

Ordinal and Multinomial Logistic Regression

A New Example Using Data From *Multilevel Thinking*

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1 Background

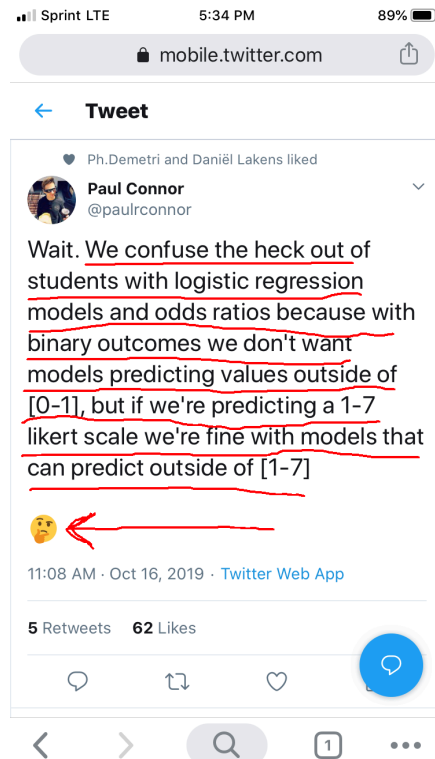


Figure 1: A Tweet

2 The Data

Data are simulated data on parent behaviors and child outcomes from *Multilevel Thinking*.

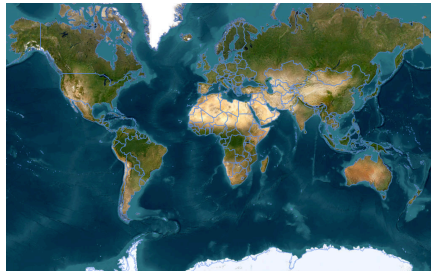


Figure 2: Simulated Data on Countries of the World

```
use "https://github.com/agrogan1/multilevel-thinking/raw/main/simulate-and-analyze-multilevel-data/simulate-and-analyze-multilevel-data/simulated_multilevel_data.dta"
describe
```

note:

```
https://github.com/agrogan1/multilevel-thinking/raw/main/simulate-and-analyze-multilevel-data/simulated_multilevel_data.dta redirected to
> https://raw.githubusercontent.com/agrogan1/multilevel-thinking/main/simulate-and-analyze-multilevel-data/simulated_multilevel_data.dta
```

```
Contains data from https://github.com/agrogan1/multilevel-thinking/raw/main/simulate-and-analyze-multilevel-data/simulated_multilevel_data.dta
```

```
Observations:      3,000
Variables:          8                               21 Apr 2023 12:38
```

Variable name	Storage type	Display format	Value label	Variable label
country	float	%9.0g		country id
HDI	float	%9.0g		Human Development Index
family	float	%9.0g		family id
id	str7	%9s		unique country family id
group	float	%9.0g		arbitrary group variable
physical_punishment	float	%9.0g		physical punishment in past week
warmth	float	%9.0g		parental warmth in past week
outcome	float	%9.0g		beneficial outcome

```
Sorted by: country family
```

3 Setup

We need to create a categorical outcome variable for demonstration purposes.

```

* create an outcome_group variable

egen outcome_group = cut(outcome), group(3) // divide outcome into groups

label define outcome_group 0 "low" 1 "medium" 2 "high" // define value labels

label values outcome_group outcome_group // attach value labels

tabulate outcome_group

```

Running C:\Users\agrogan\Desktop\GitHub\newstuff\categorical\ordinal-multinomia
> l-logistic-regression-2\profile.do .

outcome_group	Freq.	Percent	Cum.
low	1,000	33.33	33.33
medium	1,000	33.33	66.67
high	1,000	33.33	100.00
Total	3,000	100.00	

4 Ordinal Logistic Regression

$$\ln \left(\frac{p(y \leq k)}{p(y > k)} \right) = \beta_0 + \beta_1 x_1 + \dots$$

