1.211648
Bus						
income	.9743237	.0136232	-1.86	0.063	.9479852	1.001394
familysize	.4185063	.1370806	-2.66	0.008	.2202385	.7952627

(mode==Car is the base outcome)

$\exp(-.057) = .94$. Interpretation is just like odds ratios... BUT comparison is with reference category.

Multinomial Logit: Predicted Probabilities

- You can predict probabilities for each case
 - Each outcome has its own probability (they add up to 1)
- ```
. predict predtrain predbus predcar if e(sample), pr
```
- ```
. list predtrain predbus predcar
```

	predtrain	predbus	predcar
1.	.3581157	.3089684	.3329159
2.	.448882	.1690205	.3820975
3.	.3080929	.3106668	.3812403
4.	.0840841	.0562263	.8596895
5.	.2771111	.1665822	.5563067
6.	.5169058	.279341	.2037531
7.	.5986157	.2520666	.1493177
8.	.3080929	.3106668	.3812403
9.	.0934616	.1225238	.7840146
10.	.6262593	.1477046	.2260361

This case has a high predicted probability of traveling by car

This probabilities are pretty similar here...

Multinomial Logit: Predicted Probabilities

- Similar to the logit command, you can show how probabilities change across independent variables
 - Manually compute mean of predicted probabilities
 - Other variables will be left “as is” (ceteris paribus) unless you set them manually before you use “predict”

```
. mean predcar, over(familysize)
```

	Over	Mean
-----+-----		
predcar		
	1	.2714656
	2	.4240544
	3	.6051399
	4	.6232910
	5	.8719671
	6	.8097709

Probability of using car increases with family size

Note: Values bounce around because other vars are not set to common value.

Note 2: Again, scatter plots aid in summarizing such results

Multinomial Logit Assumptions

- Can also look at *ologit* (ordered outcomes) – similar setup in Stata
- Multinomial logit is designed for outcomes that are **not complexly interrelated**
- Critical assumption: Independence of Irrelevant Alternatives (IIA)
 - Odds of one outcome versus another should be **independent** of other alternatives
 - Problems often come up when dealing with individual choices...aren't most of our choices somewhat interrelated?

Power & Sample Size in Regression

- Sample size will depend on the number of predictors
- Power will depend on sample size AND the magnitude of the effect (i.e.; the size of the coefficients)
- In simple linear regression with 1 predictor we can determine this by comparing the slope (=coefficient on b) to a slope of 0 or ???
- In multiple regression you can find the sample size by knowing the number of predictors & the R^2 value
- Using the Power & Sample Size menu in Stata