Because the data are clustered by countries, we will use the `cluster(country)` option in each model. The `brant` command can be installed by typing `findit brant`, and installing the Long & Freese `spost` utilities.

```

ologit outcome_group physical_punishment warmth HDI i.group, or cluster(country) // ordinal logit

brant // brant test

margins, at(warmth = (1(1)7)) // margins at different values of warmth

marginsplot, title("Predicted Probabilities From Ordinal Logit") ///
plot(_outcome, labels("low" "medium" "high")) // graph w/ manual labels

graph export myologit.png, replace

```

Running C:\Users\agrogan\Desktop\GitHub\newstuff\categorical\ordinal-multinomia
> l-logistic-regression-2\profile.do .

Iteration 0: Log pseudolikelihood = -3295.8369

Iteration 1: Log pseudolikelihood = -3157.4676
 Iteration 2: Log pseudolikelihood = -3157.0335
 Iteration 3: Log pseudolikelihood = -3157.0333

Ordered logistic regression

Number of obs = 3,000
 Wald chi2(4) = 242.78
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0421

Log pseudolikelihood = -3157.0333

(Std. err. adjusted for 30 clusters in country)

	Odds ratio	Robust std. err.	z	P> z	[95% conf. interval]	
physical_p-t	.7962002	.0197074	-9.21	0.000	.7584964	.8357781
warmth	1.282995	.026044	12.28	0.000	1.232951	1.335069
HDI	1.00389	.0058436	0.67	0.505	.9925017	1.015409
2.group	1.322192	.0754851	4.89	0.000	1.182221	1.478735
/cut1	-.04647	.4096606			-.84939	.7564499
/cut2	1.446814	.426558			.610776	2.282853

Note: Estimates are transformed only in the first equation to odds ratios.

Brant test of parallel regression assumption

	chi2	p>chi2	df
All	1.98	0.739	4
physical_punishment	1.45	0.229	1
warmth	0.20	0.656	1
HDI	0.05	0.818	1
2.group	0.18	0.672	1

A significant test statistic provides evidence that the parallel regression assumption has been violated.

Predictive margins
 Model VCE: Robust

Number of obs = 3,000

1._predict: Pr(outcome_group==0), predict(pr outcome(0))
 2._predict: Pr(outcome_group==1), predict(pr outcome(1))
 3._predict: Pr(outcome_group==2), predict(pr outcome(2))

1._at: warmth = 1
 2._at: warmth = 2
 3._at: warmth = 3
 4._at: warmth = 4
 5._at: warmth = 5
 6._at: warmth = 6

7._at: warmth = 7

		Delta-method				[95% conf. interval]	
		Margin	std. err.	z	P> z		
_predict#_at							
1	1	.4715116	.0239632	19.68	0.000	.4245446	.5184785
1	2	.411902	.0219914	18.73	0.000	.3687996	.4550044
1	3	.3547047	.0204707	17.33	0.000	.3145829	.3948265
1	4	.3012864	.0194346	15.50	0.000	.2631953	.3393776
1	5	.2526558	.0187163	13.50	0.000	.2159724	.2893391
1	6	.2094156	.0180743	11.59	0.000	.1739907	.2448405
1	7	.1717793	.0173168	9.92	0.000	.137839	.2057196
2	1	.3210415	.0100789	31.85	0.000	.3012872	.3407958
2	2	.3376888	.0091914	36.74	0.000	.3196739	.3557037
2	3	.3465153	.0092644	37.40	0.000	.3283575	.3646731
2	4	.3467361	.010075	34.42	0.000	.3269895	.3664827
2	5	.3383307	.0114619	29.52	0.000	.3158658	.3607955
2	6	.3220464	.0133672	24.09	0.000	.2958472	.3482456
2	7	.2992734	.0156422	19.13	0.000	.2686153	.3299314
3	1	.207447	.0183764	11.29	0.000	.1714298	.2434641
3	2	.2504092	.0196723	12.73	0.000	.2118522	.2889661
3	3	.29878	.021223	14.08	0.000	.2571838	.3403763
3	4	.3519775	.0231631	15.20	0.000	.3065787	.3973762
3	5	.4090136	.0255026	16.04	0.000	.3590294	.4589977
3	6	.468538	.0280772	16.69	0.000	.4135078	.5235682
3	7	.5289473	.0305829	17.30	0.000	.469006	.5888886

Variables that uniquely identify margins: warmth

file myologit.png saved as PNG format

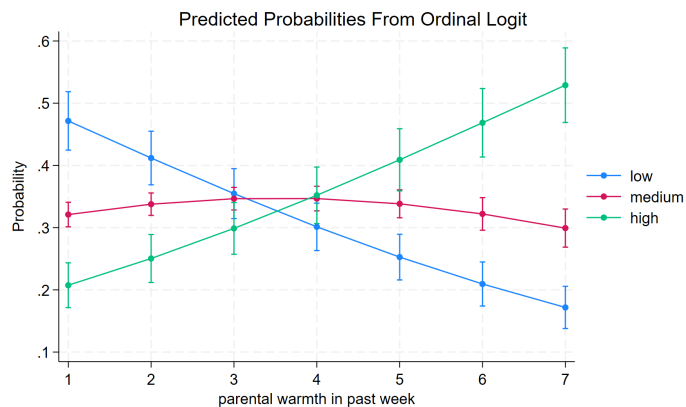


Figure 3: marginsplot from ologit

5 Multinomial Logistic Regression

$$\ln \left(\frac{P(y = y_2)}{P(y = y_1)} \right) = \ln \left(\frac{P(y = \text{something else})}{P(y = \text{something})} \right)$$
$$= \beta_0 + \beta_1 x_1 + \dots$$

$$\ln \left(\frac{P(y = y_3)}{P(y = y_1)} \right) = \ln \left(\frac{P(y = \text{something else altogether})}{P(y = \text{something})} \right)$$
$$= \beta_0 + \beta_1 x_1 + \dots$$

Because the *Brant* test was insignificant, the results below are likely to look similar. Imagine, however, if the *Brant* test were statistically significant, suggesting that we should estimate separate regression coefficients for each value of the outcome. Imagine, in addition, if we were estimating an outcome that were truly multinomial in nature, such as *post-secondary* education pursued: *none*, *vocational*, *university*. For heuristic purposes, we will relabel the outcome accordingly.

```
label define outcome_group2 0 "none" 1 "vocational" 2 "university" // define value labels
label values outcome_group outcome_group2 // attach NEW value labels

tabulate outcome_group

mlogit outcome_group physical_punishment warmth HDI i.group, rr cluster(country)

margins, at(warmth = (1(1)7)) // margins at different values of warmth

marginsplot, title("Predicted Probabilities From Multinomial Logit") ///
plot(_outcome, labels("none" "vocational" "university")) // graph w/ manual labels

graph export mymlogit.png, replace
```

Running C:\Users\agrogan\Desktop\GitHub\newstuff\categorical\ordinal-multinomia
> l-logistic-regression-2\profile.do .

outcome_gro up	Freq.	Percent	Cum.
none	1,000	33.33	33.33
vocational	1,000	33.33	66.67
university	1,000	33.33	100.00
Total	3,000	100.00	

Iteration 0: Log pseudolikelihood = -3295.8369
Iteration 1: Log pseudolikelihood = -3159.3121

Iteration 2: Log pseudolikelihood = -3157.2541
 Iteration 3: Log pseudolikelihood = -3157.2532
 Iteration 4: Log pseudolikelihood = -3157.2532

Multinomial logistic regression

Number of obs = 3,000
 Wald chi2(8) = 216.92
 Prob > chi2 = 0.0000
 Pseudo R2 = 0.0420

Log pseudolikelihood = -3157.2532

(Std. err. adjusted for 30 clusters in country)

	RRR	Robust std. err.	z	P> z	[95% conf. interval]	
outcome_group						
none	(base outcome)					
vocational						
physical_p~t	.8284144	.0268834	-5.80	0.000	.7773647	.8828166
warmth	1.172042	.0323704	5.75	0.000	1.110284	1.237235
HDI	1.003045	.0039244	0.78	0.437	.9953822	1.010766
2.group	1.244621	.1034633	2.63	0.008	1.057495	1.46486
_cons	.7248303	.2045156	-1.14	0.254	.4169312	1.26011
university						
physical_p~t	.733425	.0260105	-8.74	0.000	.6841767	.7862183
warmth	1.402776	.0404291	11.74	0.000	1.325733	1.484296
HDI	1.005061	.0080327	0.63	0.528	.9894402	1.020929
2.group	1.454744	.1119325	4.87	0.000	1.251102	1.691534
_cons	.3950266	.227379	-1.61	0.107	.1278413	1.220623

Note: _cons estimates baseline relative risk for each outcome.

Predictive margins

Number of obs = 3,000

Model VCE: Robust

1._predict: Pr(outcome_group==none), predict(pr outcome(0))
 2._predict: Pr(outcome_group==vocational), predict(pr outcome(1))
 3._predict: Pr(outcome_group==university), predict(pr outcome(2))

1._at: warmth = 1
 2._at: warmth = 2
 3._at: warmth = 3
 4._at: warmth = 4
 5._at: warmth = 5
 6._at: warmth = 6
 7._at: warmth = 7

	Margin	Delta-method std. err.	z	P> z	[95% conf. interval]	
_predict#_at						

1 1		.4655491	.0256453	18.15	0.000	.4152852	.515813
1 2		.4108856	.0225268	18.24	0.000	.3667338	.4550374
1 3		.3566849	.020455	17.44	0.000	.3165938	.3967761
1 4		.3043247	.0194768	15.62	0.000	.2661507	.3424986
1 5		.2551027	.0192162	13.28	0.000	.2174397	.2927657
1 6		.210102	.0191257	10.99	0.000	.1726162	.2475877
1 7		.170087	.0187808	9.06	0.000	.1332774	.2068966
2 1		.3312655	.0149681	22.13	0.000	.3019286	.3606025
2 2		.3403628	.010943	31.10	0.000	.318915	.3618106
2 3		.3438888	.0090929	37.82	0.000	.3260671	.3617104
2 4		.3414688	.010569	32.31	0.000	.3207539	.3621838
2 5		.3331582	.014179	23.50	0.000	.3053679	.3609485
2 6		.3194468	.0184628	17.30	0.000	.2832603	.3556333
2 7		.301194	.0227261	13.25	0.000	.2566517	.3457363
3 1		.2031854	.0183179	11.09	0.000	.1672829	.2390879
3 2		.2487516	.0194812	12.77	0.000	.2105691	.2869341
3 3		.2994263	.0210267	14.24	0.000	.2582148	.3406379
3 4		.3542065	.0231943	15.27	0.000	.3087464	.3996666
3 5		.4117391	.0260214	15.82	0.000	.3607381	.4627401
3 6		.4704512	.0292975	16.06	0.000	.4130291	.5278733
3 7		.528719	.0326555	16.19	0.000	.4647153	.5927227

Variables that uniquely identify margins: warmth

file mymlogit.png saved as PNG format

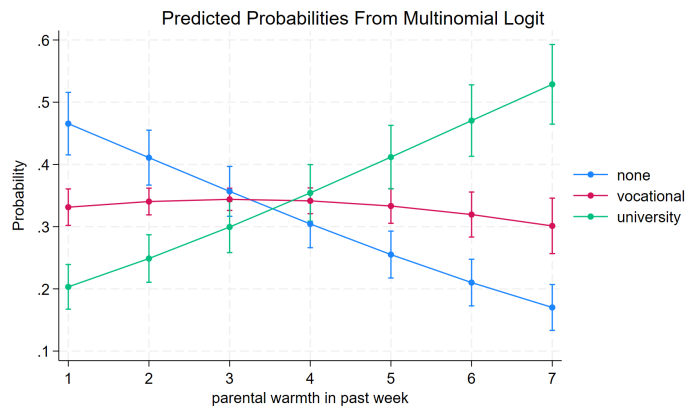


Figure 4: marginsplot from mlogit